# A PLANAR FACILITY LOCATION-ALLOCATION PROBLEM WITH FIXED AND VARIABLE COST STRUCTURES FOR RURAL ELECTRIFICATION

A THESIS SUBMITTED TO

THE GRADUATE SCHOOL OF ENGINEERING AND SCIENCE

OF BILKENT UNIVERSITY

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR

THE DEGREE OF

MASTER OF SCIENCE

IN

INDUSTRIAL ENGINEERING

By

Beste Akbaş

June 2021

A PLANAR FACILITY LOCATION-ALLOCATION PROBLEM WITH FIXED AND VARIABLE COST STRUCTURES FOR RURAL ELECTRIFICATION
By Beste Akbaş
June 2021

We certify that we have read this thesis and that in our opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science.

Ayşe Selin Kocaman(Advisor)

Bahar Yetiş

Mustafa Kemal Tural

Approved for the Graduate School of Engineering and Science:

Ezhan Karaşan
Director of the Graduate School

# ABSTRACT

## A PLANAR FACILITY LOCATION-ALLOCATION PROBLEM WITH FIXED AND VARIABLE COST STRUCTURES FOR RURAL ELECTRIFICATION

Beste Akbaş
M.S. in Industrial Engineering
Advisor: Ayşe Selin Kocaman
June 2021

One of the major impediments to the economic development of developing countries is the lack of access to affordable, sustainable, and reliable modern energy systems. Even today, hundreds of millions of people, most of whom live in rural areas, do not have access to essential electricity services. In this study, we present a planar facility location-allocation problem for the planning of decentralized energy systems in the context of rural development. We consider nano-grid and micro-grid systems to electrify the rural households. While micro-grids serve multiple households with a common generation facility, nano-grids are small-scale systems serving individual consumers. The households served by micro-grid facilities are connected to the generation point with low voltage cables, for which we employ a distance limit constraint due to the technical concerns, including the power loss and allowable voltage levels. In this problem, we minimize the total investment cost that consists of the facility opening and the low voltage connection costs. Additionally, given the diversity of cost structures in the renewable energy investments, we provide three different formulations where we incorporate different combinations of fixed and variable cost components for facilities. For this problem, we provide a mixed integer quadratically constrained problem formulation and propose six heuristic approaches. The three of these heuristic methods are multi-stage approaches in which we solve optimization models, while the other methods utilize faster clustering techniques that have been extensively studied in the literature. We conduct computational experiments on the synthetic data and real life instances from the small villages in Sub-Saharan Africa, and perform a comparative analysis of the suggested heuristic approaches.

*Keywords:* Rural electrification, decentralized energy systems, planar multi-facility location-allocation problem.

# ÖZET

# KIRSAL KESİM ELEKTRİFİKASYONU İÇİN SABİT VE DEĞİŞKEN MALİYETLİ TESİSLERİN DÜZLEMSEL YER SEÇİMİ PROBLEMİ

Beste Akbaş
Endüstri Mühendisliği, Yüksek Lisans
Tez Danışmanı: Ayşe Selin Kocaman
Haziran 2021

Gelişmekte olan ülkelerin kalkınmasının önündeki en büyük engellerden biri de uygun fiyatlı, sürdürülebilir, ve güvenilir modern enerji sistemlerine erişimin yetersiz olmasıdır. Günümüzde hâlâ çoğunluğu kırsal alanlarda ikamet etmekte olan yüz milyonlarca insanın elektriğe erişiminin olmadığı bilinmektedir. Bu doğrultuda, çalışmamızda iki farklı merkezi olmayan enerji sistemi göz önüne alınmış olup, kırsal bölgelerin kalkınması amacıyla yenilenebilir enerji tesislerinin düzlemsel yer seçimi ve atanması problemi sunulmuştur. Problemde mikro-şebeke ve nano-şebeke sistemler ele alınmıştır. Mikro-şebekeler birden fazla haneye tek bir tesis ile hizmet verirken, nano-şebekeler daha küçük boyutlu, yalnızca bir haneye hizmet verebilen sistemlerdir. Mikro-şebekelerden hizmet alan haneler enerji üretim tesisine düşük voltajlı kablolar ile bağlanmaktadır. Ancak kablo uzunluğu, voltaj düşümü ve enerji kaybı gibi teknik kaygılar sebebiyle belirli mesafe eşikleri ile sınırlandırılmıştır. Problem farklı ölçeklerdeki tesislerin açılma maliyetleri ile hane ve tesis bağlantılarını sağlayan kablo maliyetleri toplamını en küçükleyecek şekilde modellenmiştir. Ayrıca, kullanılacak yenilenebilir enerji teknolojisine bağlı olarak değişebilen maliyet yapısının modellenebilmesi için amaç fonksiyonuna değişken maliyet bileşeninin de dahil edildiği üç farklı formülasyon oluşturulmuştur. Problemin çözümüne yönelik olarak karışık tamsayı programlama modeli sunulmuş ve altı sezgisel metot geliştirilmiştir. Bu sezgisel metotlardan üçü optimizasyon modellerinin de çözüldüğü çok-aşamalı yaklaşımlardan, diğer metotlar ise literatürde çokça çalışılmış olan kümeleme tekniklerinden oluşmaktadır. Geliştirilen sezgisel metotlar hem deneysel örnekler hem de Sahra-altı Afrika bölgesinden seçilmiş gerçek örnekler üzerinde test edilmiş ve sezgisel metotların karşılaştırmalı analizi yapılmıştır.

*Anahtar sözcükler*: Kırsal kesim elektrifikasyonu, merkezi olmayan enerji sistemleri, sürekli düzlemde çoklu yer seçimi ve ataması problemi.

# Acknowledgement

First of all, I would like to express my heartfelt gratitude to Asst. Prof. Ayşe Selin Kocaman, who provided me endless support and precious opportunities throughout my graduate study. She has always encouraged me on the path to my lifelong academic journey, and guided me to shape my future goals. Besides her invaluable supervision, I feel incredibly fortunate for having the opportunity to work with such an inspiring and kind-hearted supervisor, and honored to be one of her students.

I would also like to express my thankfulness to Prof. Bahar Yetiş and Asst. Prof. Mustafa Kemal Tural for devoting their valuable time to read and review my thesis and their substantial remarks.

I am indebted to my greatest friends Özgegül Dönmez, Zehra Ağır, and Ülkem Ercin for their continuous support, amazing friendship, and always being there for me to overcome difficulties for the last ten years. I would also like to thank Sinem Savaşer Kınay and Ömer Burak Kınay for their encouragement from the first day of my undergraduate study. Besides them, many thanks go to Nilsu Uzunlar, Serkan Turhan, Mahsa Abbaszadeh Nakhost, and all other EA305 members for the family-like atmosphere at the office.

Finally, words are not enough to express my gratitude to my dearest parents and my best friends, Yeşim Özlem Akbaş and Murat Akbaş, who have always motivated and supported me to achieve my dreams. I am deeply grateful for their unconditional love and limitless sacrifices to make my dreams come true. I would never be able to do it without them. I dedicate this thesis to my parents and my dear grandma, Mualla Teke, who is truly the sweetest person I have ever known.

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# Chapter 1

# Introduction

In 2015, the United Nations member states adopted seventeen Sustainable Development Goals (SDGs) as a universal call "to action to end poverty, protect the planet and improve the lives and prospects of everyone, everywhere" along with a 15-year plan as a part of the 2030 Agenda for Sustainable Development [2]. Among these goals, Sustainable Development Goal 7 (SDG7) includes specific targets to provide access to "affordable, reliable, sustainable and modern energy for all" [3] and has a direct impact on other SDGs such as no poverty (SDG1), quality education (SDG4), economic growth (SDG8) and climate action (SDG14).

There is a significant progress towards reaching SDG7 in recent years with the number of people without electricity access dropping from 1 billion in 2016 to 840 million in 2019 [4]. Yet, the current progress is found to be insufficient to achieve the universal access target outlined in SDG7. According to International Energy Agency (IEA) projections, the number of people without access to electricity is expected to reduce to around 620 million by 2030. However, this number is projected to increase again to 740 million by 2050 due to population growth surpassing the electrification growth [5]. The majority of the unelectrified population reside in rural areas of Sub-Saharan Africa (SSA) [6]. Currently, 44% of the population in SSA has access to electricity, whereas this rate drops to 25% when only rural areas are taken into consideration [7]. Rural electrification is, therefore, considered to be the main focus area to achieve universal access to energy.

Mathematical modeling and optimization methods can make significant contributions to the rural electrification efforts towards the SDG7. These efforts involve connecting the hardest to reach households to the electricity and usually require new strategies specific to the geography and demographics of the areas. In this thesis, we first conducted a literature review to assess research trends on the rural electrification efforts and identified the recent studies presenting a novel optimization frameworks. In the review process, we surveyed the 20 years from 2000 to the time of analysis through 2020 and obtained 102 papers focusing on different aspects of rural electrification problems. We classified these articles into four categories based on the characteristics of the rural electrification problem they addressed, and provided a detailed analysis of each electrification problem type.

The survey has revealed that the literature on the rural electrification problem lacks analyses on the trade-off between different electrification options using the household-level data. The majority of the existing work compares the electrification alternatives using village or county-level datasets. Hence, motivated by a research gap in the "last-mile" problems concerning the final consumer level energy planning, we introduced a planar facility location-allocation problem in the context of rural electrification towards universal access to electricity.

In this study, we consider nano-grid and micro-grid systems to provide electricity to remote or hilly areas that would be difficult to connect with the grid option. The number of households allocated to the serving facilities determines the type of the decentralized energy system. For instance, the decentralized systems serving more than one consumer are called micro-grids, whereas isolated stand-alone systems serving a single consumer are considered as nano-grids. The households served by micro-grid facilities are connected to the generation point with a low voltage network having star topology. However, these connections must be within a specific distance limit due to technical constraints such as power loss and the maximum permitted voltage drop. This study aims to determine the locations of nano-grid and micro-grid source facilities on the continuous space for the given spatial locations of the rural households while minimizing the facility opening costs and the cost of the low voltage network. Unlike many other facility location problems in the literature, facilities can be located anywhere on the continuous space. Thus the set of candidate facilities does not include a finite number of elements.

The costs of the source facilities are assumed to be different for nano-grid and micro-grid systems. Although economies of scale applies to the micro-grid facility costs, the additional cost of the local distribution network can enforce energy planners to choose between nano-grid and micro-grid systems [8]. The cost structure of the decentralized systems can include different cost components depending on the renewable technologies used to electrify the rural households. While the cost of modular generators such as solar panels generally depends on the size of the installed module, wind turbines and similar generation components require fixed upfront costs for the given bulk generation capacities. Similarly, the socio-demographics, geographical characteristics, and other country-specific attributes are also considered as the key drivers affecting the cost structures and the cost trends in different markets. Especially the unit costs of solar home systems and solar mini-grid components are observed to change in wider ranges depending on the country-specific factors such as the logistics, material and labor expenses [9]. Therefore, given the diversity in the cost components of different renewable technologies and the significant cost variations in the installation costs, we incorporate multiple cost structures, including fixed facility costs and variable cost components, to investigate several investment decisions that energy planners can encounter.

In this thesis, we introduce a similar location-allocation problem to Gokbayrak and Kocaman [10], where the decentralized systems are assumed to have the same fixed opening costs. However, in this study, we incorporate different combinations of fixed and variable cost components to evaluate the trade-off between the decentralized systems. To analyze the trade-off between two decentralized energy options and provide a cost-efficient network design for rural settlements, we first developed a mixed-integer quadratically constrained model. As our problem can be reduced to well-known NP-Hard problems, we propose three mathematical modeling-based heuristics and three clustering-based algorithms for this planar facility location and allocation problem. We present a comparative analysis of the solution methods in terms of the solution quality and computational efficiency. In the first heuristic approach, we adopted the multi-stage method proposed in Gokbayrak and Kocaman [10] and applied it to our problem. Considering the demand nodes and the additional promising points as the candidate locations, we first solve the discrete counterpart of the problem in order to obtain better initial estimates. For the given discrete solution, we implement a modified version of Coopers's iterative algorithm [11] to improve the facility locations on the continuous space and reallocate the households depending on the proposed locations of serving facilities. While alternating between the location and allocation steps, we project the facility locations using a modified version of a well-known algorithm called Weiszfeld Algorithm [12].

Additionally, we propose a new methodology to identify the promising candidate locations to enrich the domain of the discrete problem that could lead to further improvements. We also propose to apply a post-processing step to adapt the multi-stage heuristic with unicost structure as in [10] to a multi-cost version. In addition to the model-based multi-stage heuristic approaches, we also developed faster heuristic algorithms using top-down and bottom-up clustering techniques. Employing the well-known partitioning algorithms such as agglomerative clustering [13], DBSCAN [14], and k-means algorithm [15], we provide hybrid solution methods that benefit from simple and practical approaches.

The chapters of this thesis are outlined as follows: In Chapter 2, we present a literature review on rural electrification and planar facility location-allocation problems. Chapter 3 defines a Planar Facility Location-Allocation Problem in the context of rural energy planning and provides mixed-integer quadratically-constrained programming models considering different cost structures. In Chapter 4, we provide the details of the multi-stage optimization frameworks and clustering-based heuristic algorithms. Chapter 5 includes the numerical results and the comparative analysis of the solution methods proposed in Chapter 4. Finally, in Chapter 6, we present the summary of the contributions of this study and discuss the possible extensions for future work.

# Chapter 2

# Literature Review

The rural electrification problem that we discuss in this thesis is strongly related to some of the well-known problems in location theory literature. In the first section, we present the recent works on rural electricity planning problems with an optimization perspective. In the latter section, we discuss the studies conducted upon planar facility location-allocation problems.

## 2.1 Review of Rural Electrification Problem

Despite a large number of review papers on the optimization studies around the sustainable energy area, the literature lacks a survey that reviews the optimization efforts rural electrification . In this regard, we conducted a literature review focusing on the existing work that presents a novel optimization framework for rural electrification problems, and we surveyed academic articles ranging from 2000 to 2020. We employed a systematic approach to identify the relevant articles using Web of Science database as the primary source and utilized "rural electrification" and "Optim*" keywords in the search. To expand the scope of the surveyed papers, we also used additional keywords, including "least-cost," "energy planning," and "electrification." After having the relevant articles identified, we evaluated 433 articles by title and abstract and narrowed down our focus to 102 articles for a detailed analysis. The preliminary analysis of the existing work directed us to propose a categorization based on four distinct problem types: (i) optimal system configuration and unit sizing, (ii) optimal power dispatch strategy,(iii) optimal technology choice, and (iv) optimal network design.

In general, optimal system configuration and Unit Sizing studies involve the selection of appropriate energy resources and unit sizing of the components for the design of hybrid energy systems. The choice of proper energy sources plays a vital role in providing continuous and reliable electricity to rural areas. The sizing of the system components is also a critical decision for the energy planners due to the intermittent nature of the renewable energy sources. Thus, optimal system configuration and unit sizing studies provide an optimization framework for the choice of generation technologies based on the technical and economic viability, and develop a guide for energy planners to determine the optimal sizing of each system component. In Table 2.1, we summarize the reviewed articles in terms of methodology, optimization criteria, and components of the hybrid systems, and we provide the details of the case studies with the geographical scale of optimization and the resolution of data.

Optimal power dispatch strategy problem, on the other hand, focuses on the scheduling of operational activities, including the electricity generation and the power flow between components. The economic viability of hybrid energy systems is strongly dependent on the operating costs which arise from the daily activities during electricity generation. Moreover, the allocation of energy resources and the power flow scheduling significantly impact the reliability of on-grid and off-grid hybrid energy systems. Thereby, planning the power dispatch strategy constitutes a critical part of the electrification projects to provide affordable and reliable electricity to the consumers living in rural areas. In Table 2.2, we summarize the articles focusing on the optimization of the control strategies, including the scheduling of power flows and electricity generation of hybrid systems.

The main focus of the optimal technology choice articles is to compare off-grid and on-grid electrification alternatives for each demand point, identify the cost-efficient electrification option and provide a power network design between the grid-compatible nodes. Although centralized systems mainly rely on fossil fuels for electricity generation, they are considered a more reliable form of electrification in the long term. Decentralized systems, on the other hand, can be a cost-competitive off-grid option for remote and hilly areas where connection to the main grid is inconvenient. Even though identifying the best means of electrification for each consumer can be particularly challenging when the number of alternatives is large, hybrid options combining on-grid systems with decentralized technologies can provide interesting solutions worthy of consideration. Therefore, optimal technology choice studies evaluate the trade-off between different alternatives to determine the appropriate electrification option for each demand node. Table 2.3 lists the reviewed articles that fall into the optimal technology choice category and summarizes the optimization approaches, objective function, the details of the case studies, geographical scale of the optimization, and the resolution of the data used in the analysis.

The optimal network design studies conduct a detailed analysis of the networked options for rural electrification. These studies generally incorporate on-grid electrification options such as grid expansion, mini-grid, and micro-grid systems to electrify remote settlements. In table 2.4, we detail the studies in terms of proposed optimization frameworks, load-balancing and power flow requirements, case studies in underdeveloped and developing countries, and the solution space considered in these papers.

While there is substantial literature on rural electrification efforts, the distribution of the reviewed articles by problem type has revealed the literature gap on the networked options and the optimal technology choice problems. Figure 2.1 presents a Venn diagram with the number of studies that fall under these four categories. The majority of the reviewed studies address a single problem type. Nevertheless, some studies integrate two different problem types into one optimization framework as visible in the intersection areas of the diagram. As shown in Figure 2.1, the optimal system configuration and optimal dispatch strategy constitutes a significant portion of the existing work, whereas the optimal network design and optimal technology studies observed to be understudied.

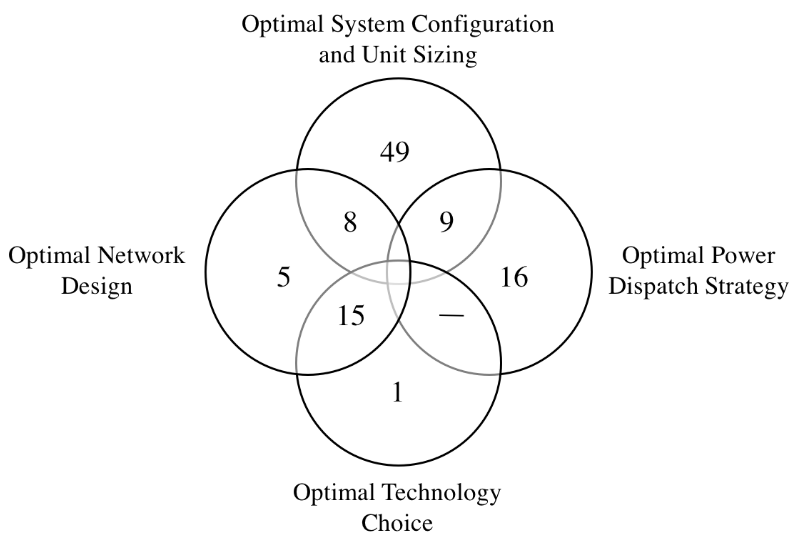


Figure 2.1: Problem categories

Another important conclusion is that the unequal distribution of the rural electrification studies can be improved by drawing the attention of the researchers to the lack of relevant studies for the areas having inadequate electrification rates. Figure 2.2 illustrates the geographical distribution of the reviewed articles and the electricity access rate of the respective countries reported by World Bank in 2018 ([1]). As demonstrated in Figure 2.2, only 11% of the articles address the countries having electrification rates below 50%. Hence, our analysis reveals a mismatch between the electrification rates and the number of optimization studies, highlighting a need for more studies in countries with low access rates.

Additionally, the majority of the studies conduct computational experiments on the village or county-level data. However, the distribution patterns of the demand settlements plays a vital role to identify the best electrification option among several alternatives with higher accuracy. Preliminary analyses of the geospatial location of the final consumers in rural Ethiopia demonstrate that high inter-household distances lead to higher "last-mile" cost of low voltage connections. Hence, given crucial role of the geospatial household settlement patterns in energy planning, this review highlights the scarcity of the analyses on the final consumer level.

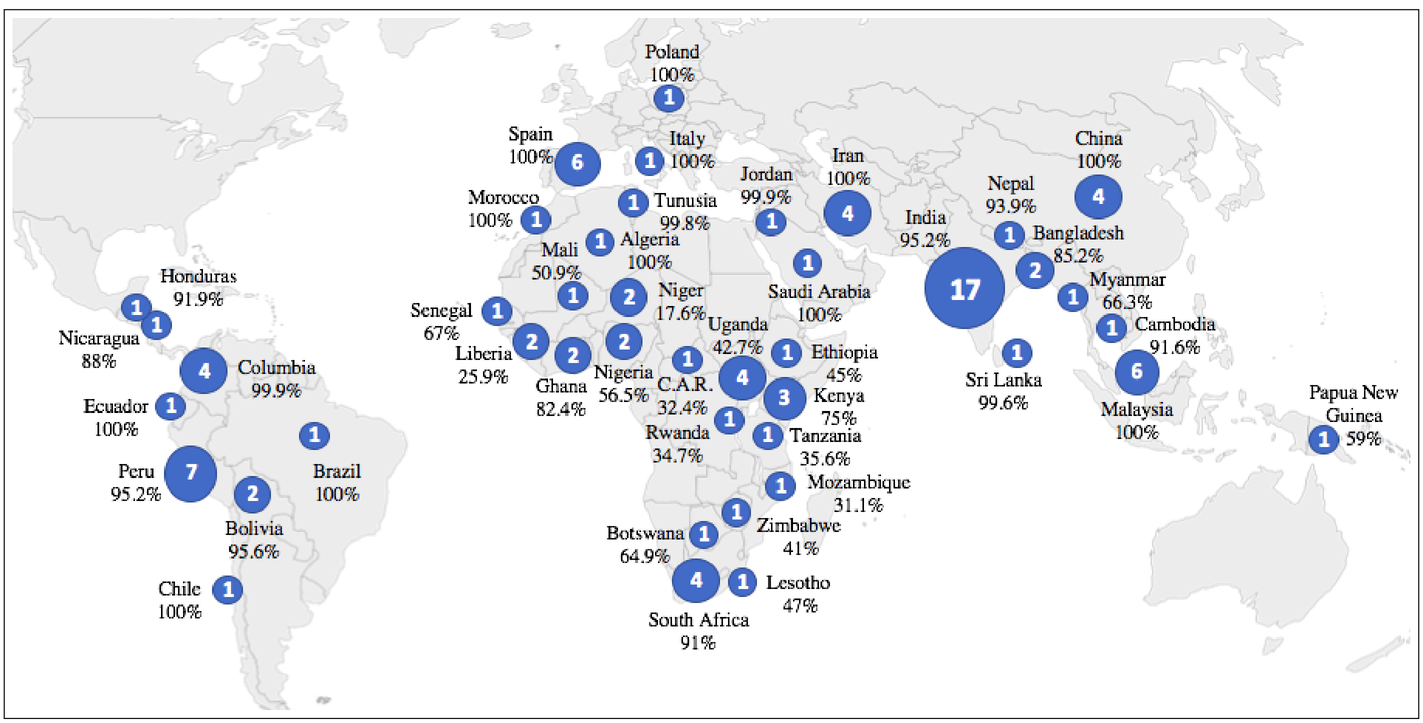


Figure 2.2: Distribution map of the reviewed articles and associated electrification rates reported by the World Bank ([1])

Table 2.1: Optimal System Configuration and Unit Sizing

| Article | Heuristics - Metaheuristics | Model | Objective | Uncertainty | Grid Connected | PV | Wind | Diesel | Hydro | Biomass | Biogas | Battery | Country | Scale |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Bala & Siddique (2009) | GA | | Cost | - | - | ✓ | - | ✓ | - | - | - | ✓ | Bangladesh | Village |
| Perera et al. (2013) | Steady $\varepsilon$-State Evolutionary Algorithm | | Cost, GHG Emission | - | - | ✓ | ✓ | - | - | - | - | - | Sri Lanka | Village |
| Borhanazad et al. (2014) | MOPSO | | Cost, LPSP | - | - | ✓ | ✓ | ✓ | - | - | - | ✓ | Iran | Village |
| Domenech et al. (2015) | | MILP | Cost | - | - | ✓ | ✓ | - | - | - | - | - | Peru | Village |
| Gonzalez et al. (2015) | GA | | Cost | - | - | ✓ | ✓ | - | - | - | - | - | Spain | Village |
| Gonzalez et al. (2015) | GA | | Cost | - | - | ✓ | ✓ | - | - | ✓ | - | - | Spain | Village |
| Ranaboldo et al. (2015) | Greedy Heuristic | | Cost | - | - | ✓ | ✓ | - | - | - | - | - | Nicaragua | Village |
| Cristobal-Monreal & Dufo-Lopez (2016) | MOEA, GA | | Cost | - | - | ✓ | - | ✓ | - | - | - | ✓ | Central African Republic | Household |
| Dufo-Lopez et al. (2016) | GA | | Cost | - | - | ✓ | ✓ | ✓ | - | - | - | ✓ | Algeria | Village |

| Article | Heuristics - Metaheuristics | Model | Objective | Uncertainty | Grid Connected | PV | Wind | Diesel | Hydro | Biomass | Biogas | Battery | Country | Scale |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Dufo-Lopez et al. (2016) | GA Monte Carlo Simulation | | Cost | ✓ | - | ✓ | ✓ | ✓ | - | - | - | ✓ | Spain | Village |
| Gonzalez et al. (2016) | GA | | Cost, CO2 Emission | - | - | ✓ | ✓ | - | - | ✓ | - | - | Spain | Village |
| Kanyarusoke et al. (2016) | | MILP | Cost | - | - | ✓ | - | - | - | - | - | - | Sub-Saharan Africa | Household |
| Rajanna & Saini (2016) | GA | | Cost | - | - | ✓ | ✓ | - | ✓ | ✓ | ✓ | - | India | Village |
| Sigarchian et al. (2016) | PSO | | Cost | - | - | ✓ | - | ✓ | - | - | - | ✓ | Lesotho | Village |
| Chauhan & Saini (2017) | HS | | Cost | - | - | ✓ | ✓ | - | ✓ | ✓ | ✓ | - | India | Village |
| Homayouni et al. (2017) | PSO | | Cost | - | - | ✓ | - | ✓ | - | - | - | ✓ | Iran | Household |
| Kocaman & Modi (2017) | | MILP | Cost | ✓ | - | ✓ | - | ✓ | - | - | - | - | India | Multiple Villages |
| Ruiz-Alvarez et al. (2017) | | LP | Cost | - | - | ✓ | ✓ | ✓ | - | - | - | ✓ | Colombia | Village |
| Sundaramoorthy (2017) | | LP | Cost | - | ✓/ - | ✓ | ✓ | - | ✓ | ✓ | - | - | India | Village |
| Eteiba et al. (2018) | FPA, HS, ABC, FA | | Cost | - | - | ✓ | - | - | - | ✓ | - | - | Egypt | Village |

| Article | Heuristics - Metaheuristics | Model | Objective | Uncertainty | Grid Connected | PV | Wind | Diesel | Hydro | Biomass | Biogas | Battery | Country | Scale |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Huang et al. (2018) | GA | | Cost | - | - | ✓ | ✓ | - | - | - | - | - | China | Village |
| Nasir et al. (2018) | | LP | Cost | - | - | ✓ | - | - | - | - | - | - | India | Village |
| Patel & Singal (2018) | PSO | | Cost | - | - | ✓ | ✓ | - | - | ✓ | ✓ | - | India | Village |
| Roberts et al. (2018) | GA | | Cost, LPSP | ✓ | - | ✓ | ✓ | ✓ | - | - | - | ✓ | Brazil | Village |
| Abuzeid et al. (2019) | PSO | | Cost | - | - | ✓ | ✓ | ✓ | - | - | - | ✓ | Jordan | Household |
| Aliyu & Tekbiyik-Ersoy (2019) | | LP | Cost | - | ✓/ - | ✓ | ✓ | - | - | - | - | - | Nigeria | Village |
| Balderrama et al. (2019) | | MILP | Cost | ✓ | - | ✓ | ✓ | ✓ | ✓ | - | - | ✓ | Bolivia | Village |
| Kumar et al. (2019) | PSO | | Cost | - | - | ✓ | - | ✓ | ✓ | - | - | ✓ | India | Village |
| Kumar et al. (2019) | | MILP | Cost | ✓ | - | ✓ | - | - | - | - | ✓ | - | India | Village |
| Malekpoor et al. (2019) | | BO-MILP | Cost, Ranking of Generators | - | - | ✓ | ✓ | ✓ | - | - | - | ✓ | NA | Village |
| Lombardi et al. (2019) | | MILP | Cost | ✓ | - | ✓ | - | ✓ | - | - | - | ✓ | Bolivia | Village |

| Article | Heuristics - Metaheuristics | Model | Objective | Uncertainty | Grid Connected | PV | Wind | Diesel | Hydro | Biomass | Biogas | Battery | Country | Scale |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Moretti et al. (2019) | | MILP | Cost | - | - | ✓ | - | ✓ | - | - | - | ✓ | Sub-Saharan Africa | Village |
| Viteri et al. (2019) | | ISO | Cost | ✓ | - | ✓ | ✓ | ✓ | ✓ | - | - | ✓ | Colombia | Village |
| Zhang et al. (2019) | NSGA-II | | Cost, LPSP | - | - | ✓ | ✓ | - | - | - | - | - | China | Village |
| Alshammari & Asumadu (2020) | PSO, Jaya HS | | Cost | - | - | ✓ | ✓ | - | - | ✓ | - | - | Saudi Arabia | Village |
| Ashtiani et al. (2020) | TLBO | | Cost | - | ✓ | ✓ | - | - | - | - | - | - | Iran | Household |
| Bandopadhyay & Roy (2020) | MFO | | Cost | - | - | ✓ | ✓ | ✓ | - | - | - | ✓ | India | Village |
| Barakat et al. (2020) | Multi-Objective PSO | | Cost, LPSP, RE Fraction | - | ✓ | ✓ | ✓ | - | - | - | - | - | Egypt | Village |
| Benalcazar et al. (2020) | | LP | Cost | - | - | ✓ | ✓ | ✓ | - | - | - | ✓ | Ecuador | Village |
| Bhayo et al. (2020) | PSO | | Cost | - | - | ✓ | - | - | ✓ | - | - | - | Malaysia | Household |
| Alberizzi et al. (2020) | | MILP | Cost | - | - | ✓ | ✓ | ✓ | - | - | - | ✓ | Italy | Village |
| Hernandez et al. (2020) | | MILP | NPV | - | - | - | - | - | ✓ | - | - | - | Peru | Village |

| Article | Heuristics - Metaheuristics | Model | Objective | Uncertainty | Grid Connected | PV | Wind | Diesel | Hydro | Biomass | Biogas | Battery | Country | Scale |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Jaszczur et al. (2020) | NSGA-II | | Cost, CO2 Emission | - | - | ✓ | ✓ | ✓ | - | - | - | ✓ | Poland | Household |
| Maqbool et al. (2020) | HS | | Cost, LPSP, RE Fraction, Job Creation | - | - | ✓ | - | - | - | ✓ | - | - | India | Village |
| Mouachi et al. (2020) | Multimodal Delayed PSO | | Cost, CO2 | - | ✓/ - | ✓ | ✓ | ✓ | - | - | - | ✓ | Morocco | Village |
| Namaganda-Kiyimba& Mutale (2020) | | MILP | Cost | - | - | ✓ | - | - | - | - | - | - | Uganda | Village |
| Oviedo et al. (2020) | Heuristic Approx. of GD | | Cost | - | - | ✓ | - | ✓ | - | - | - | ✓ | Colombia | Village |
| Rathish et al. (2020) | GA | | Cost, CO2 Emission, Unmet Load | - | - | ✓ | ✓ | ✓ | - | - | - | ✓ | India | Village |
| Ridha et al. (2020) | MOPSO | | Cost, LLP | - | - | ✓ | - | - | - | - | - | - | Malaysia | Village |
| Ridha et al. (2020) | MO-SSO | | Cost, LLP | - | - | ✓ | - | - | - | - | - | - | Malaysia | Village |
| Ridha et al. (2020) | PESA-II | | Cost, LLP | - | - | ✓ | - | ✓ | - | - | - | ✓ | Malaysia | Village |
| Ridha et al. (2020) | MADE | | Cost, LLP | - | - | ✓ | - | - | - | - | - | - | Malaysia | Village |

| Article | Heuristics - Metaheuristics | Model | Objective | Uncertainty | Grid Connected | PV | Wind | Diesel | Hydro | Biomass | Biogas | Battery | Country | Scale |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Samy et al. (2020) | MOPSO | | Cost, LPSP | - | - | - | - | ✓ | - | ✓ | - | - | Egypt | Village |
| Stevanato et al. (2020) | | LP | Cost | ✓ | - | ✓ | ✓ | ✓ | - | - | - | ✓ | Chile | Village |
| Suresh et al. (2020) | GA | | Cost | - | - | ✓ | ✓ | ✓ | - | ✓ | ✓ | ✓ | India | Multiple Villages |
| Tapia et al. (2020) | GA | | Cost, Power Generated | - | - | - | - | - | ✓ | - | - | - | Honduras | Village |

| Article | Heuristics - Metaheuristics | Model | Objective | Uncertainty | Grid Connected | PV | Wind | Diesel | Hydro | Biomass | Biogas | Battery | Country | Scale |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Yimen et al. (2020) | GA | | Cost | - | - | ✓ | ✓ | ✓ | - | - | - | ✓ | Nigeria | Village |
| Zhang et al. (2020) | HS | | Cost, LPSP | - | - | ✓ | ✓ | - | - | - | - | - | Iran | Village * |

**Abbrevations:** Artificial Bee Colony Algorithm (ABC), Firefly Algorithm (FA), Flower Pollination Algorithm (FPA), Genetic Algorithm (GA), Harmony Search (HS), Implicit Stochastic Optimization (ISO), Linear Programming (LP), Mixed Integer Linear Programming (MILP), Moth-flame Optimization (MFO), Mutation Adaptive Differential Evolution (MADE), Pareto Envelope-based Selection Algorithm (PESA-II), Particle Swarm Optimization (PSO), Salp Swarm Algorithm (SSO), Teaching-Learning Based Optimization (TLBO)
Renewable Energy (RE), Loss of Power Supply Probability (LPSP), Loss of Load Probability (LLP)

Table 2.2: Optimal Power Dispatch Strategy

| Article | Heuristics - Metaheuristics | Model | Objective | Uncertainty | Grid Connected | PV | Wind | DG | Hydro | Biomass | Battery | Country | Scale |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Balamurugan et al. (2009) | | LP | Curtailed Energy | - | - | ✓ | ✓ | - | - | ✓ | - | India | Village |
| Herran & Nakata (2012) | | LP | Cost | - | ✓ | - | - | - | - | ✓ | - | Colombia | Village |
| Balamurugan & Kumaravel (2014) | | LP | Supplied Energy | - | - | ✓ | ✓ | - | - | ✓ | - | India | Village |
| Kusakana (2015) | | NLP | Cost | - | - | - | - | ✓ | ✓ | - | - | South Africa | Village |
| Kusakana (2016) | Interior-Point Algorithm | | Cost | - | - | ✓ | ✓ | ✓ | ✓ | - | ✓ | South Africa | Village |
| Li & Qiu (2016) | NSGA-II | | Variance of the Power Generation | - | ✓ | ✓ | - | - | ✓ | - | - | China | Village |
| Mazzola et al. (2016) | | MILP | Cost | - | - | ✓ | - | ✓ | - | ✓ | ✓ | India | Village |
| Yahyaoui et al. (2016) | GA | | Cost | - | - | ✓ | ✓ | - | - | - | - | Tunisia | Household |
| Nwulu & Xia (2017) | | MILP | Cost | - | ✓ | ✓ | ✓ | - | - | - | - | Zimbabwe | Village |
| Koko et al. (2018) | | NLP | Cost, RE Generation | - | ✓ | - | - | - | ✓ | - | - | South Africa | Village |
| Kusakana (2018) | | LP | Grid Utilization | - | ✓ | ✓ | - | - | ✓ | - | - | South Africa | Village |

| Article | Heuristics - Metaheuristics | Model | Objective | Uncertainty | Grid Connected | PV | Wind | DG | Hydro | Biomass | Battery | Country | Scale |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Li et al. (2018) | NSGA-II | | Energy Generation, Consumption - Generation Gap | - | ✓ | ✓ | - | - | ✓ | - | - | China | - |
| Lee & Kum (2019) | | DP | Cost | - | - | ✓ | ✓ | ✓ | - | - | ✓ | - | - |
| Siraj et al. (2019) | | LP | Cost | - | ✓ | ✓ | - | - | - | - | - | India | Household |
| Gbadamosi & Nwulu (2020) | | LP | Cost | ✓ | - | ✓ | ✓ | - | - | - | - | NA | Household |
| Naval et al. (2020) | | MILP | Profit | - | ✓ | ✓ | ✓ | - | ✓ | - | - | Spain | Village |

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Table 2.3: Optimal Technology Choice: Decentralized vs. Centralized Systems

| Article | Heuristics - Metaheuristics | Model | Objective | Country | Scale | Resolution | Existing Grid |
|---|---|---|---|---|---|---|---|
| Lambert & Hittle (2000) | Modified Prim's Algorithm Simulated Annealing | | Cost | N/A | Village | Household | - |
| Parshall et al. (2009) | Kruskal's Algorithm | | Cost | Kenya | National | Grid Cells (15 $km^2$) | ✓ |
| Nagai et al. (2010) | | LP | Cost | Papua New Guinea | National | County | ✓ |
| Deichmann et al. (2011) | Modified Prim's Algorithm | | Cost | Ethiopia Ghana, Kenya | National | Village | - |
| Levin & Thomas (2012) | Weighted Composite Prim's Algorithm | | Cost | Botswana Uganda Bangladesh | National | Grid Cells (15 arcminutes $km^2$) | ✓ |
| Sanoh et al. (2012) | Modified Kruskal's Algorithm | | Cost | Senegal | National | Village | ✓ |
| Levin & Thomas (2013) | | MIP | Cost | Rwanda | National | Grid Cells (2.5 arcminutes) | - |
| Ranaboldo et al. (2013) | Greedy Heuristic | | Cost | Peru | Village | Household | - |
| Zeyringer et al. (2015) | | MILP | Cost | Kenya | National | Grid Cells (2000 $km^2$) | ✓ |
| Abdul-Salam & Phimister (2016) | Hierarchical Lexicographic Optimization | | Cost | Ghana | National | Village | ✓ |

| Article | Heuristics - Metaheuristics | Model | Objective | Country | Scale | Resolution | Existing Grid |
|---|---|---|---|---|---|---|---|
| Bolukbasi & Kocaman (2018) | | MILP | Cost | N/A | Multiple Villages | Village | - |
| Trotter et al. (2019) | | MO-MILP | Cost, Energy Equity | Uganda | National | County | ✓ |
| Corigliano et al. (2020) | Kruskal's Algorithm Dijkstra Algorithm | | Cost | Mozambique | Village | Grid Cells (0.04 $km^2$) | - |
| Nock et al. (2020) | | MILP | Overall Stakeholder Utilitiy | Liberia | National | County | - |
| Karsu & Kocaman (2021) | SPEA2, NSGA-II | BO-MILP | Cost, CO2 Emission | N/A | Multiple Villages | Village | - |

**Abbrevations:** Artificial Bee Colony Algorithm (ABC), Firefly Algorithm (FA), Flower Pollination Algorithm (FPA), Genetic Algorithm (GA), Harmony Search (HS), Implicit Stochastic Optimization (ISO), Linear Programming (LP), Mixed Integer Linear Programming (MILP), Moth-flame Optimization (MFO), Mutation Adaptive Differential Evolution (MADE), Pareto Envelope-based Selection Algorithm (PESA-II), Particle Swarm Optimization (PSO), Salp Swarm Algorithm (SSO), Teaching-Learning Based Optimization (TLBO)
Renewable Energy (RE), Loss of Power Supply Probability (LPSP), Loss of Load Probability (LLP)

Table 2.4: Network Design and Facility Location

| Article | Heuristics - Metaheuristics | Model | Power Flow | Country | Scale | Resolution | Solution Space |
|---|---|---|---|---|---|---|---|
| Zvoleff et al. (2009) | Composite Prim's Algorithm | | - | Tanzania, Senegal, Uganda, Mali | Village | Household | Discrete |
| Ferrer-Marti et al. (2011) | | MILP | ✓ | Peru | Village | Household | Discrete |
| Kocaman et al. (2012) | Agglomerative Hierarchical Clustering<br>Essau & Williams's Heuristic<br>Prim's Algorithm | | - | Sub-Saharan Africa | Village | Household | Continuous |
| Ferrer-Marti et al. (2013) | | MILP | ✓ | Peru | Village | Household | Discrete |
| Ranaboldo et al. (2014) | | MILP | ✓ | Cape Verde | Village | Household | Discrete |
| Ranaboldo et al. (2014) | Greedy Heuristic | | ✓ | Peru | Village | Household | Discrete |
| Bazmi et al. (2015) | | MINLP | - | Malaysia | State (Johor) | Market Center | Discrete |
| Triado-Aymerich et al. (2016) | Relax and Fix<br>Corridor Method<br>Increasing Radius | | ✓ | Peru | Village | Household | Discrete |
| Shrestha et al. (2016) | Kruskal's Algorithm | | - | Nepal | Village | Household | Discrete |

| Article | Heuristics - Metaheuristics | Model | Power Flow | Country | Scale | Resolution | Solution Space |
|---|---|---|---|---|---|---|---|
| Domenech et al. (2018) | | MILP | ✓ | Spain | Village | Household | Discrete |
| Bonamini et al. (2019) | | LP | - | India | Village | Household | Discrete |
| Vai et al. (2020) | Shortest Path Algorithm<br>GA | | - | Cambodia | Village | Household | Discrete |
| Fobi et al. (2021) | Agglomerative Hierarchical Clustering<br>Essau & Williams's Heuristic<br>Prim's Algorithm | | - | Kenya | National | Household | Continuous |

**Abbrevations:** Artificial Bee Colony Algorithm (ABC), Firefly Algorithm (FA), Flower Pollination Algorithm (FPA), Genetic Algorithm (GA), Harmony Search (HS), Implicit Stochastic Optimization (ISO), Linear Programming (LP), Mixed Integer Linear Programming (MILP), Moth-flame Optimization (MFO), Mutation Adaptive Differential Evolution (MADE), Pareto Envelope-based Selection Algorithm (PESA-II), Particle Swarm Optimization (PSO), Salp Swarm Algorithm (SSO), Teaching-Learning Based Optimization (TLBO)

Renewable Energy (RE), Loss of Power Supply Probability (LPSP), Loss of Load Probability (LLP)

## 2.2 Review of Planar Facility Location-Allocation Problems and Clustering Algorithms

Facility location and allocation decisions constitute a significant part of the spatial planning of energy systems. Some studies determine the optimal facility locations among a finite set of candidate sites. In the greenfield development problems, on the other hand, the facilities can be placed at any point on the continuous space as the greenfield regions are the areas with no existing infrastructure. Therefore, the discrete facility location problems are referred to as site-selecting problems, whereas the problems locating facilities in the continuous space are called site-generating problems [16].

The problem we present in this study is related to well-known problems in continuous facility location literature. Weber Problem is one of the most widely studied problems, where the aim is to generate a site for a single facility in continuous space while minimizing the weighted sum of the point-to-facility distances. Multisource Weber Problem (MWP), on the other hand, locates exactly $p$ facilities in the Euclidean space and minimizes the total weighted distance between the demand points and the serving facilities. Hence, Weber Problem corresponds to MWP for the special case with $p = 1$. Furthermore, for a given $p$ and no distance limitation between the facility and demand points our problem reduces to MWP, which is shown to be an NP-hard problem in [17].

Due to the non-polynomial nature of the problem and the summation of non-convex terms in the objective function, the literature on the multi-source weber problem is prone to heuristic algorithms. Therefore, exact methods are generally implemented to the small-sized instances. For large scale problems, heuristic approaches and metaheuristics can provide near-optimal solutions within reasonable computational time. However, the quality of the final solution can be adversely affected when the algorithms converge to a local optimum deviating from the global optimum dramatically. Similarly, degenerate local solutions that result in open facilities serving no customer increase the complexity of the problem even further [18].

Brimberg et al. [19] presented a detailed survey on the continuous location-allocation problems and examined the optimization frameworks, including exact methods, heuristics, and metaheuristics. The survey indicated that exact methods are generally applicable to small-sized problems. For $p = 2$, Ostresh [20] developed an efficient method by partitioning demand points into two groups and tackled the problem by optimizing them independently. Following this study, Drezner [21] improved this solution procedure for minimax (two-center) and minisum (two-median) problems. This algorithm is shown to be convenient for instances with up to 100 customers. Similarly, Chen et al. [22] adopted a d-c programming technique to solve the problem and reported the computational results up to 1000 demand points. For the general problem, Ostresh [23], and Kuenne and Soland [24] developed branch-and-bound algorithms to be used only on the small scale problems where the number of demand points is less than 50 and the number of facilities is less than 4. Rosing [25] improved the idea by listing all feasible convex hulls and using them to cover the fixed points of the problem. A significant improvement is accomplished in Krau [26] where an efficient method based on a column generation approach and a branch-and-bound algorithm is presented. The optimal solutions were obtained for relatively larger instances with 287 demand points and up to 100 facilities. However, it is worth noticing that the performance of the column generation approach highly depends on the quality of the starting solution, and various heuristics approaches have been developed to identify better starting solutions.

On the contrary to exact solution methods, heuristic approaches and metaheuristics can provide reasonable solutions for large scale problems with higher computational efficiency. Especially metaheuristics are observed perform effectively as they can generate diverse solutions and go beyond the restrictions of the local search exploring a narrower scope [19].

One of the well-known heuristics for MWP is presented by Cooper in 1964 [11]. The idea behind Cooper's iterative algorithm is to locate $p$ number of facilities and reallocate customers to the nearest facility repeatedly until there is no room for improvement. For the given customer-facility assignments, the problem is divided into $p$ single facility location problems, which is much easier to solve by using Weiszfeld's famous iterative procedure [12]. Weiszfeld algorithm is used to identify the optimal facility location for each subproblem, and it generally converges to the geometric median unless the proposed location coincides with a demand point. However, a modified version of the Weiszfeld's algorithm proposed by Vardi and Zhang [27] eliminates this necessity to guarantee the convergence. Computational experiments indicated that Cooper's algorithm terminates with a local optimum at the end of a small number of iterations [19].

Unlike Cooper's iterative algorithm where location and allocation steps are performed individually, Murtagh and Niwattisyawong [28] presented another approach for multi-depot location-allocation problems. In the solution method, both steps are performed simultaneously by using large-scale nonlinear programming. At the first step, $p$ arbitrary facility locations are chosen, and the optimal customer allocations are obtained based on the fixed facility locations. After an initial solution is attained, both location and allocation variables are determined simultaneously using a large-scale nonlinear optimization model.

Similarly, Bongartz et al. [29] developed an algorithm, which solves for location and allocation variables simultaneously by using a projection method. The authors derived simple projection formulas on the subspaces of the domain and used them to obtain descent directions. The authors also presented a multi-start version of their method by generating random initial solutions and reported promising results compared to Murtagh and Niwattisyawong [28]. Moreno et al. [30] presented a constructive type heuristic starting with an initial solution having $N$ clusters, where $p \leq N \leq 2p$. After the clusters are identified, surplus facilities are closed one by one until exactly $p$ facilities remain. This alternative strategy is referred to as "drop and add" heuristics in the literature. An extensive discussion on different strategies based on "add" or "drop" decisions and the comparative analysis of heuristics is presented in [31]. Another heuristic approach is proposed in Hansen et al. [32], where the discrete formulation is taken into consideration to divide the problem into $p$ distinct single facility location problems. After the optimal solution of the $p-$median problem is obtained, facility locations are improved in the continuous space for each cluster individually.Brimberg et al. [31] proposed a new neighborhood structure, which simply focuses on the relocation of facilities rather than customer reallocations. This structure diversifies the solutions by expanding the scope of the local search with single moves and examines the unexplored candidate locations in a systematic fashion. The facility locations are updated one at a time, and all possible single moves construct the neighborhood exchange. Cooper's iterative algorithm is then implemented with the selected portion of the one-exchange neighborhood. Another constructive algorithm is developed by Gamal and Salhi [33] based on the furthest distance rule to avoid clustered facilities at specific regions. Osman and Christofides [34] also proposed a neighborhood search approach for the initial facility locations to be evenly distributed.

The prior studies that we have discussed so far primarily focused on the variations of multi-start Cooper's alternate heuristic or neighborhood structures. One of the first metaheuristic attempts is presented in Brimberg and Mladenovic [35] using basic Tabu Search rules. In the algorithm, a neighborhood is constructed around the current solution and all $n(p-1)$ points are examined before relocating the existing facilities. Houck et al. [36] suggested a new approach by using genetic algorithm to solve multi-source Weber problem. Similarly, Salhi and Gamal [37] presented a genetic algorithm, where the selection and removal process is based on groups of chromosomes rather than single entities. Hence, they introduced three categories of chromosomes, good, mediocre, and poor, to diversify the search process and avoid the early convergence. However, the method fails for large number of facilities. Drezner et al. [38] proposed a much simpler variation of the genetic algorithm presented in [37] by using an effective merging process to generate offsprings. The new hybrid approach combining the distribution-based variable neighborhood search with genetic algorithm is shown to obtain improved solutions compared to basic variable neighborhood search and genetic algorithm.

Network design problems for rural electrification are usually subject to a distance constraint due to the transmission loss concerns and maximum permitted voltage drop. Drezner et al. [39] proposed a distance-limited version of Weber problem where the service provided by a distant facility is considered useless if the cut-off distance is exceeded. Gokbayrak and Kocaman [10] introduced a distance-limited continuous location-allocation problem, where the number of facilities is considered as a decision variable. In the first stage of the proposed multi-stage solution methodology, the minimum number of facilities is determined by solving planar set covering problem (PSCP). The discrete counterpart of the problem is solved in the second stage to identify the facility locations and the consumer allocations. The set of candidate sites for the discrete problem is formed by the demand nodes and the additional locations from the optimal solution of the PSCP. Then, in the final stage, Cooper's iterative algorithm is applied to the discrete solution for fine-tuning on continuous space.

Kocaman et al. [40] proposed an agglomerative clustering technique for a two-level power distribution network, where there is a distance limitation between transformers and the serving transformers. Assuming each customer is a singleton cluster initially, the algorithm searches for two closest groups and locates a single facility to the center of mass in an iterative fashion. If the proposed site does not violate the distance limit, these two clusters are merged into a single cluster, and the current facility locations are replaced with the new one located at the centroid. This merging process continues until none of the clusters can be merged within the distance limit. The algorithm provides the configuration having the least overall cost as the final solution.

The other well-known clustering techniques are also frequently used to solve multi-facility location problems. For instance, Esnaf and Küçükdeniz [41] proposed a hybrid method by using spherical and elliptical fuzzy clustering methods to create initial clusters. After initial clusters are formed using the fuzzy c-means clustering algorithm, each one is optimized individually as a single facility location problem. Similarly, Geetha et al. [42] developed a k-means based solution approach to create $k$ disjoint clusters and identify the optimal customer-facility allocations. Sahraeian and Kaveh [43] presented another hybrid method combining k-means clustering with the fixed neighborhood search algorithm. Based on the initial locations that the k-means method yields, the fixed neighborhood algorithm improves the facility locations and the customer allocations. However, the final output of the k-means algorithm is susceptible to the randomly selected centroids selected as the initial solution. Therefore, the k-means algorithm is repeated multiple times to choose the best solution among several alternatives with different initial seedings.

Corigliano et al. [44] also used the k-means and agglomerative hierarchical clustering algorithms to locate secondary substations as a part of power distribution network design problem. The authors proposed various heuristic algorithms to create population clusters using different clustering approaches. Firstly, the k-means clustering algorithm is executed for a predetermined number of substations. Then, the low voltage connections are checked if the distance threshold is exceeded. The clusters violating the distance limitation are all subdivided iteratively until each one conforms to the distance threshold. Secondly, an agglomerative clustering-based approach is presented to merge consumers one by one until the maximum number of clusters is attained within the distance limitation. The selected linkage method is specified as complete-linkage-clustering. In the comparative analysis, the agglomerative clustering approach is found to be more effective than the other methods proposed in the study. Another transformer substation siting problem discussed in González-Sotres et al. [45] utilized k-means algorithm to divide rural settlements into small regions. The proposed algorithm starts with $k = 1$ and increments the number of transformers by one at each iteration. The algorithm records the total cost of the distribution network and the transformers for each cluster and calculates the medium voltage network cost between the transformers. The algorithm returns the least-cost configuration as the final solution.

To our best knowledge, the problem we proposed has not been studied with the various cost structures in the literature yet. However, given the variations in the cost structure of different power generation technologies, it becomes a necessity to consider different combinations of fixed and variable cost components for the design of energy systems. Because, in addition fixed upfront costs for the generation technologies with bulk capacities, highly modular generation technologies that could be adapted to small or large-scale systems require variable cost components. Therefore, in this thesis, we introduce a planar facility location-allocation problem with fixed and variable cost structures to design decentralized energy systems for rural electrification. The proposed methodologies include practical clustering techniques and the multi-stage heuristic, which is shown to be effective in planar facility location-allocation problems.

# Chapter 3

# Problem Formulation

In this study, we propose Planar Facility Location-Allocation Problem with fixed and variable cost structures for the electrification of rural areas using decentralized energy systems. This study aims to contribute the greenfield development and provide immediate solutions to unelectrified households living in underdeveloped communities. The decentralized electrification options considered in this problem involve nano-grid and micro-grid systems. Micro-grids denote a small set of households electrified together by a single generation point, whereas nano-grids are isolated standalone systems generating electricity for individual consumers. The households electrified by micro-grids are directly connected to the generation points with low voltage cables. Therefore, we also design a single-level low voltage network of star topology to distribute the electricity to final consumers. However, low voltage connections cannot exceed a specific distance limit, $distLim$, due to technical constraints such as power loss and voltage drop limitations. There are similar studies incorporating distance limitations for the coverage criteria in the literature as in Gokbayrak and Kocaman [10]).

In a small rural settlement, the index set of demand points are denoted by $\mathcal{N} = \{1, ..N\}$. The coordinates of each demand point $i \in \mathcal{N}$ is given as $(a_i, b_i)$ and $N$ denotes the number of demand points that need to be electrified using either nano-grid or micro-grid option. We assume that households are identical, and thus the consumption level is the same for all households.

The index set of the candidate generation points is also denoted by $\mathcal{N} = \{1, ..N\}$ and each generation point $j \in \mathcal{N}$ is located at $(c_j, d_j)$. Because the maximum number of generators is obtained when each household has a nano-grid, the upper bound on the number of generation points is equal to the number of households $|\mathcal{N}| = N$. The generation points can be located anywhere on the continuous space; therefore $(c_j, d_j)$, $\forall j \in \mathcal{N}$ are considered as continuous decision variables in the mathematical formulations.

The objective of the problem is to minimize the total investment cost. In addition to costs of the facilities, low voltage network cost is also taken into consideration to calculate the total investment required. We assume that all distances between generation points and households are Euclidean. The low voltage connection cost per unit distance is denoted by $c_L$, and the total connection cost is proportional to the total length of low voltage cables in micro-grids.

The nano-grid and micro-grid systems have different facility opening costs. Depending on the type of the generators in micro-grids and nano-grids, we use different cost structures reflecting economies of scale and making micro-grids an attractive alternative to nano-grids. Besides the fixed upfront cost of the systems with bulk generation capacities, we also incorporate variable cost components for the highly modular technologies that could be easily scaled up to different sizes. Therefore, to solve this planar facility location-allocation problem, we propose three mixed integer quadratically constrained programming (MIQCP) problem considering different cost structures, including fixed, variable, and fixed and variable cost components, for micro-grid investments.

## 3.1 A Planar Facility Location-Allocation Problem Formulation with Fixed Facility Costs

In this formulation, nano grids and micro-grids are assumed to have different fixed facility costs. Below we define the decision variables and parameters that we use in our mathematical formulations.

**Decision Variables:**

$$x_{ij} = \begin{cases} 1, & \text{if household } i \in \mathcal{N} \text{ is served by generation facility } j \in \mathcal{N} \\ 0, & \text{otherwise} \end{cases}$$

$$v_j = \begin{cases} 1, & \text{if generation facility } j \in \mathcal{N} \text{ is open} \\ 0, & \text{otherwise} \end{cases}$$

$$k_j = \begin{cases} 1, & \text{if generation facility } j \in \mathcal{N} \text{ is a nano-grid} \\ 0, & \text{otherwise} \end{cases}$$

$$t_j = \begin{cases} 1, & \text{if generation facility } j \in \mathcal{N} \text{ is a micro-grid} \\ 0, & \text{otherwise} \end{cases}$$

$\gamma_i :$ Distance between household $i \in \mathcal{N}$ and the facility it is assigned to

$d_{ij} :$ Distance between household $i \in \mathcal{N}$ and facility $j \in \mathcal{N}$

$d^x_{ij} :$ x-coordinate difference between household $i \in \mathcal{N}$ and facility $j \in \mathcal{N}$

$d^y_{ij} :$ y-coordinate difference between household $i \in \mathcal{N}$ and facility $j \in \mathcal{N}$

**Parameters:**

$F1 :$ Micro-grid facility cost

$F2 :$ Nano-grid facility cost

$L \times W :$ Dimensions of the rectangular greenfield region

**PFLAP-Fixed:**

$$\min \quad \sum_{i\in\mathcal{N}} c_L\gamma_i + \sum_{j\in\mathcal{N}} F1.t_j + \sum_{j\in\mathcal{N}} F2.k_j \tag{3.1}$$

$$\text{s.t.} \quad \sum_{j\in\mathcal{G}} x_{ij} = 1, \qquad i\in\mathcal{N} \tag{3.2}$$

$$x_{ij} \le v_j, \qquad i\in\mathcal{N},\ j\in\mathcal{N} \tag{3.3}$$

$$\sum_{i\in\mathcal{N}} x_{ij} \le k_j + Nt_j, \qquad j\in\mathcal{N} \tag{3.4}$$

$$k_j + t_j = v_j, \qquad j\in\mathcal{N} \tag{3.5}$$

$$d^x_{ij} = a_i - c_j, \qquad i\in\mathcal{N},\ j\in\mathcal{N} \tag{3.6}$$

$$d^y_{ij} = b_i - d_j, \qquad i\in\mathcal{N},\ j\in\mathcal{N} \tag{3.7}$$

$$d^2_{ij} \ge (d^x_{ij})^2 + (d^y_{ij})^2, \qquad i\in\mathcal{N},\ j\in\mathcal{N} \tag{3.8}$$

$$\gamma_i \ge \sqrt{L^2\times W^2}(x_{ij}-1) + d_{ij}, \qquad i\in\mathcal{N},\ j\in\mathcal{N} \tag{3.9}$$

$$\gamma_i \le distLim, \qquad i\in\mathcal{N} \tag{3.10}$$

$$v_j \in \{0,1\}, \qquad j\in\mathcal{N} \tag{3.11}$$

$$k_j \in \{0,1\}, \qquad j\in\mathcal{N} \tag{3.12}$$

$$t_j \in \{0,1\}, \qquad j\in\mathcal{N} \tag{3.13}$$

$$x_{ij} \in \{0,1\}, \qquad i\in\mathcal{N},\ j\in\mathcal{N} \tag{3.14}$$

$$c_j,\ d_j \in \mathbb{R}, \qquad j\in\mathcal{N} \tag{3.15}$$

$$d^x_{ij},\ d^y_{ij} \in \mathbb{R}, \qquad i\in\mathcal{N},\ j\in\mathcal{N} \tag{3.16}$$

$$d_{ij} \ge 0, \qquad i\in\mathcal{N},\ j\in\mathcal{N} \tag{3.17}$$

$$\gamma_i \ge 0, \qquad i\in\mathcal{N} \tag{3.18}$$

The objective function in (3.1) minimizes the total investment cost that involves the cost of deploying generation facilities and the total low voltage connection cost. Constraints (3.2) guarantee that each household is served by exactly one generation facility. We ensure in (3.3) that closed facilities cannot provide electricity service. Constraints (3.4) determines if a facility serves more than one consumer. In other words, the type of the facility, namely nano-grid and micro-grid, is identified by these constraints. The constraint set (3.5) indicate that an open facility is either a nano-grid or a micro-grid. The x-coordinate and y-coordinate differences are defined in constraints (3.6) and (3.7) respectively. Using the differences in x,y coordinates and the quadratic constraints (3.8), the Euclidean distances between the facilities and the households are determined. The distance between the households and the serving facilities is calculated in constraints (3.9). The constraint set (3.10) impose a distance limit on the low voltage connections between the micro-grid facilities and the households. Finally, the decision variables are introduced in (3.11)-(3.18).

## 3.2 A Planar Facility Location-Allocation Problem Formulation with Variable Facility Costs

In this formulation, we assume that micro-grid facility costs are dependent on the number of households it serves. Therefore, instead of charging a fixed facility cost, we consider a new cost parameter, $F3$, denoting the contribution of each household to the micro-grid investment cost. Given the additional low-voltage cable costs, $F3$ must be less than or equal to $F2$ for a micro-grid system to be considered as an attractive alternative.

The mathematical formulation for the planar location-allocation problem with variable facility cost (PFLAP-Var) is as follows:

**PFLAP-Var:**

$$\min \quad \sum_{i \in \mathcal{N}} c_L \gamma_i + \sum_{j \in \mathcal{G}} (F2 - F3).k_j + F3.N$$

$$\text{s.t.} \quad (3.2) - (3.3) \quad \& \quad (3.6) - (3.18), \; and$$

$$\sum_{i \in \mathcal{N}} x_{ij} + k_j \geq 2v_j, \qquad j \in \mathcal{N} \tag{3.19}$$

$$k_j \leq v_j, \qquad j \in \mathcal{N} \tag{3.20}$$

The constraint set (3.19) and (3.20) determines if an open decentralized facility is a nano-grid.

## 3.3 A Planar Facility Location-Allocation Problem Formulation with Fixed and Variable Facility Costs

Here, we assume that micro-grid investments consist of fixed and variable costs components. The previous assumptions also hold for this problem.

**PFLAP-Fixed&Var:**

$$\begin{aligned} \min \quad & \sum_{i \in \mathcal{N}} c_L \gamma_i + \sum_{j \in \mathcal{G}} F1.t_j + \sum_{j \in \mathcal{G}} (F2 - F3).k_j + F3.N \\ \text{s.t} \quad & (3.2) - (3.18) \end{aligned}$$

# Chapter 4

# Solution Methodology

Our problem reduces to MWP, which is shown to be NP-Hard [17], for a predetermined number of single type facilities, and relaxed distance limitation. Therefore, in this thesis, we propose six heuristic approaches to solve this planar location-allocation problem. Here, we classify the heuristic methods as model-based or clustering based approaches depending on the major characteristics of the solution methodologies.

The model-based approaches involve the modified versions of the multi-stage heuristic proposed in Gokbayrak and Kocaman [10]. These multi-stage heuristics benefit from the solution of the discrete counterpart as suggested in Hansen et al. [32]. Based upon the discussions on optimal facility locations being very close to customers [46], employing the demand points as potential facility sites may provide reasonable estimates for the continuous problem. Hence, following a similar approach that Hansen et al. [32] presented, we first solve a distance limited facility location problem in discrete space, and then improve the existing configuration in the continuous space with projections. In the first model-approach, we adapt the multi-stage heuristic proposed in Gokbayrak and Kocaman [10] to our problem. Alternatively, we discuss two variants of the existing solution in the second and the third solution approaches.

As we assume that the investment cost of decentralized systems are different, the trade-off between nano-grid and micro-grid options is observed constrain the performance of the multi-stage heuristics in terms of the solution time. Thus, we present three additional heuristic approaches based on fast clustering techniques, including density-based spatial clustering applications with noise (DBSCAN), k-means algorithm and agglomerative clustering, to develop a tool for energy planners to make rapid assessments. Since clustering problems and MWP share some common characteristics, clustering analysis has been frequently used as a solution methodology for planar facility location-allocation problems (eg. [47],[44],[45],[48]).

## 4.1 Model-Based Heuristic Approaches

### 4.1.1 MB-I: Multi-Stage Heuristic Approach

In this solution method, we present a modified version of the three-stage heuristic that Gokbayrak and Kocaman [10] proposed. Following the idea presented in Hansen et al. [32], we solve the DFLAP to obtain the initial clusters by using a set of promising points as the candidate facility locations. Using the solution of SCP, we identify these promising points to insert the domain of the discrete problem, and solve the discrete version of the planar facility location-allocation formulation with a distance limit. Provided that the cost structure of the decentralized systems varies in the problems presented in Chapter 3, we consider different discrete formulations in the second stage of the heuristic method. After the initial facility locations and the household allocations are determined, we implement Cooper's algorithm in the third stage to enhance the existing configuration. In this study, we also propose an alternative augmentation method to expand the domain of the discrete problem with the other common intersection points.

#### 4.1.1.1 Stage-1: Identifying Candidate Facility Locations with PSCP

Exploiting the idea suggested in Church and ReVelle [49], we use the circle intersection points to obtain the optimal solution of PSCP by solving its discrete counterpart. Therefore, we determine all the intersection points of the circles centered at demand locations with the radius *distLim*. We also note that if the circle around a demand point does not intersect with any other circle, then the only possible facility location for this particular demand node within the coverage criterion is itself.

To visualize the solution methodology graphically, we provide a running instance with 15 demand nodes as illustrated in Figure 4.1. Assuming each demand point is identical, we show all the circle intersections in Figure 4.2 for the given coverage threshold with $distLim = 30$ m. The augmented set of the circle intersection points and the demand locations is denoted by $\mathcal{A}$. In our running example, the cardinality of the augmented set $|\mathcal{A}|$ is equal to 61. For the formulation of the discrete set covering problem, let us also define a coverage indicator $\alpha_{ij}$ to identify if $j \in \mathcal{A}$ is eligible to cover demand point $i \in \mathcal{N}$.

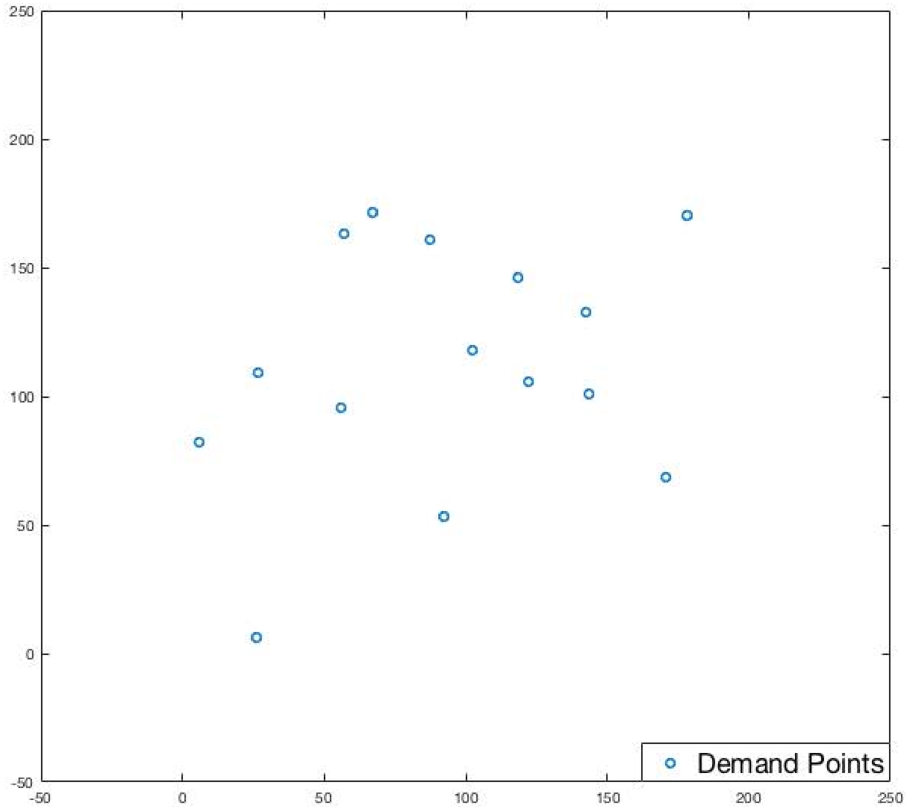



Figure 4.1: Demand Points

**Parameters:**

$\mathcal{A}$ : $\mathcal{N} \cup$ Circle Intersection Points

$d_{ij}$ : Euclidean distance between demand point $i \in \mathcal{N}$ and candidate site $j \in \mathcal{A}$

$$\alpha_{ij} = \begin{cases} 0, & \text{if } d_{ij} \leq distLim \\ 1, & \text{otherwise} \end{cases}$$

**Decision Variables:**

$$v_j = \begin{cases} 0, & \text{if facility } j \in \mathcal{A} \text{ is open} \\ 1, & \text{otherwise} \end{cases}$$

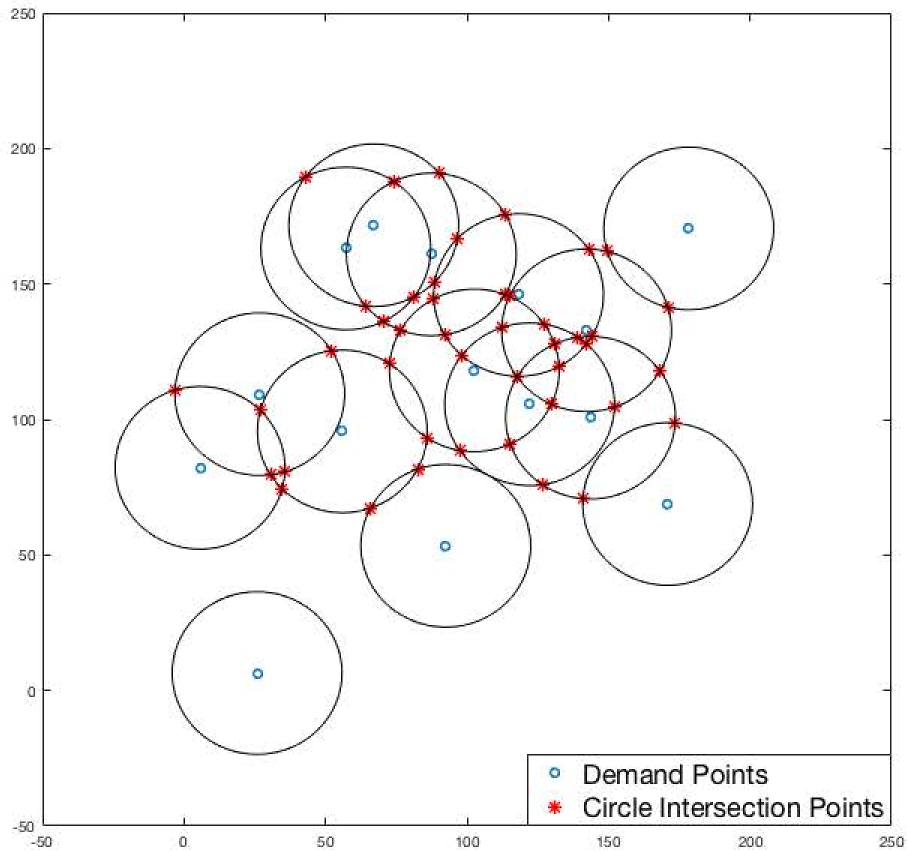



Figure 4.2: Circle Intersection Points

Considering these decision variables and parameters, we solve the following SCP formulation in order to find the minimum number of facilities required to cover all the demand points within the coverage limit:

**Model:**

$$\min \quad \sum_{j \in \mathcal{A}} v_j \tag{4.1}$$

$$\text{s.t} \quad \sum_{j \in \mathcal{A}} \alpha_{ij} v_j \geq 1, \qquad i \in \mathcal{N} \tag{4.2}$$

$$v_j \in \{0, 1\}, \qquad j \in \mathcal{A} \tag{4.3}$$

The objective function (4.1) minimizes the number of facilities required to cover all the demand points. In constraint set (4.2), we ensure that each demand node must be covered by at least one facility. The PCSP solution of the running example is illustrated in Figure 4.3. The optimal solution to this problem yields the additional candidate points that we will be considering in the following step of the heuristic. In fact, the set $\{j \in \mathcal{A} \setminus \mathcal{N} : \; v_j = 1\}$ denotes the candidate sites that we employ in addition to the demand nodes. For the second stage of the heuristic, we augment the set of demand points with the optimal sites obtained in SCP and solve the discrete facility location-allocation problem (DFLAP) using these locations.

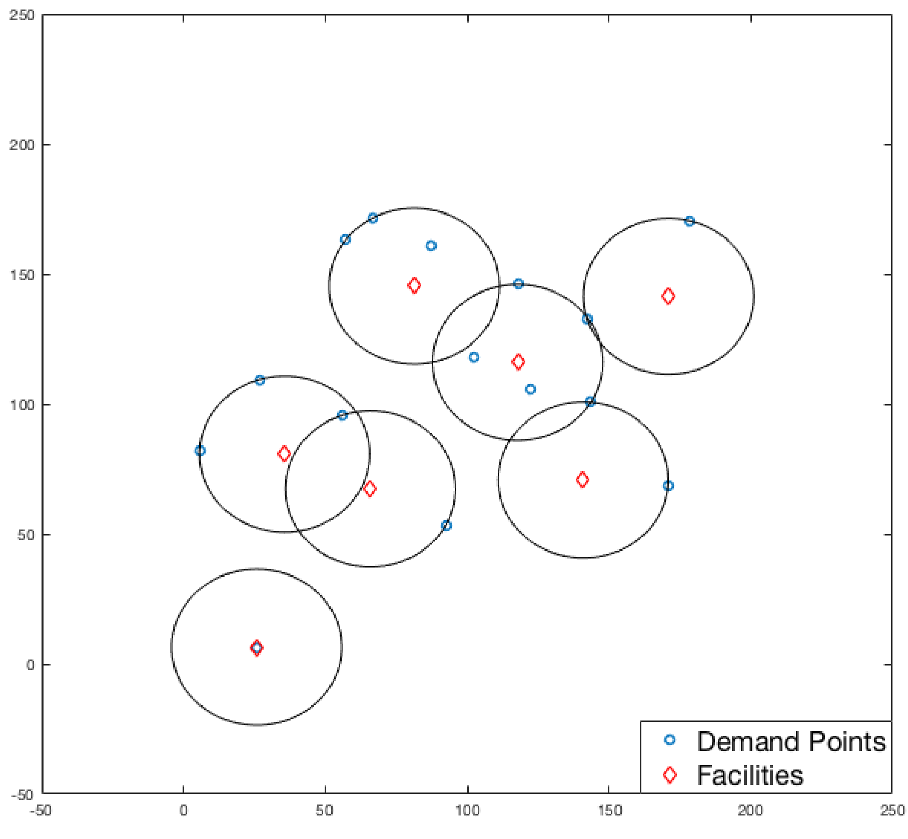



Figure 4.3: PSCP Solution

#### 4.1.1.2 Stage-2: Determining the Facilities and Initial Household Allocations

In the second stage of the heuristic, we determine the initial facility locations and assign the households to these facilities by solving the discrete counterpart of the planar facility location-allocation problem (PFLAP). We solve DFLAP by using the augmented set of the demand nodes and the additional candidate locations attained from the optimal solution of PSCP. In other words, we expand the domain of the problem to obtain a better initial estimate, instead of incorporating only the set of the demand nodes as in Hansen et al. [32]. Hence, at the end of the second stage, we aim to achieve a good starting solution to be improved in the third stage of the heuristic approach.

Given that nano-grid and micro-grid investments may involve different cost components as in the formulations provided in the Chapter 3, we propose three mathematical models for the corresponding problems. The set of candidate facility locations ($\mathcal{N} \cup \{j \in \mathcal{A} | \ v_j = 1\}$) is denoted by $\mathcal{G}$ in our formulation and the number of candidate facilities $|\mathcal{G}|$ is observed to be 21 in the running example. The mathematical models we propose for the discrete facility location-allocation problem with fixed (DFLAP-Fixed), variable (DFLAP-Var), and fixed & variable (DFLAP-Fixed&Var) facility costs are presented as follows:

**Decision Variables:**

$$x_{ij} = \begin{cases} 1, & \text{if household } i \in \mathcal{N} \text{ is served by generation facility } j \in \mathcal{G} \\ 0, & \text{otherwise} \end{cases}$$

$$v_j = \begin{cases} 1, & \text{if generation facility } j \in \mathcal{G} \text{ is open} \\ 0, & \text{otherwise} \end{cases}$$

$$k_j = \begin{cases} 1, & \text{if generation facility } j \in \mathcal{G} \text{ is a nano-grid serving a single consumer} \\ 0, & \text{otherwise} \end{cases}$$

$$t_j = \begin{cases} 1, & \text{if generation facility } j \in \mathcal{G} \text{ is a micro-grid serving more than one consumer} \\ 0, & \text{otherwise} \end{cases}$$

**Parameters:**

$F1$ : Micro-grid facility cost

$F2$ : Nano-grid facility cost

$F3$ : Micro-grid cost per household

$c_L$ : Low voltage connection cost per unit distance

$d_{ij}$ : Distance between household $i \in \mathcal{N}$ and candidate facility $j \in \mathcal{G}$

**DFLAP-Fixed:**

$$\min \quad \sum_{i \in \mathcal{N}} \sum_{j \in \mathcal{G}} c_L x_{ij} d_{ij} + \sum_{j \in \mathcal{G}} F1.t_j + \sum_{j \in \mathcal{G}} F2.k_j \tag{4.4}$$

$$\text{s.t.} \quad \sum_{j \in \mathcal{G}} x_{ij} = 1, \qquad i \in \mathcal{N} \tag{4.5}$$

$$\sum_{j \in \mathcal{G}} x_{ij} d_{ij} \leq distLim, \qquad i \in \mathcal{N} \tag{4.6}$$

$$x_{ij} \leq v_j, \qquad i \in \mathcal{N},\ j \in \mathcal{G} \tag{4.7}$$

$$\sum_{i \in \mathcal{N}} x_{ij} \leq k_j + N t_j, \qquad j \in \mathcal{G} \tag{4.8}$$

$$k_j + t_j = v_j, \qquad j \in \mathcal{G} \tag{4.9}$$

$$v_j \in \{0, 1\}, \qquad j \in \mathcal{G} \tag{4.10}$$

$$k_j \in \{0, 1\}, \qquad j \in \mathcal{G} \tag{4.11}$$

$$t_j \in \{0, 1\}, \qquad j \in \mathcal{G} \tag{4.12}$$

$$x_{ij} \in \{0, 1\}, \qquad i \in \mathcal{N},\ j \in \mathcal{G} \tag{4.13}$$

**DFLAP-Var:**

$$\begin{aligned} \min \quad & \sum_{i \in \mathcal{N}} \sum_{j \in \mathcal{G}} c_L x_{ij} d_{ij} + \sum_{j \in \mathcal{G}} (F2 - F3).k_j + F3.N \\ \text{s.t.} \quad & (4.5) - (4.7) \quad \& \quad (4.10) - (4.13), \ and \\ & \sum_{i \in \mathcal{N}} x_{ij} + k_j \geq 2v_j, \qquad j \in \mathcal{G} \qquad (4.14) \\ & k_j \leq v_j, \qquad j \in \mathcal{G} \qquad (4.15) \end{aligned}$$

**DFLAP-Fixed&Var:**

$$\begin{aligned} \min \quad & \sum_{i \in \mathcal{N}} c_L \gamma_i + \sum_{j \in \mathcal{G}} F1.t_j + \sum_{j \in \mathcal{G}} (F2 - F3).k_j + F3.N \\ \text{s.t} \quad & (4.5) - (4.13) \end{aligned}$$

In the first formulation, we assume that both nano-grids and micro-grids have fixed facility costs, implying that the cost of a micro-grid facility is independent of the number of households it serves. In the second formulation, on the other hand, we assume that micro-grid facility costs are calculated depending on the number of households connected to the generation point. Finally, the third formulation includes three cost components for decentralized facilities. In addition to the fixed costs of nano-grids and micro-grids, we charge an additional cost for each household electrified by micro-grid facilities. The constraint sets (4.5)-(4.7) are common in three of the formulations. Constraints (4.5) guarantees that each household will be served by exactly one facility. We also ensure that each household will be electrified by a facility within the distance threshold in constraints (4.6). In constraint set (4.7), we assign households to facility $j \in \mathcal{G}$ only if it is opened. To determine if a facility is a nano-grid or a micro-grid, we define the constraints in (4.8) and (4.9). The constraints (4.14) and (4.15) serve the same purpose in the variable cost problem formulation. Note that the number of households electrified by a particular facility distinguishes the type of the decentralized system. The remaining constraint sets (4.10)-(4.13) represent the decision variables.

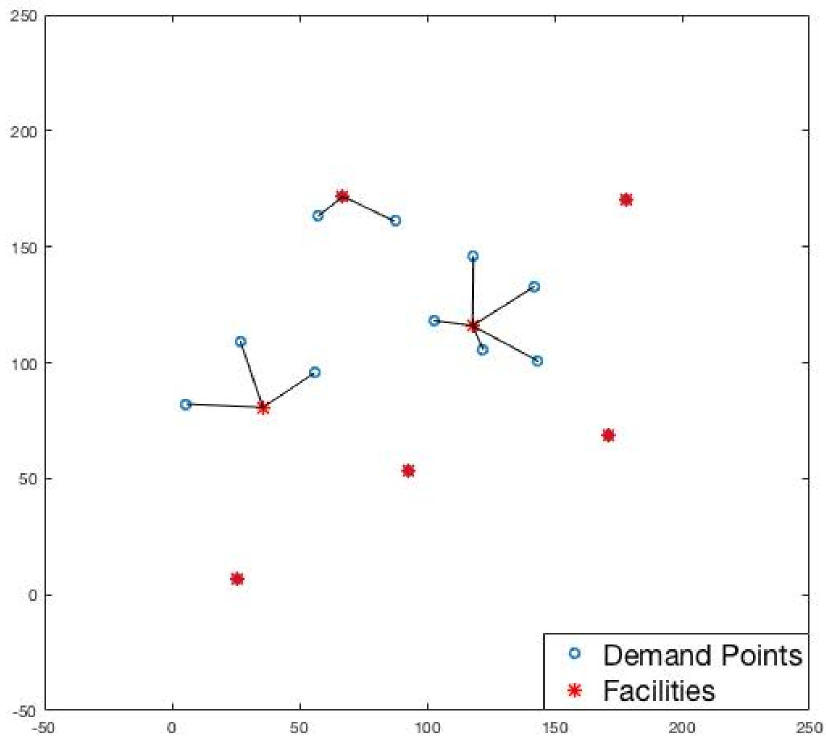



Figure 4.4: DFLAP Solution

DFLAP yields the initial system configuration and customer allocations in the discrete space. Assuming the same fixed cost for both facilities as in Gokbayrak and Kocaman [10], the solution of the second stage is shown in Figure 4.4. The facility and unit connection cost is considered as $F = 1000$ and $c_L = 1$, respectively. Note that there are four nano-grids in the solution, and the rest of the demand nodes are connected to micro-grids in a star topology. The demand node located at (100,50) could also join one of the micro-grids nearby if it did not violate the distance limitation.

In the following stage of the heuristic approach, we use the initial configuration attained in the solution of DFLAP. Considering the initial facility locations and household allocations, we implement Cooper's iterative algorithm to improve the total investment cost and provide closer estimates to the solution of the continuous problem.

#### 4.1.1.3 Stage-3: Cooper's Iterative Algorithm

In the third stage, we perform Cooper's well-known heuristic which iteratively improves the existing configuration while alternating between location and allocation steps. For the given household assignments obtained in the previous stage, each cluster is treated as a Weber Problem to optimize the facility locations. Since we assume that the households are identical, Weber Problem converges to the geometric median, which minimizes the total point-to-facility distances for each cluster. Nevertheless, there exists no straightforward formulation in the literature to calculate the geometric median. Weber [50] also proved that an explicit formulation can not be derived to find the geometric median. Therefore, convergence algorithms are extensively used in order to generate closer estimates. Considering the convexity property of the summation of convex functions (distance function), these approximation algorithms generally do not fall into local optimality traps with one exception [51]. Weiszfeld algorithm presented in [12] converges to the geometric median unless the proposed facility location overlaps a demand point in one of the iterations. However, an extension of the algorithm that Vardi and Zhang [27] propose eliminates this particular problem. Hence, in the location step of the Cooper's heuristic, we implement the modified version of Weiszfeld algorithm [27] in order to project the facility locations to the geometric median.

The modified version of the Weiszfeld algorithm suggests a new location for a facility iteratively, until no further change in the proposed location is observed. In the first iteration, we initialize the facility location as the center of the smallest circle $(c_0, d_0)$ encompassing all the demand nodes in the cluster. Note that $(a_i, b_i)$ denotes the location of the demand point $i \in \mathcal{N}$ allocated to facility (cluster) $j$, and the set of households served by this particular facility is denoted by $C_j = \{i \in \mathcal{N} | \, x_{ij} = 1\}$. Let us also denote the facility location at iteration $t$ as $(c_t, d_t)$, and the distance between node $i \in C_j$ and the serving facility as $d_i^t$. If the facility location at iteration $t$ does not coincide with any demand point in the cluster $C_j$, the algorithm suggests a new location based on the following expression:

$$(c_p, d_p) = \widetilde{F}(c_t, d_t) = \frac{\displaystyle\sum_{i \in C_j, d_i^t > 0} (a_i, b_i) \frac{c_L}{\|(a_i, b_i) - (c_t, d_t)\|}}{\displaystyle\sum_{i \in C_j, d_i^t > 0} \frac{c_L}{\|(a_i, b_i) - (c_t, d_t)\|}} = \frac{\displaystyle\sum_{i \in C_j, d_i^t > 0} (a_i, b_i) \frac{c_L}{d_i^t}}{\displaystyle\sum_{i \in C_j, d_i^t > 0} \frac{c_L}{d_i^t}}$$

However, if $(c_t, d_t)$ overlaps a demand point in $C_j$, the algorithm determines the magnitude of the total attraction between the current facility location and the remaining demand points in $C_j$

$$\sigma(c_t, d_t) = \left\| \sum_{\substack{i \in C_j, \\ d_i^t > 0}} c_L \frac{(a_i, b_i) - (c_t, d_t)}{\|(a_i, b_i) - (c_t, d_t)\|} \right\|.$$

In addition to the attraction indicator $\sigma$, the resistance to movement is also determined

$$\eta(c_t, d_t) = \begin{cases} \sigma, & \text{if } (c_t, d_t) \in C_j \\ 0, & \text{otherwise} \end{cases}$$

in order to observe if the facility location is worth moving. If the resistance to movement $\eta$ is higher than the attraction indicator $\sigma$, the algorithm does not change the current facility location. Otherwise, a new facility location is suggested as follows:

$$(c_p, d_p) = \left(1 - \frac{\eta(c_t, d_t)}{\sigma(c_t, d_t)}\right) \widetilde{F}(c_t, d_t) + \frac{\eta(c_t, d_t)}{\sigma(c_t, d_t)} (c_t, d_t)$$

As Vardi and Zhang's convergence algorithm does not consider any distance limitation, the suggested facility location may not necessarily obey the coverage limit. After the algorithm converges to a location, we project the proposed location to a feasible point, where it conforms to the distance limit constraint for each demand point in the cluster. Hence, the facility location in the next iteration $(c_{t+1}, d_{t+1})$ is updated after the infeasible point is projected into the feasible region as shown in Figure 4.5.

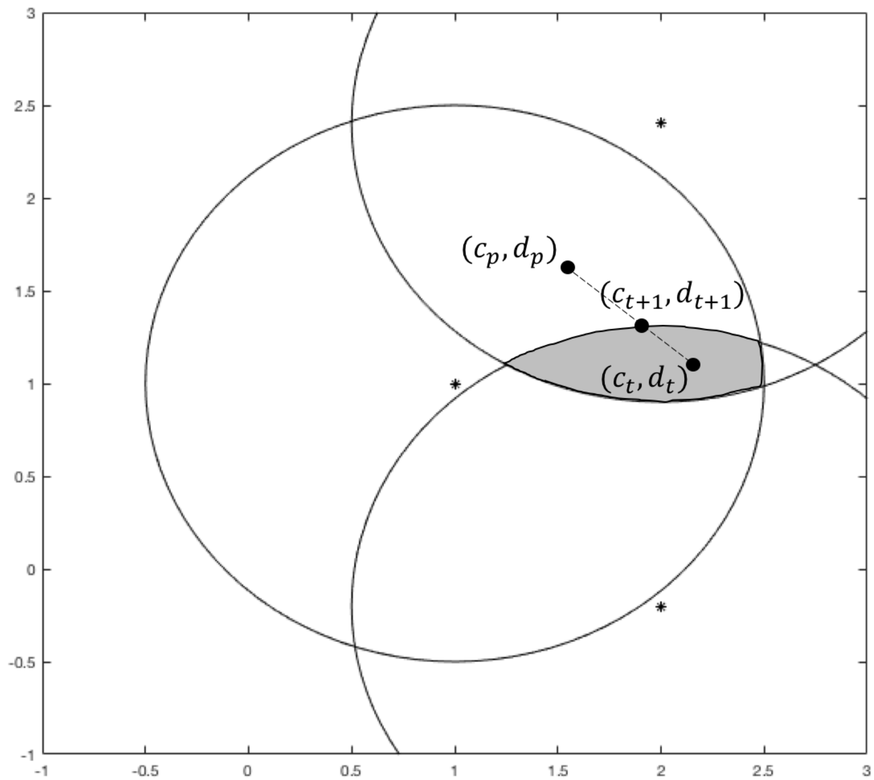



Figure 4.5: Projection

In this study, we adopt the same projection methodology proposed in Gokbayrak and Kocaman [10] to move the suggested facility to a feasible location. In this projection methodology, If the proposed location $(c_p, d_p)$ conforms the coverage threshold, we update the existing location for the next iteration as $(c_{t+1}, d_{t+1}) = (c_p, d_p)$ for the given cluster. Otherwise, we identify the possible closest location to the geometric median within the feasible region using the line segment between the proposed $(c_p, d_p)$ and current $(c_t, d_t)$ facility locations. Any point on the line segment between $(c_p, d_p)$ and $(c_t, d_t)$ can be defined as $(c_t, d_t) + \beta(c_p - c_t, d_p - d_t)$, where $\beta \in [0, 1]$. Using this equation, we identify a feasible point $(c_i, d_i) = (c_t, d_t) + \beta_i(c_p - c_t, d_p - d_t)$ on the line segment, which is positioned exactly $distLim$ away from the demand node $(a_i, b_i)$. To derive $\beta_i$ for each demand node in the cluster, we solve the following second order polynomial equation:

$$(c_t + \beta_i(c_p - c_t))^2 + (d_t + \beta_i(d_p - d_t))^2 = distLim^2$$

A common feasible point for the entire cluster lies only on the portion of the segment, where $\beta \in [0, \beta_i]$ for all $i \in C_j$. Hence, we identify $\beta_{min} = \min_{i \in C} \beta_i$ to obtain a new location conforming the distance limitation for this particular cluster and update the facility location as $(c_{t+1}, d_{t+1}) = (c_t, d_t) + \beta_{min}(c_p - c_t, d_p - d_t)$. We call this new facility location as the distance-limited geometric median.

After the facility locations are optimized, households are reallocated to the facilities in a way that the total cost is decreased. Unlike the original allocation step of Cooper's algorithm, allocating the households to the nearest facility may not be a cost-efficient move. Because decentralized systems have different facility costs, the new assignment opportunities need to be carefully evaluated. Especially, the transitions from micro-grids to nano-grids require a rigorous consideration of available options. Therefore, in this solution method, we allocate the households one by one to the nearest facility if the reallocation results in a cost-efficient configuration. To determine if a new assignment opportunity is cost-efficient, we calculate the potential cost improvements after the potential move is performed based on the existing household allocations. For the reallocation of the households, we consider two special cases. The first special case occurs when a member of a micro-grid connecting more than three households is reassigned to a former nano-grid. In this case, as the former nano-grid transforms into a micro-grid, the cost of this new micro-grid cluster needs to be calculated accordingly. The second special case, on the other hand, involves the transfer of an household from a micro-grid connecting two-households to a any another micro-grid. As this reassignment results in the first micro-grid with two households being transformed into a nano-grid, the facility costs need to be recalculated based on the change in the facility types.

Location and allocations steps are repeated until the change in the objective value is less than an $\varepsilon$ threshold. Note that the final solution and the number of iterations strongly depend on the value of $\varepsilon$.

### 4.1.2 MB-I: An Extension of the Multi-Stage Heuristic

During the computational experiments, we have noticed that SCP may provide multiple optimal solutions, especially when the same demands nodes are enclosed by several intersection points. However, SCP incorporates a single intersection point among multiple alternatives. The intersection point we inserted to the domain of DFLAP, on the other hand, plays a vital role in the optimal system configuration. Because the objective function accounts for the total distance between the demand points and the facilities, the optimal solution of DFLAP could be significantly affected by the choices we make in the first stage. In Figure 4.6, we illustrate this argument with a small example. For the different intersection points that SCP yields, the total LV connections are observed to change considerably even in this small instance.

As an alternative augmentation methodology, we propose to identify other multiple optimal solutions of PSCP. For this purpose, we find other common intersection points covering the same demand nodes that the optimal solution of the PSCP has covered. With this approach, we aim to capture the other intersection points that may yield a lower connection cost. As a result, instead of inserting only the optimal locations we obtained in PSCP, we also consider these additional intersection points in the candidate facility locations of DFLAP. In the running example, PSCP yields 7 candidate facility locations as shown in Figure 4.3. However, with the new methodology, the set of candidate facilities of DFLAP consist of 17 potential locations as illustrated in Figure 4.7. The solutions of DFLAP-Fixed with the original (PSCP locations) and the extended set of candidate facilities (Common Intersection Points) are provided in Figure 4.8. The total connection cost reduces from 238 to 218 in the running example when the common intersection points are taken into consideration. Computational experiments have indicated that inserting these additional points slightly increase the solution time. Although it may create a computational burden especially for dense instances as the number of common intersection point increases, this new augmentation strategy can provide significant savings in the objective function.

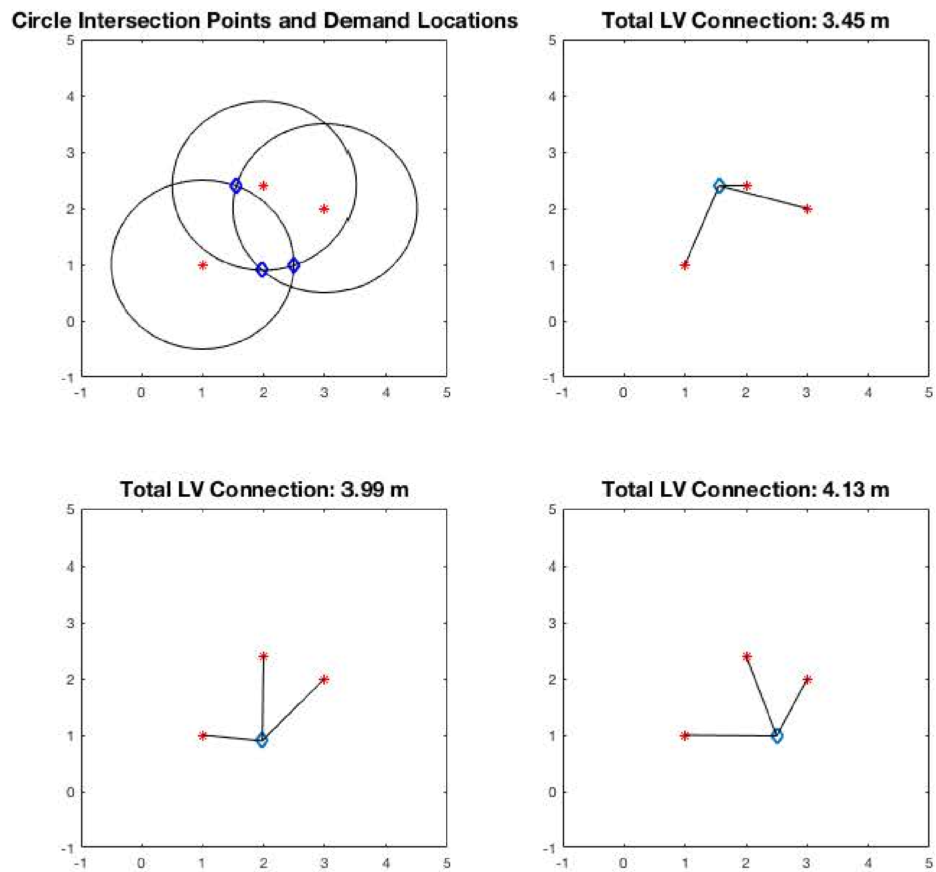



Figure 4.6: The Effect of the SCP Solution on DFLA Connection Cost

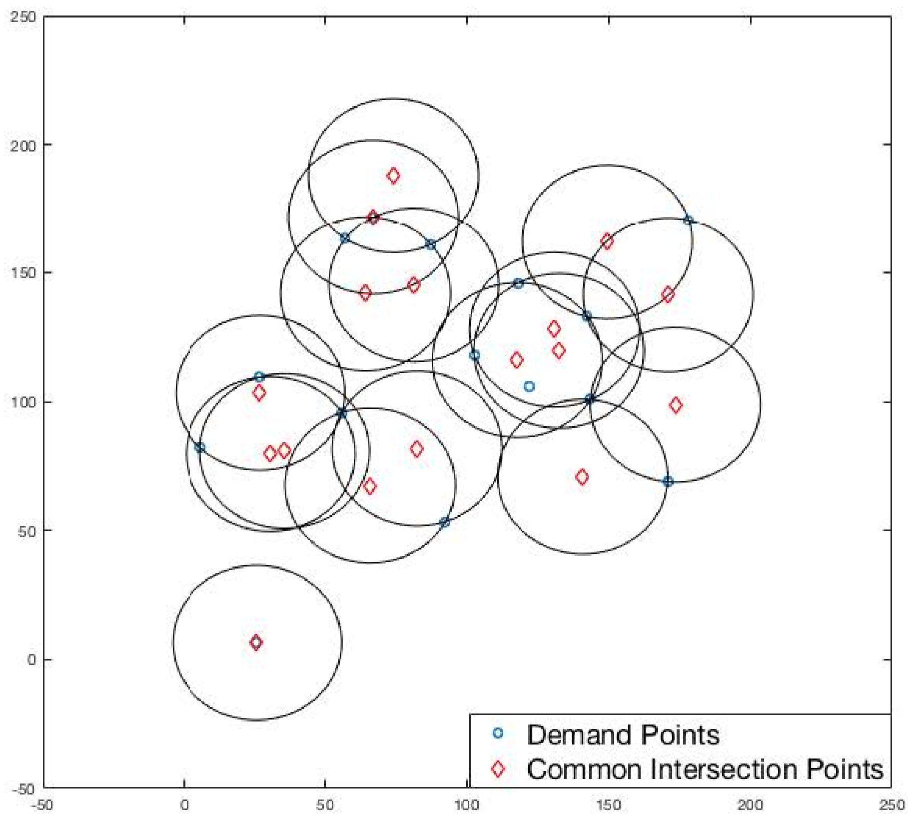
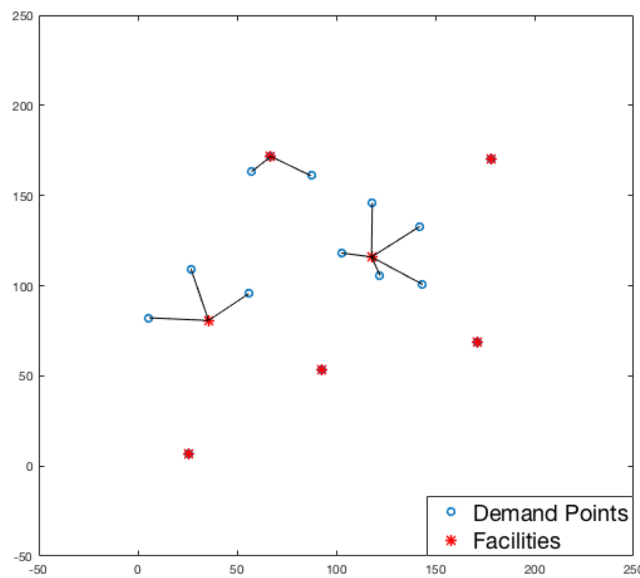
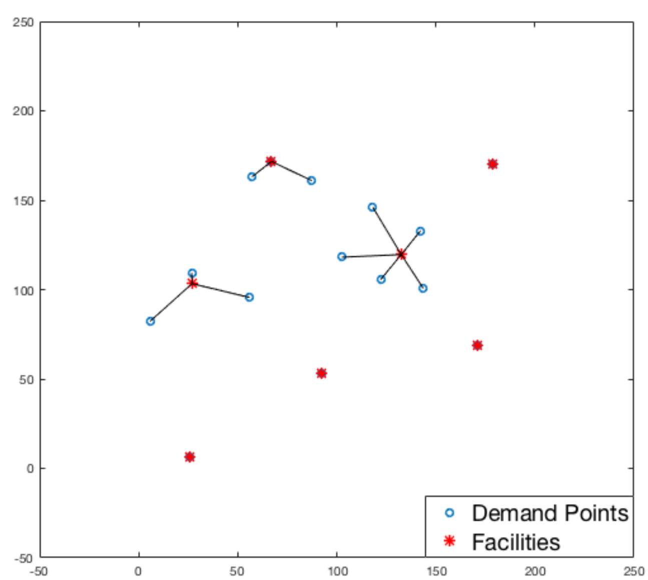



Figure 4.7: Common Intersection Points




(a) DFLPA-Fixed with PSCP Locations, Total LV Length = 238 m




(b) DFLAP-Fixed with Common Intersection Points, Total LV Length = 218 m

Figure 4.8: Comparison of Augmentation Methodologies

### 4.1.3 MB-III: Unicost Multi-Stage Heuristic with Post Process

As an alternative model-based heuristic approach, we propose to use the same methodology presented in Gokbayrak and Kocaman [10]. Assuming nano-grids and micro-grids have the same fixed facility cost, we solve the multi-stage heuristic with the DFLAP-Fixed formulation in the second stage. After the existing configuration is enhanced with Cooper's algorithm, we apply post-processing to revert facility costs to the multi-cost scheme. In the computational experiments, we consider the micro-grid fixed facility cost for both nano-grids and micro-grids, and change the cost of the single clusters to nano-grid cost. We also note that we implement this heuristic approach only on the problems with the fixed-cost scheme. For the fixed cost and fixed & variable cost problems, we only use the modified version of the multi-stage heuristic and its extended version.

## 4.2 Clustering-Based Heuristic Approaches

### 4.2.1 Agglomerative Clustering based Heuristic Approach

The computational experiments have demonstrated that model-based heuristic approaches may have difficulty in solving the mathematical models optimally within a predetermined time limit. In fact, for large instances having a dense settlement pattern, a CPU time limit of 24 hours would not be sufficient to reach the optimal solution. Hence, we propose clustering-based heuristic algorithms to provide immediate solutions without the need for a commercial solver.

To enable energy planers to make quick assessments, we develop a heuristic algorithm using the hierarchical agglomerative clustering, which is a well-known technique to group objects into clusters based on their proximity. It is a bottom-up approach, where each entity is considered as an individual cluster initially (i.e., each demand point is a singleton cluster) and merged together to create larger clusters based on their dissimilarity.

In Figure 4.9, we provide a flowchart of the proposed method. In this approach, we use our distance limit as the stopping criterion for agglomeration. Hence, agglomeration is performed iteratively based on the proximity of the clusters until the most similar pairs can not be merged due to the distance threshold. At each step of the clustering, we identify the least dissimilar pair of clusters based on a specific dissimilarity measure, and locate a new single facility to the distance-limited geometric median of the merged clusters. While the number of clusters is reduced iteratively, we record the total cost and the resulting configuration in order to provide the least-cost design as the final solution. However, some micro-grid clusters may not reach an ideal number of households making the micro-grids a cost-competitive alternative, which is determined based on the trade-off between facility costs. Hence, we apply post-processing to disintegrate the expensive micro-grid clusters into singleton clusters and/or assign some individual

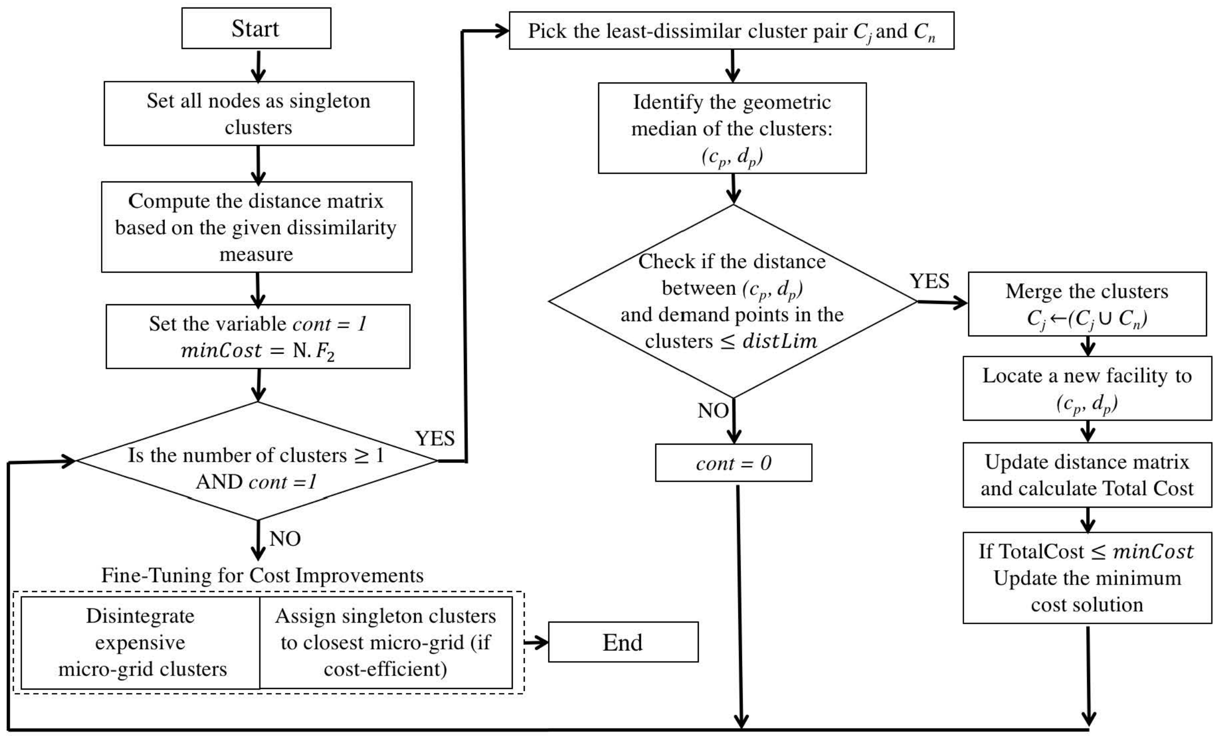



Figure 4.9: Flowchart of Agglomerative Clustering based Heuristic Approach

stand-alone systems to the closest micro-grid within the distance limit if it is cost-efficient. To determine the facility location for each cluster, we employ Vardi and Zhang's modified Weiszfeld algorithm and the projection methodology to shift the suggested facility location to the distance-limited geometric median, which is mentioned in Section 4.1.1.3 previously.

The dissimilarity measure plays a vital role in the agglomeration process. Various measures have been proposed in the literature to define the dissimilarity between clusters. The comparative analysis on these measures has indicated that there is no clear evidence showing that a specific measure is superior to others. Hence, we investigate well-known dissimilarity measures such as single-linkage, complete-linkage, average-linkage, minimax-linkage, centroid method, Hausdorff distance, and Ward's minimum variance to identify the best option for each problem among different alternatives.

As Johnson [52] presented, the single-linkage method (4.16) defines the dissimilarity as the minimum distance between the points of two separate clusters

$$d(j,n) = \min_{i \in C_j, m \in C_n} ||(a_i, b_i) - (a_m, b_m)||, \tag{4.16}$$

while complete-linkage (4.17) follows an opposite direction, defining the dissimilarity between clusters as the maximum distance between the point $i \in C_j$ and $n \in C_m$

$$d(j,n) = \max_{i \in C_j, m \in C_n} ||(a_i, b_i) - (a_m, b_m)||. \tag{4.17}$$

The third measure, average-linkage (4.18), defines the dissimilarity between the clusters as the average distance between the points in cluster $C_j$ and cluster $C_m$

$$d(j,n) = \frac{1}{|C_j|.|C_n|} \sum_{i \in C_j} \sum_{m \in C_n} ||(a_i, b_i) - (a_m, b_m)||. \tag{4.18}$$

This method is also referred to as the unweighted pair group method with arithmetic mean as presented in Sneath et al. [53].

Bien and Tibshirani [54] presented another dissimilarity measure called as minimax method (4.19), where the dissimilarity between the clusters $C_j$ and $C_m$ is determined as the radius of the smallest circle centered at a point either in $C_j$ or $C_m$, and encompassing all the points in both clusters

$$d(j,n) = \min_{i \in C_j \cup C_n} \max_{l \in C_j \cup C_n} ||(a_i, b_i) - (a_m, b_m)||. \tag{4.19}$$

In centroid-linkage (4.20), as the name hints, the dissimilarity is defined as the distance between the centroid of the clusters $C_j$ and $C_m$

$$d(j,n) = \left|\left| \frac{1}{|C_j|} \sum_{i \in C_j} (a_i, b_i) - \frac{1}{|C_n|} \sum_{i \in C_n} (a_m, b_m) \right|\right|. \tag{4.20}$$

Unlike the previous methods, Ward proposed a minimum variance method

(4.21), where the loss due to the agglomeration of the clusters is analyzed using an objective function [55]. This objective function can be adjusted in accordance with the problem characteristics. In this method, the dissimilarity between two clusters is defined as the increase in the error sum of squares after the clusters are agglomerated. Hence, using the same approach presented in [55], we calculate the total within-cluster sum of squares to determine the dissimilarity between two clusters in terms of Ward's minimum variance measure. The within-cluster sum of squares is specified as the sum of the squares of distances between the centroid and the points within the cluster.

$$d(j,n) = \sqrt{\frac{2|C_j||C_n|}{|C_j|+|C_n|}} \left\| \frac{1}{|C_j|} \sum_{i \in C_j} (a_i, b_i) - \frac{1}{|C_n|} \sum_{i \in C_n} (a_m, b_m) \right\|. \tag{4.21}$$

Finally, the Hausdorff clustering in [56] defines the dissimilarity between clusters $C_j$ and $C_m$ as the maximum of the distances between the closest pairs of points that belong to different clusters.

$$d(j,n) = \max(\max_{i \in C_j} \min_{m \in C_n} ||(a_i, b_i) - (a_m, b_m)||, \max_{m \in C_n} \min_{i \in C_j} ||(a_i, b_i) - (a_m, b_m)||) \tag{4.22}$$

In addition to these existing measures, we propose an additional method called GeomDiff. This new method defines the dissimilarity between clusters as the increase in the sum of point-to-facility distance due to agglomeration. In other words, we consider the potential increase in the total length of the low voltage connections to measure the dissimilarity between two clusters. Since GeomDiff also analyzes a loss due to the agglomeration, it can be considered as a version of Ward's variance method having a different objective function. To define the dissimilarity between two clusters, let us first denote the total sum of demand point-to-facility distances of the cluster $C_j$ as $Geom(C_j)$. Then, the objective of the GeomDiff is formulated as follows:

$$d(j,n) = Geom(C_j \cup C_n) - Geom(C_j) - Geom(C_n) \tag{4.23}$$

### 4.2.2 A Hybrid Heuristic Approach Based on DBSCAN and Agglomerative Clustering

In this heuristic approach, we propose to implement density-based spatial clustering applications with noise (DBSCAN)[57] to form micro-grid and nano-grid clusters. DBSCAN is one of the most extensively studied clustering approaches in the literature to group closely situated points in a given region. The algorithm has been frequently used as it has several distinguishing characteristics making the DBSCAN an attractive way for spatial clustering. Firstly, the algorithm does not require a predetermined value for the number of clusters, unlike the other well-known clustering approaches such as the k-means algorithm. Secondly, the algorithm is able to detect the remote points (outliers) so that they can be individually clustered.

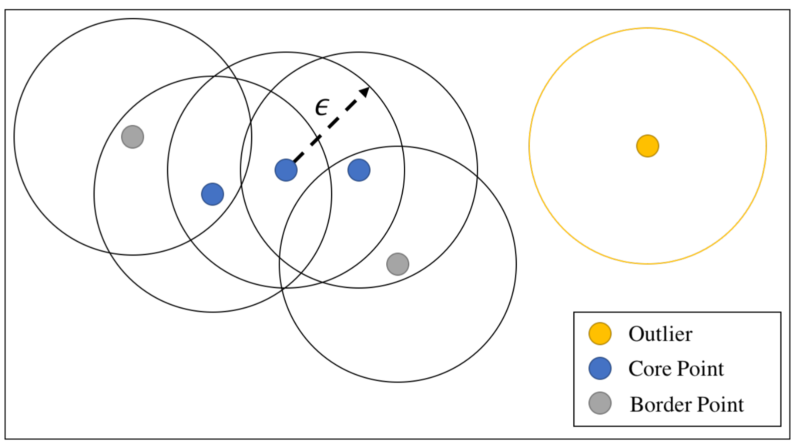



Figure 4.10: Classification of the points in DBSCAN algorithm ($minPts = 3$)

The algorithm incorporates two parameters, $minPts$ and $\epsilon$, that could significantly affect the performance of the algorithm. In the algorithm, $minPts$ denotes the minimum number of points required in the $\epsilon-$neighborhood of a node to define it as a core point. The neighborhood radius, on the other hand, is denoted by the parameter $\epsilon$. Each cluster consists of the connected core points and the non-core (border) points covered by the core nodes in the cluster. The nodes having zero points in the $\epsilon-$neighborhood are considered as outliers, as shown in Figure 4.10. The steps of the DBSCAN algorithm are also provided in Figure 4.11.

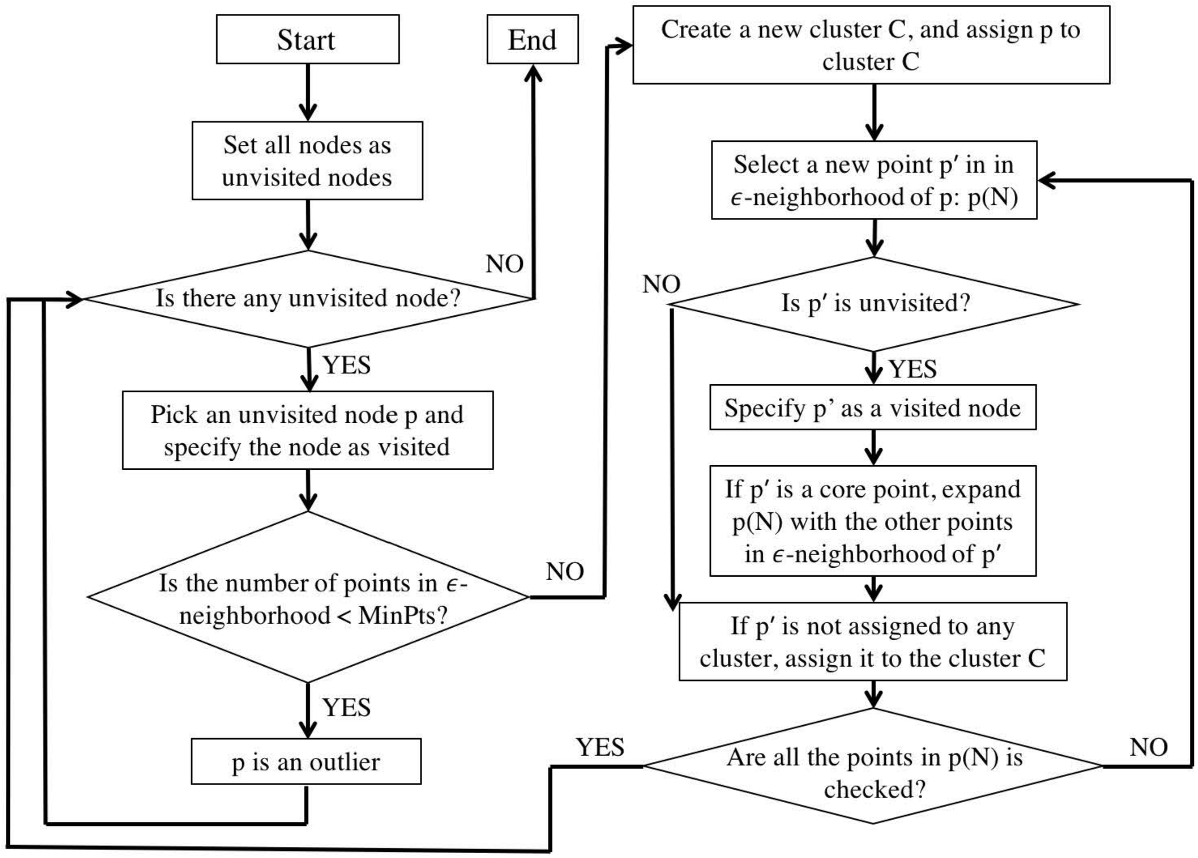



Figure 4.11: Flowchart of DBSCAN Clustering

In the algorithm, we used $\epsilon = distLim$ to determine the nodes in the $\epsilon-$neighborhood. The choice of $MinPts$, on the other hand, was not as trivial as the the choice of the $\epsilon$ parameter. For our problem, we chose $MinPts = 2$ intuitively, as the mini-grid requires at least two consumers. We also performed a sensitivity analysis to determine the ideal value for the $MinPts$ parameter. The sensitivity analysis on the dense and dispersed datasets has shown that the algorithm's ability to form micro-grid clusters decreases as we enforce higher values on $MinPts$. Therefore, the algorithm yields an expensive investment cost as the micro-grid option is used infrequently.

The flowchart of the hybrid DBSCAN-agglomerative clustering method is provided in Figure 4.12. In this hybrid solution approach, we implement a DBSCAN algorithm to identify the nano-grids and form the initial micro-grid clusters. We also calculate the radius of the smallest circle surrounding the demand locations

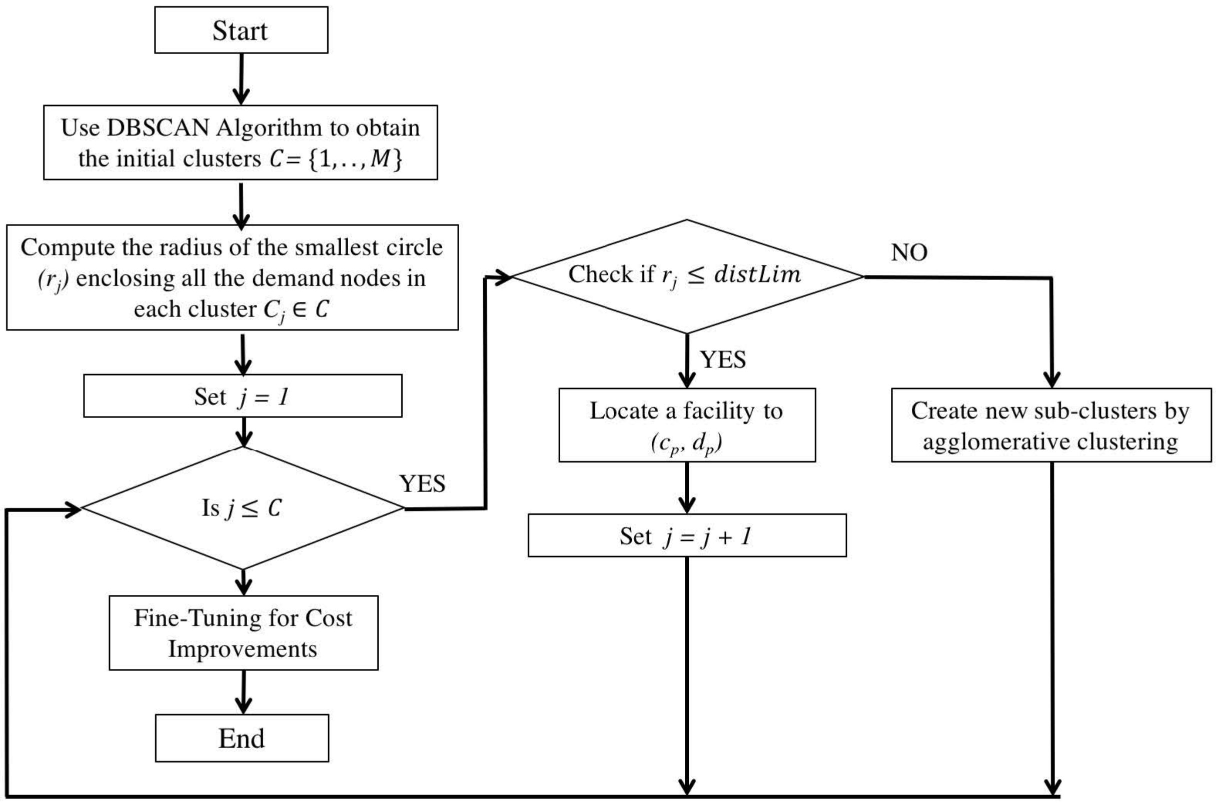



Figure 4.12: Flowchart of the Hybrid DBSCAN-Agglomerative Clustering Method

for each cluster serving more than one consumer. Although we specify the $\epsilon$ parameter as the coverage threshold, the distance between the demand points and the cluster center may not necessarily be within the distance limit. If the radius of the circle does not violate the distance limit constraint (i.e there is a feasible solution satisfying $distLim$, we locate a facility to the geometric median by using the modified version of the Weiszfeld Algorithm and project the suggested location by using the projection method provided in Section 4.1.1.3. Otherwise, we perform the agglomerative hierarchical clustering algorithm for this particular cluster assuming that each node within the cluster is a singleton cluster, and create new sub-clusters conforming to the distance threshold. After the final configuration is obtained, we apply a post-processing step for fine-tuning for cost improvements. In the post-processing step, we detach the households from the expensive microgrids having an insufficient number of households (i.e if total investment cost is cheaper when all consumers in the cluster are electrified individually), and allocate the singleton clusters to the closest micro-grid within the coverage threshold if it improves the total infrastructure cost.

### 4.2.3 A Hybrid Heuristic Approach Based on DBSCAN and K-Means Algorithms

This heuristic method follows a similar approach to the hybrid methodology proposed in the previous section. To create initial nano-grid and micro-grid clusters, we implement the DBSCAN algorithm using the same system parameters. Then, we find the minimum circle covering all the demand nodes in the cluster for each micro-grid. If the radius of the minimum circle exceeds the distance threshold, the cluster is iteratively divided into two sub-clusters using the k-means clustering technique until each sub-group conforms to the distance limit constraint. For each cluster meeting distance limit, we locate a facility to the geometric median and apply the same post-processing steps for fine-tuning at the end of the algorithm. The major steps of this hybrid approach are summarized in Figure 4.13.

K-means algorithm is one of the most well-known partitioning techniques in the literature. The algorithm is considered as a practical way of partitioning as it provides the final solution with high computational efficiency and requires only a single parameter $k$ (the number of clusters). The k-means clustering technique consists of the location and allocation steps as in Cooper's iterative heuristic. First, the algorithm picks $k$ random locations and forms $k$ clusters after assigning the points to the nearest location. Then, it computes the centroid of each cluster and reassigns the demand points to the closest center of mass. The algorithm repeatedly recalculates the centroids and performs the reallocation step until no further change is observed in two consecutive steps. However, it has been stated that the final configuration is susceptible to the starting clusters, and trying different initial assignments would improve the performance of the algorithm [58]. Therefore, we repeat k-means clustering 100 times to ensure a higher clustering accuracy.

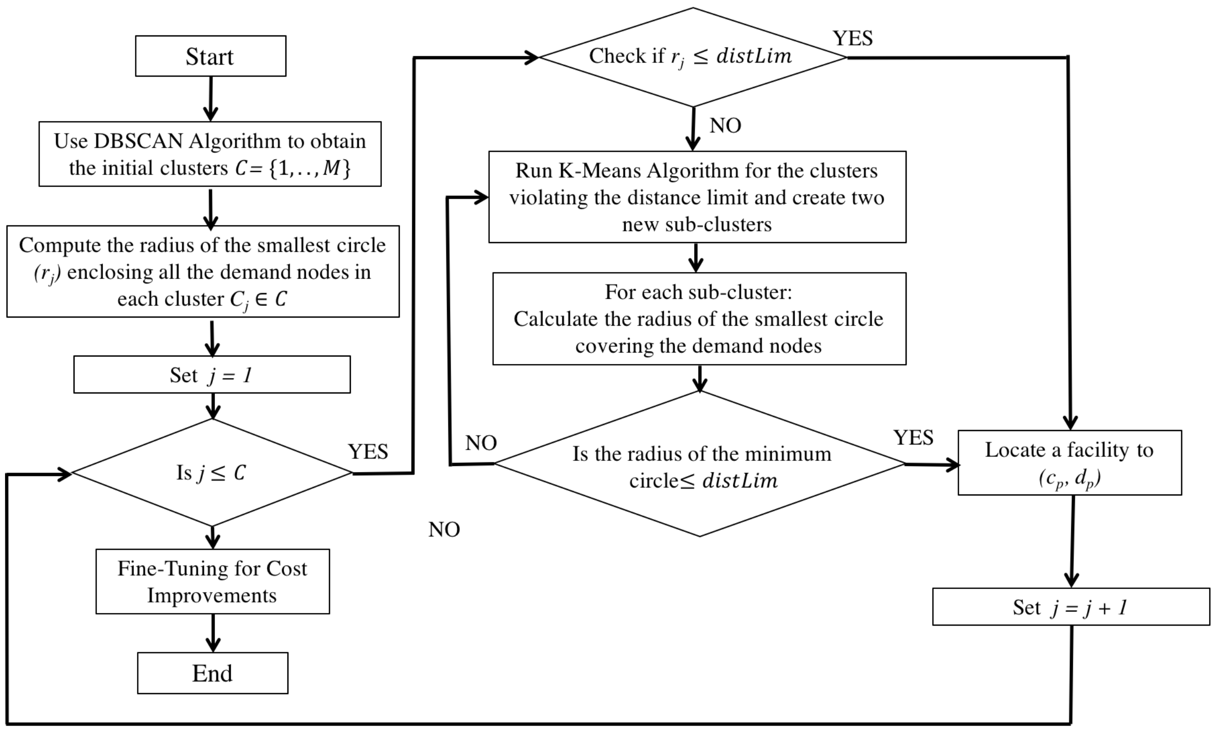
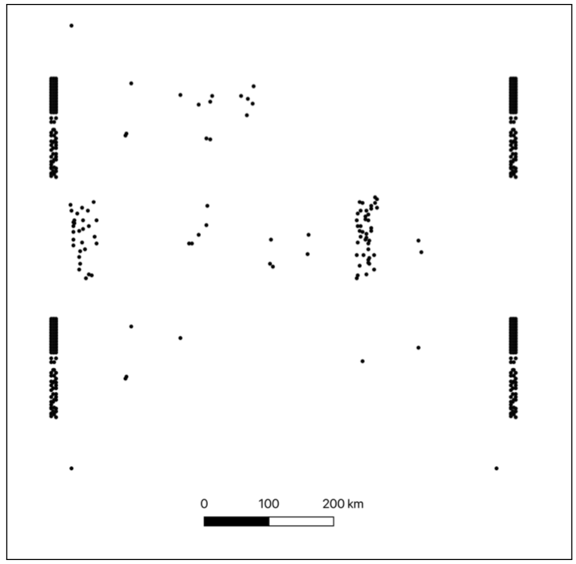



Figure 4.13: Flowchart of DBSCAN - K-Means Clustering based Heuristic Approach

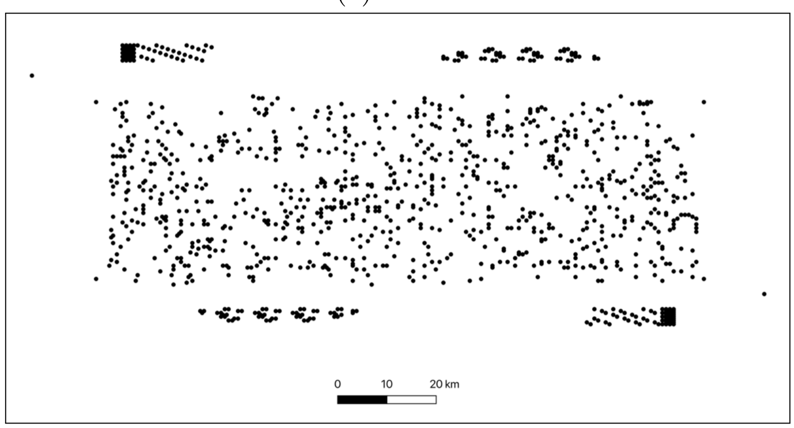
# Chapter 5

# Computational Results

In this section, we analyze the performance of the solution methodologies. We conduct experiments with synthetic and real data sets that are commonly used in MWP literature [31, 46, 59]. The synthetic data sets include 654 and 1060 customer problems provided in the TSP library [60] and denoted by S654 and S1060 in our study. Figures 5.1a and 5.1b show the distribution of demand points in the synthetic data sets. Our real data sets are obtained from four Millennium Villages sites located in Sub-Saharan Africa. Millennium Villages Project is an initiative to lift African countries out of the serious challenges they face, including poverty, hunger, disease and gender inequality [61]. This project aimed to achieve the rural development towards the Millennium Development Goals of United Nations, using an integrated model that addresses multiple aspects of the aforementioned challenges. In this study, we select four sites among nine millennium villages to test our solution methodology using realistic cost parameters. These sites (Tiby, Mali - Mbola, Tanzania - Potou, Senegal; Ruhiira, Uganda) [62] consists of 2496, 1175, 1797 and 6343 households, respectively, with different settlement patterns. As the mathematical modeling-based approaches could be computationally inefficient for such large instances, we selected four 2 x 2 $km^2$ sample sites with different densities from the villages as shown in Figures 5.2-5.5.




(a) S654




(b) S1060

Figure 5.1: Demand Points in S654 and S1060

For all the instances of S654, S1060 and real data sets, we assume that households are identical and they consume the same amount of electricity. In the experiments on S654 and S1060, micro-grid (F1) and nano-grid (F2) facility costs take values from the sets F1=$\{1000, 2000, 5000\}$, F2=$\{500, 750, 1000\}$ for the fixed cost problem, and F1=$\{1000\}$, F2=$\{1000, 2000, 5000\}$ for the fixed an variable cost problem. The nano-grid facility cost in the variable cost problem also takes values in the set F2=$\{1000, 2000, 5000\}$ as in the fixed and variable cost problem. These two problems include an additional cost component (F3) to charge the households connected to a micro-grid. F3 takes values from the set

F3=$\{500, 750, 1000\}$ in both problem types. The distance limit threshold $distLim$ is chosen from the set $\{200, 400, 600, 800, 1000\}$, and the unit cost of single phase low voltage connections is \$1 for S654 and S1060 as in Gokbayrak and Kocaman [10].

In the experiments on real-life instances, we considered realistic cost parameters and distance limit thresholds for the low voltage connections. The cost of low-voltage connections between the generation points and the consumers is set to $\$4/m$, and the maximum allowable length of these single-phase cables can take values from the set $distLim = \{30, 50, 100, 200\}$ as in Papathanassiou et al. [63], Stephen et al. [64], Short [65]. The nano-grid generation capacity is considered as 100 W, as the capacity of solar home systems generally ranges between 20 and 100 W in the rural areas of Sub-Saharan Africa [9]. Hence, the cost of deploying nano-grid is selected from the set $F2 = \{750, 1000\}$. The cost of stand-alone PV systems with capacities less than 1kW ranges from \$4/W to \$16/W across Sub-Saharan Africa. However, the cost reduces to \$2/W to \$8/W for the solar systems with more than 1 kWp installed capacities [9, 66]. Since solar PVs with higher scales can benefit from the economies of scale, we assume that the fixed cost of micro-grid facilities is either \$3000 or \$4000 in our experiments. Moreover, the additional charge of connecting households to micro-grids are selected from the set $F3 = \{500, 600\}$ in variable cost and fixed and variable cost problems.

The computational experiments are conducted on a dual 2.4 GHz Intel XeonE5-2630 v3 CPU server with 64GB RAM. All of the heuristic methods are implemented in Matlab 2020a and the optimization methods are solved using CPLEX 12.10. For all the optimization models, we enforce a CPU time limit of three hours. The convergence threshold $\varepsilon$ in the Cooper's iterative algorithm is employed as 0.1 for the multi-stage heuristic approaches.

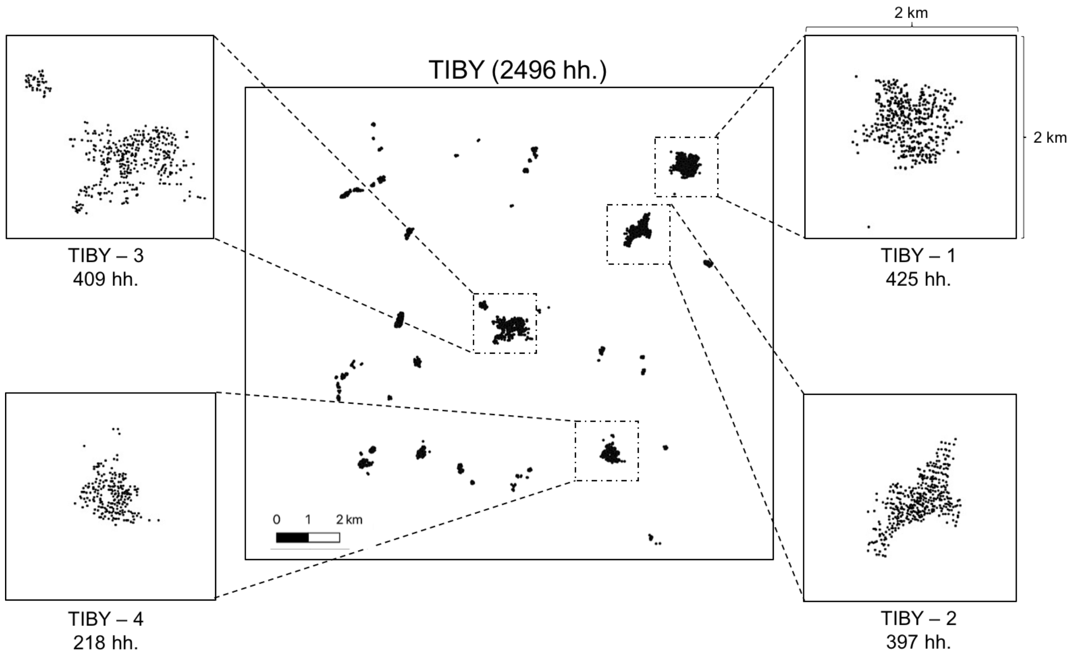



Figure 5.2: Tiby

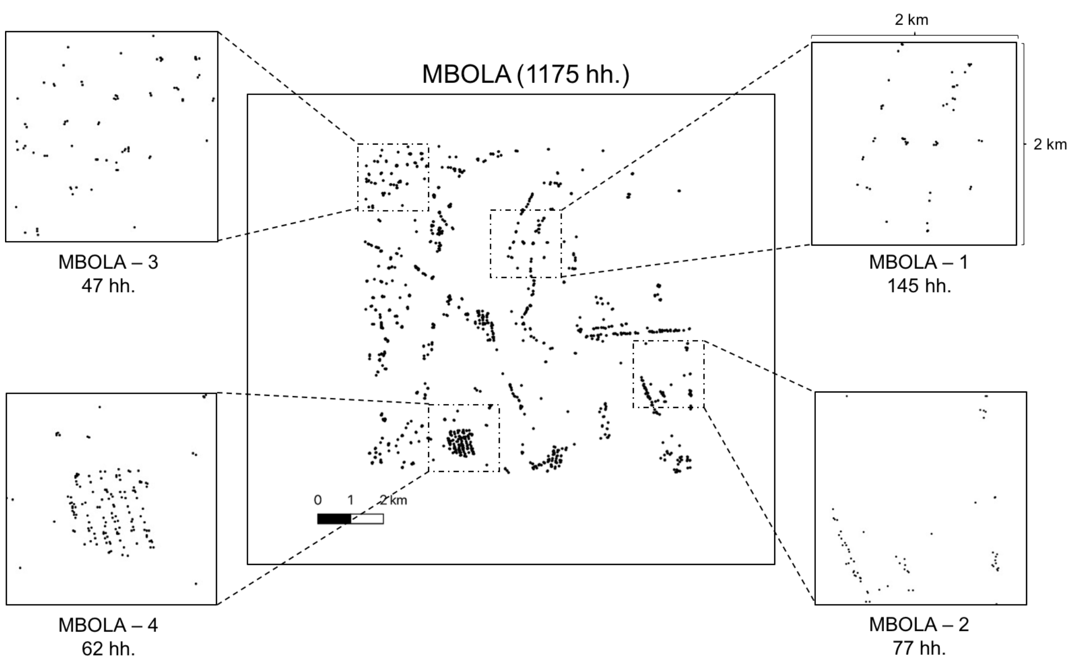



Figure 5.3: Mbola

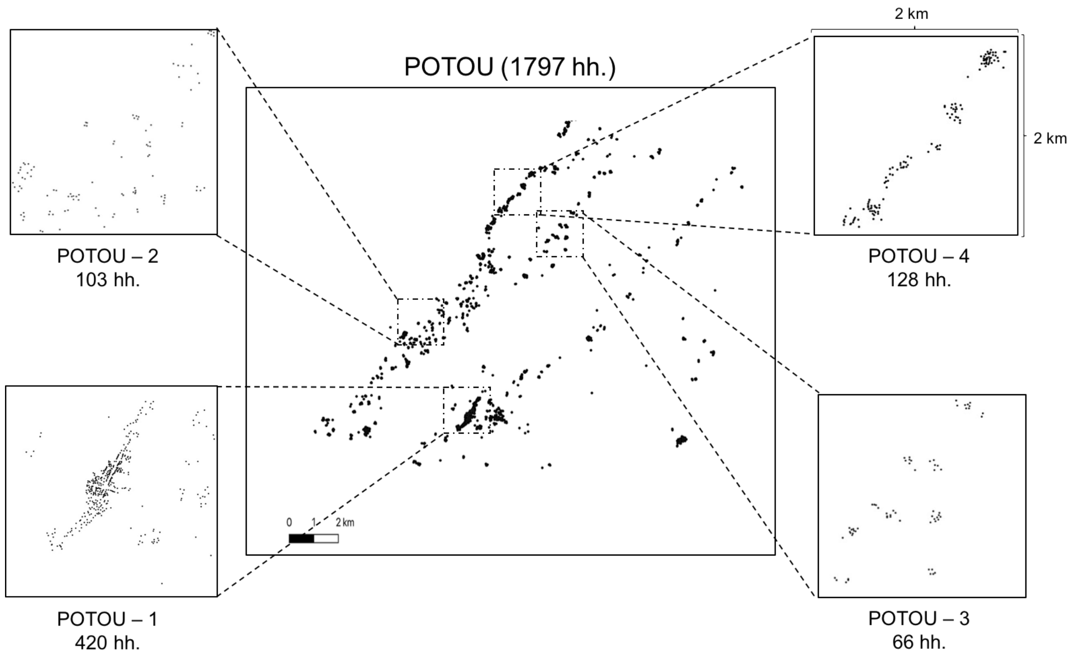



Figure 5.4: Potou

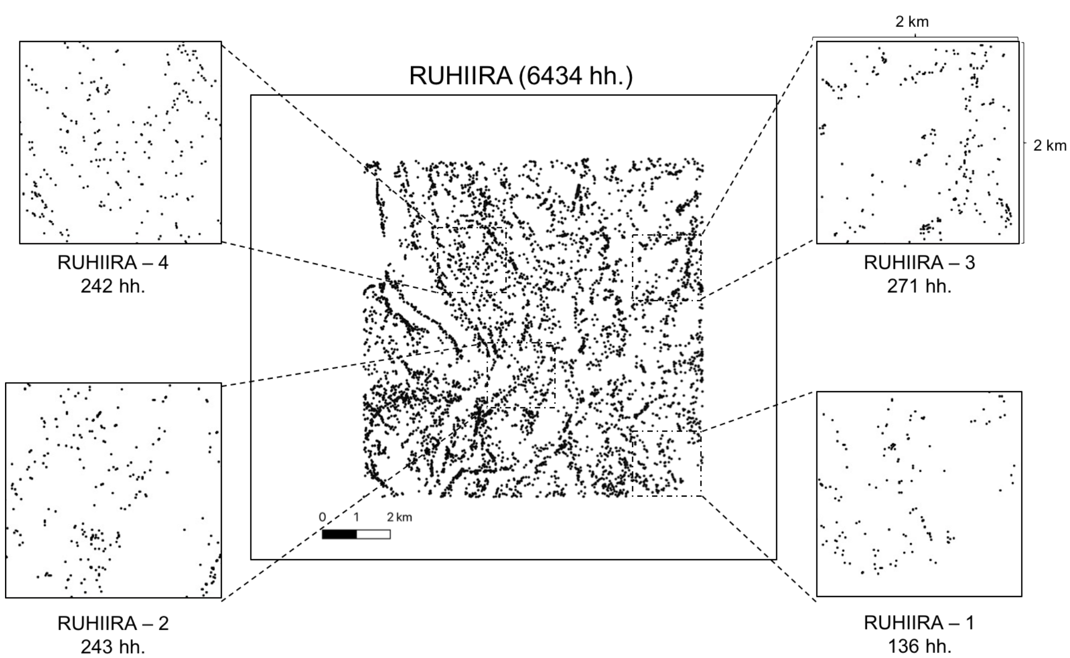



Figure 5.5: Ruhiira

## 5.1 Computational Results on the Synthetic Data

The performances of the model-based and clustering-based heuristics on our synthetic data sets are discussed in this section. For the analysis, we first compared the model-based and clustering-based methods separately, and identified the best performing methods for each type. The detailed results for the model-based and clustering-based heuristics can be found in Appendix C - E for different cost structures. In this section, we present the best-performing model-based and clustering-based solution methods and compare them in terms of the solution quality and running time. The computational results on S654 and S1060 are provided in Tables 5.1 - 5.3 and Tables 5.4 - 5.6, where the least-cost solutions are indicated by the boldface letters.

In Table 5.1, both model-based and clustering-based approaches seem to perform effectively in terms the solution quality in S654 for the fixed cost problem. The cost differences are observed to range between -1.5% to 2.2%, where the positive cost differences imply the superiority of the model-based heuristics. However, the model-based methods are observed have significantly longer running times with respect to the clustering-based approaches. While the multi-stage heuristic approach (MB-I) and its extended version (MB-II) exceed the time CPU time limit of three hours especially for the larger values of *distLim*, agglomerative clustering (Agg.), hybrid DBSCAN-k-means (DB-KM) and the DBSCAN-agglomerative clustering (DB-Agg.) approaches provide the final output within 11 CPU seconds in all instances. The unicost multi-stage heuristic (MB-III), on the other hand, can be considered as an attractive alternative for the cases where the other model-based approaches violate the CPU time-limit. In fact, this method is shown to perform better than MB-I and MB-II in some instances with more than 800 m distance limit.

With regard to the clustering-based approaches, agglomerative clustering is found to perform better than the other clustering-based methods in almost all instances, except for some instances with 200 m or 400 m distance limits. For the agglomerative clustering, we conducted a preliminary analysis of the performances of the proposed and existing dissimilarity measures on the synthetic data sets. The details of this analysis is provided in Appendix A. Regarding the results of the preliminary analysis, we restrict the choice of dissimilarity measures to three alternatives, namely, Complete measure, Ward's variance method, and GeomDiff for the experiments on the synthetic and real data. Therefore, the performance of the agglomerative clustering and the hybrid DBSCAN-agglomerative clustering methods are reported based on these three dissimilarity measures. In the agglomeration steps, Complete measure is observed to outperform the other dissimilarity measures as the difference between the nano-grid and micro-grid facility costs increases. GeomDiff, on the other hand, provides better solutions especially for the larger distance limits.

For the variable cost problem, Table 5.2 indicates that the performance of the clustering-based algorithms fall behind the model-based approaches. The extended version of the multi-stage heuristic (MB-II) also seems to work less effectively than MB-I in terms of the total investment cost. Although, the new augmentation methodology is shown to have a positive impact on the second-stage solutions, Cooper's algorithm converges to a local optima faster with the DFLAP-Ext. solution. Therefore, the third-stage improvements remain insufficient for the extended multi-stage heuristic (MB-II) to surpass MB-I in some instances. In Appendix B, we discuss the effects of the new augmentation methodology in detailed based on the second-stage results for the synthetic data sets. Finally, for the fixed and variable cost formulation, Table 5.3 shows that the cost difference between the model-based and clustering-based methods is the minimum among all problem types. The difference between the total costs ranges between 0.1% to 0.2% in the majority of instances. Additionally, agglomerative clustering dominates the other clustering algorithms as in the fixed cost formulation. In these instances, GeomDiff is observed to be the prominent dissimilarity measure as it performs better than the Complete measure and the Ward's variance method.

The numerical experiments on S1060 with the fixed cost structure is given in Table 5.4. Here, the cost differences are observed to be more significant than that of the fixed cost problem on S654. This result can be associated with the fact that the second-stage optimization models can not be solved to optimality for the majority of the instances in S654 as the data is densely populated. However, although we have larger instances in S1060, more than 80% of the instances are solved optimally in the second stage, leading to higher cost differences. For the variable cost structure, the cost differences increase further, especially under the 200 m distance limit. In these instances, the extended version of the multi-stage heuristic (MB-II) is observed outperform the other model-based heuristic approach. Finally, the computational experiments provided in Table 5.6 indicate that the clustering-based approaches show the best performance for the fixed and variable cost problems. The methods with agglomeration steps outperform the hybrid DBSCAN-kmeans algorithm in all instances. While the cost difference remains below 1% for the instances with more than 400 distance limit, the cost percentage falls below 0% in two instances, implying that the clustering-based algorithms surpass the model-based approaches.

Table 5.1: Comparison of Heuristic Methods on 654 (Fixed Cost)

| | | | | Best Model-based Heuristic | | | Best Clustering-based Heuristic | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | DistLim | F1 | F2 | Cost | Time | Method | Cost | Time | Method | Diff. |
| 654 | 200 | 1000 | 500 | **73766** | 5674.4 | MB-II | 74313 | 1.9 | DB-Agg. | 0.7% |
| | 200 | 1000 | 750 | **76362** | 2633.8 | MB-II | 78002 | 2.7 | Agg. | 2.1% |
| | 200 | 1000 | 1000 | **78612** | 125.3 | MB-II | 80252 | 2.3 | Agg. | 2.1% |
| | 200 | 2000 | 500 | **101032** | 10843.2 | MB-I | 101416 | 3.5 | DB-KM | 0.4% |
| | 200 | 2000 | 750 | **105724** | 10884.4 | MB-II | 107293 | 3.0 | DB-KM | 1.5% |
| | 200 | 2000 | 1000 | **111002** | 7519.6 | MB-I, MB-II | 113043 | 3.8 | DB-KM | 1.8% |
| | 200 | 5000 | 500 | **155233** | 10864.1 | MB-I | 158717 | 1.4 | DB-Agg. | 2.2% |
| | 200 | 5000 | 750 | **168694** | 10884.7 | MB-II | 169658 | 1.6 | DB-Agg. | 0.6% |
| | 200 | 5000 | 1000 | **177653** | 10885.3 | MB-II | 179408 | 1.4 | DB-Agg. | 1.0% |
| | 400 | 1000 | 500 | **72621** | 7581.5 | MB-I | 73147 | 4.4 | Agg. | 0.7% |
| | 400 | 1000 | 750 | **74542** | 37.1 | MB-III | 75042 | 5.0 | Agg. | 0.7% |
| | 400 | 1000 | 1000 | **75292** | 53.8 | MB-I, MB-II, MB-III | 75889 | 5.4 | Agg. | 0.8% |
| | 400 | 2000 | 500 | 99402 | 10845.9 | MB-I | **99127** | 3.9 | Agg., DB-Agg. | -0.3% |
| | 400 | 2000 | 750 | **101965** | 10845.5 | MB-I | 103430 | 4.7 | Agg., DB-Agg. | 1.4% |
| | 400 | 2000 | 1000 | **104627** | 10888.5 | MB-II | 105951 | 4.5 | Agg. | 1.3% |
| | 400 | 5000 | 500 | 144688 | 10886.2 | MB-II | **144243** | 1.7 | Agg. | -0.3% |
| | 400 | 5000 | 750 | 154529 | 10846.5 | MB-I | **153361** | 4.8 | DB-Agg. | -0.8% |
| | 400 | 5000 | 1000 | 160755 | 10884.8 | MB-II | **159361** | 5.2 | DB-Agg. | -0.9% |
| | 600 | 1000 | 500 | **72552** | 10852.1 | MB-I | 73960 | 6.6 | Agg. | 1.9% |
| | 600 | 1000 | 750 | **74260** | 224.2 | MB-I, MB-II | 75132 | 6.8 | Agg. | 1.2% |
| | 600 | 1000 | 1000 | **74686** | 94.7 | MB-II, MB-III | 75479 | 6.9 | Agg. | 1.1% |
| | 600 | 2000 | 500 | **98756** | 10852.9 | MB-I | 100537 | 6.0 | Agg. | 1.8% |
| | 600 | 2000 | 750 | **102070** | 10879.7 | MB-II | 103590 | 6.1 | Agg. | 1.5% |
| | 600 | 2000 | 1000 | **103144** | 10853.0 | MB-I | 104639 | 6.5 | Agg. | 1.4% |
| | 600 | 5000 | 500 | 144130 | 10853.3 | MB-I | **142975** | 1.8 | Agg. | -0.8% |
| | 600 | 5000 | 750 | 153249 | 10880.8 | MB-II | **151003** | 2.5 | Agg. | -1.5% |
| | 600 | 5000 | 1000 | 158026 | 10855.4 | MB-I | **156253** | 2.2 | Agg. | -1.1% |
| | 800 | 1000 | 500 | **73149** | 10917.1 | MB-II | 73593 | 8.1 | Agg. | 0.6% |
| | 800 | 1000 | 750 | **73871** | 534.1 | MB-I, MB-II | 74495 | 7.8 | Agg. | 0.8% |
| | 800 | 1000 | 1000 | **73968** | 88.8 | MB-I, MB-II, MB-III | 74591 | 7.6 | Agg. | 0.8% |
| | 800 | 2000 | 500 | 99872 | 10875.1 | MB-I | **99648** | 7.9 | Agg. | -0.2% |
| | 800 | 2000 | 750 | **102302** | 10918.1 | MB-II | 102688 | 7.5 | Agg. | 0.4% |
| | 800 | 2000 | 1000 | **102660** | 81.6 | MB-III | 103729 | 8.0 | Agg. | 1.0% |
| | 800 | 5000 | 500 | **143849** | 10875.3 | MB-I | 145183 | 2.1 | Agg. | 0.9% |
| | 800 | 5000 | 750 | **151799** | 10872.7 | MB-I | 152350 | 7.3 | Agg. | 0.4% |
| | 800 | 5000 | 1000 | **155425** | 10872.0 | MB-I | **155461** | 2.3 | Agg. | 0.0% |
| | 1000 | 1000 | 500 | **72622** | 10893.9 | MB-I | 73593 | 9.7 | Agg. | 1.3% |
| | 1000 | 1000 | 750 | **73871** | 366.0 | MB-I | 74495 | 9.5 | Agg. | 0.8% |
| | 1000 | 1000 | 1000 | **73968** | 87.6 | MB-III | 74591 | 9.6 | Agg. | 0.8% |
| | 1000 | 2000 | 500 | **99244** | 10944.0 | MB-II | 100843 | 2.1 | Agg. | 1.6% |
| | 1000 | 2000 | 750 | **102257** | 88.2 | MB-III | 103564 | 9.4 | Agg. | 1.3% |
| | 1000 | 2000 | 1000 | **102257** | 87.5 | MB-III | 103805 | 9.6 | Agg. | 1.5% |
| | 1000 | 5000 | 500 | 144909 | 10897.3 | MB-I | **143968** | 2.0 | Agg. | -0.6% |
| | 1000 | 5000 | 750 | 153211 | 10945.0 | MB-II | **151141** | 2.2 | Agg. | -1.4% |
| | 1000 | 5000 | 1000 | 154698 | 10892.9 | MB-I | **154030** | 1.9 | Agg. | -0.4% |

Table 5.2: Comparison of Heuristic Methods on 654 (Variable Cost)

| | | | | Best Model-based Heuristic | | | Best Clustering-based Heuristic | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F3 | F2 | Cost | Time | Method | Cost | Time | Method | Diff. |
| 654 | 200 | 500 | 1000 | **339281** | 113.6 | MB-I | 345574 | 1.3 | DB-Agg. | 1.9% |
| | 200 | 500 | 2000 | **347072** | 112.8 | MB-I | 358574 | 0.7 | DB-Agg. | 3.3% |
| | 200 | 500 | 5000 | **371070** | 111.2 | MB-I | 386162 | 3.3 | Agg. | 4.1% |
| | 200 | 750 | 1000 | **500595** | 112.2 | MB-I | 505824 | 0.8 | DB-Agg. | 1.0% |
| | 200 | 750 | 2000 | **508572** | 114.6 | MB-I | 518824 | 0.8 | DB-Agg. | 2.0% |
| | 200 | 750 | 5000 | **532570** | 111.2 | MB-I | 547662 | 3.2 | Agg. | 2.8% |
| | 200 | 1000 | 1000 | **654000** | 153.0 | MB-I, MB-II | **654000** | 2.9 | Agg., DB-KM, DB-Agg. | 0.0% |
| | 200 | 1000 | 2000 | **670072** | 113.9 | MB-I | 679074 | 0.8 | DB-Agg. | 1.3% |
| | 200 | 1000 | 5000 | **694070** | 114.7 | MB-I | 709162 | 3.2 | Agg. | 2.2% |
| | 400 | 500 | 1000 | **338150** | 121.5 | MB-I, MB-II | 348140 | 6.0 | DB-Agg. | 3.0% |
| | 400 | 500 | 2000 | **338204** | 122.0 | MB-I, MB-II | 356140 | 5.6 | DB-Agg. | 5.3% |
| | 400 | 500 | 5000 | **338204** | 121.3 | MB-I, MB-II | 374665 | 2.8 | Agg. | 10.8% |
| | 400 | 750 | 1000 | **500529** | 169.9 | MB-II | 508765 | 5.8 | DB-Agg. | 1.6% |
| | 400 | 750 | 2000 | **501704** | 121.1 | MB-I, MB-II | 517640 | 5.7 | DB-Agg. | 3.2% |
| | 400 | 750 | 5000 | **501704** | 122.3 | MB-I, MB-II | 537415 | 2.5 | Agg. | 7.1% |
| | 400 | 1000 | 1000 | **654000** | 162.7 | MB-I, MB-II | **654000** | 4.4 | Agg., DB-KM, DB-Agg. | 0.0% |
| | 400 | 1000 | 2000 | **665204** | 123.2 | MB-I, MB-II | 679140 | 5.0 | DB-Agg. | 2.1% |
| | 400 | 1000 | 5000 | **665204** | 119.8 | MB-I, MB-II | 700165 | 2.1 | Agg. | 5.3% |
| | 600 | 500 | 1000 | **338083** | 129.7 | MB-I | 351120 | 7.1 | Agg. | 3.9% |
| | 600 | 500 | 2000 | **338204** | 129.2 | MB-I | 360918 | 7.0 | Agg. | 6.7% |
| | 600 | 500 | 5000 | **338204** | 128.0 | MB-I | 369516 | 7.5 | Agg. | 9.3% |
| | 600 | 750 | 1000 | **500528** | 164.2 | MB-II | 510259 | 2.4 | Agg. | 1.9% |
| | 600 | 750 | 2000 | **501704** | 128.9 | MB-I | 522168 | 7.1 | Agg. | 4.1% |
| | 600 | 750 | 5000 | **501704** | 129.9 | MB-I | 532766 | 6.9 | Agg. | 6.2% |
| | 600 | 1000 | 1000 | **654000** | 168.8 | MB-I, MB-II | **654000** | 6.8 | Agg., DB-KM, DB-Agg. | 0.0% |
| | 600 | 1000 | 2000 | **665204** | 131.5 | MB-I | 683418 | 6.8 | Agg. | 2.7% |
| | 600 | 1000 | 5000 | **665204** | 129.3 | MB-I | 696016 | 6.4 | Agg. | 4.6% |
| | 800 | 500 | 1000 | **338081** | 209.8 | MB-II | 351120 | 7.7 | Agg. | 3.9% |
| | 800 | 500 | 2000 | **338204** | 152.8 | MB-I | 360918 | 8.1 | Agg. | 6.7% |
| | 800 | 500 | 5000 | **338204** | 149.8 | MB-I | 366261 | 7.9 | Agg. | 8.3% |
| | 800 | 750 | 1000 | **500533** | 154.1 | MB-I, MB-II | 510259 | 2.4 | Agg. | 1.9% |
| | 800 | 750 | 2000 | **501704** | 150.2 | MB-I | 522168 | 7.8 | Agg. | 4.1% |
| | 800 | 750 | 5000 | **501704** | 151.5 | MB-I | 529761 | 7.3 | Agg. | 5.6% |
| | 800 | 1000 | 1000 | **654000** | 189.4 | MB-I, MB-II | **654000** | 7.2 | Agg., DB-KM, DB-Agg. | 0.0% |
| | 800 | 1000 | 2000 | **665204** | 152.9 | MB-I | 683418 | 7.8 | Agg. | 2.7% |
| | 800 | 1000 | 5000 | **665204** | 155.3 | MB-I | 693261 | 7.5 | Agg. | 4.2% |
| | 1000 | 500 | 1000 | **338015** | 182.6 | MB-I, MB-II | 351120 | 9.5 | Agg. | 3.9% |
| | 1000 | 500 | 2000 | **338071** | 181.8 | MB-I, MB-II | 360918 | 9.9 | Agg. | 6.8% |
| | 1000 | 500 | 5000 | **338071** | 184.3 | MB-I, MB-II | 366261 | 10.6 | Agg. | 8.3% |
| | 1000 | 750 | 1000 | **500531** | 242.1 | MB-II | 510259 | 3.2 | Agg. | 1.9% |
| | 1000 | 750 | 2000 | **501571** | 179.0 | MB-I, MB-II | 522168 | 9.1 | Agg. | 4.1% |
| | 1000 | 750 | 5000 | **501571** | 185.5 | MB-I, MB-II | 529761 | 9.3 | Agg. | 5.6% |
| | 1000 | 1000 | 1000 | **654000** | 216.0 | MB-I, MB-II | 654000 | 9.8 | Agg., DB-KM, DB-Agg. | 0.0% |
| | 1000 | 2000 | 665082.46 | **665071** | 183.3 | MB-I, MB-II | 683418 | 9.8 | Agg. | 2.8% |
| | 1000 | 5000 | 665082.46 | **665071** | 179.5 | MB-I, MB-II | 693261 | 9.3 | Agg. | 4.2% |

Table 5.3: Comparison of Heuristic Methods on 654 (Fixed and Variable Costs)

| | | | | | Best Model-based Heuristic | | | Best Clustering-based Heuristic | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | DistLim | F1 | F2 | F3 | Cost | Time | Method | Cost | Time | Method | Diff. |
| 654 | 200 | 1000 | 1000 | 500 | **400766** | 5642.7 | MB-II | 401313 | 0.4 | DB-Agg. | 0.1% |
| | 200 | 1000 | 1000 | 750 | **557291** | 10852.6 | MB-I | 557906 | 0.3 | DB-Agg. | 0.1% |
| | 200 | 1000 | 2000 | 500 | **410123** | 125.3 | MB-II | 411752 | 2.3 | Agg. | 0.4% |
| | 200 | 1000 | 2000 | 750 | **571373** | 136.7 | MB-II | 573002 | 2.7 | Agg. | 0.3% |
| | 200 | 1000 | 5000 | 500 | **437123** | 127.6 | MB-II | 437474 | 4.2 | Agg. | 0.1% |
| | 200 | 1000 | 5000 | 750 | **598373** | 138.6 | MB-II | 598974 | 3.8 | Agg. | 0.1% |
| | 400 | 1000 | 1000 | 500 | **399621** | 7671.7 | MB-I | 400147 | 4.7 | Agg. | 0.1% |
| | 400 | 1000 | 1000 | 750 | 558212 | 10852.0 | MB-I | **557906** | 4.6 | Agg., DB-Agg. | -0.1% |
| | 400 | 1000 | 2000 | 500 | **403828** | 57.8 | MB-I, MB-II | 404389 | 5.5 | Agg. | 0.1% |
| | 400 | 1000 | 2000 | 750 | **566542** | 58.4 | MB-I, MB-II | 567139 | 5.8 | Agg. | 0.1% |
| | 400 | 1000 | 5000 | 500 | **412828** | 57.6 | MB-I, MB-II | 413389 | 4.8 | Agg. | 0.1% |
| | 400 | 1000 | 5000 | 750 | **575578** | 57.0 | MB-I, MB-II | 576139 | 5.1 | Agg. | 0.1% |
| | 600 | 1000 | 1000 | 500 | **399564** | 10856.4 | MB-I | 400960 | 7.2 | Agg. | 0.3% |
| | 600 | 1000 | 1000 | 750 | **558465** | 10883.6 | MB-I | 559149 | 2.8 | Agg. | 0.1% |
| | 600 | 1000 | 2000 | 500 | **402213** | 96.7 | MB-II | 402508 | 7.0 | Agg. | 0.1% |
| | 600 | 1000 | 2000 | 750 | **565436** | 98.3 | MB-II | 566008 | 6.8 | Agg. | 0.1% |
| | 600 | 1000 | 5000 | 500 | 405213 | 96.9 | MB-II | **402508** | 6.8 | Agg. | -0.7% |
| | 600 | 1000 | 5000 | 750 | 568463 | 96.9 | MB-II | **566008** | 6.9 | Agg. | -0.4% |
| | 800 | 1000 | 1000 | 500 | **400149** | 10920.9 | MB-II | 400593 | 7.8 | Agg. | 0.1% |
| | 800 | 1000 | 1000 | 750 | **558372** | 10877.6 | MB-I | 559102 | 7.9 | Agg. | 0.1% |
| | 800 | 1000 | 2000 | 500 | **400968** | 89.2 | MB-I, MB-II | 401591 | 8.6 | Agg. | 0.2% |
| | 800 | 1000 | 2000 | 750 | **564468** | 89.6 | MB-I, MB-II | 565091 | 8.3 | Agg. | 0.1% |
| | 800 | 1000 | 5000 | 500 | **400968** | 89.4 | MB-I, MB-II | 401591 | 8.3 | Agg. | 0.2% |
| | 800 | 1000 | 5000 | 750 | **564468** | 89.5 | MB-I, MB-II | 565091 | 8.3 | Agg. | 0.1% |
| | 1000 | 1000 | 1000 | 500 | **399622** | 10896.3 | MB-I | 400593 | 9.3 | Agg. | 0.2% |
| | 1000 | 1000 | 1000 | 750 | **558078** | 10950.5 | MB-II | 559102 | 9.3 | Agg. | 0.2% |
| | 1000 | 1000 | 2000 | 500 | **400981** | 111.2 | MB-I, MB-II | 401591 | 9.8 | Agg. | 0.2% |
| | 1000 | 1000 | 2000 | 750 | **564481** | 112.1 | MB-I, MB-II | 565091 | 9.4 | Agg. | 0.1% |
| | 1000 | 1000 | 5000 | 500 | **400981** | 111.7 | MB-I, MB-II | 401591 | 9.6 | Agg. | 0.2% |
| | 1000 | 1000 | 5000 | 750 | **564481** | 111.5 | MB-I, MB-II | 565091 | 9.8 | Agg. | 0.1% |

Table 5.4: Comparison of Heuristic Methods on 1060 (Fixed Cost)

| | | | | Best Model-based Heuristic | | | Best Clustering-based Heuristic | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | Cost | Time | Method | Cost | Time | Method | Diff. |
| | 200 | 1000 | 500 | **399356** | 724.7 | MB-II | 414687 | 7.1 | Agg. | 3.8% |
| | 200 | 1000 | 750 | **427688** | 623.6 | MB-II | 449138 | 5.6 | Agg. | 5.0% |
| | 200 | 1000 | 1000 | **434954** | 397.8 | MB-I, MB-III | 459888 | 5.4 | Agg. | 5.7% |
| | 200 | 2000 | 500 | **496098** | 1415.1 | MB-I | 500836 | 7.4 | DB-KM | 1.0% |
| | 200 | 2000 | 750 | **629406** | 942.5 | MB-II | 665723 | 5.5 | Agg. | 5.8% |
| | 200 | 2000 | 1000 | **683864** | 775.6 | MB-II | 740232 | 6.2 | Agg. | 8.2% |
| | 200 | 5000 | 500 | **522579** | 1466.0 | MB-I, MB-II | 525373 | 5.8 | DB-KM | 0.5% |
| | 200 | 5000 | 750 | **769799** | 1770.7 | MB-II | 772836 | 7.1 | DB-KM | 0.4% |
| | 200 | 5000 | 1000 | **991598** | 1506.5 | MB-I | 1004579 | 6.1 | DB-KM | 1.3% |
| | 400 | 1000 | 500 | **360124** | 560.9 | MB-II | 368356 | 1.6 | DB-Agg. | 2.3% |
| | 400 | 1000 | 750 | **367651** | 525.8 | MB-II | 374026 | 2.1 | DB-Agg. | 1.7% |
| | 400 | 1000 | 1000 | **369562** | 461.6 | MB-II | 377276 | 1.8 | DB-Agg. | 2.1% |
| | 400 | 2000 | 500 | **462040** | 1120.3 | MB-II | 473487 | 40.9 | DB-KM | 2.5% |
| | 400 | 2000 | 750 | **507511** | 2956.3 | MB-II | 524285 | 1.7 | DB-Agg. | 3.3% |
| | 400 | 2000 | 1000 | **517047** | 1633.6 | MB-II | 535973 | 1.8 | DB-Agg. | 3.7% |
| | 400 | 5000 | 500 | **517160** | 1480.6 | MB-I, MB-II | 517373 | 40.5 | DB-KM | 0.0% |
| | 400 | 5000 | 750 | **726444** | 1238.8 | MB-II | 739134 | 41.4 | DB-KM | 1.7% |
| | 400 | 5000 | 1000 | **815516** | 2049.2 | MB-II | 859585 | 5.1 | Agg. | 5.4% |
| | 600 | 1000 | 500 | **357808** | 388.1 | MB-I | 364106 | 6.2 | Agg., DB-Agg. | 1.8% |
| | 600 | 1000 | 750 | **361776** | 274.5 | MB-I | 366380 | 7.1 | Agg., DB-Agg. | 1.3% |
| | 600 | 1000 | 1000 | **363257** | 378.6 | MB-II | 367380 | 6.8 | Agg., DB-Agg. | 1.1% |
| | 600 | 2000 | 500 | **457612** | 1674.1 | MB-II | 464874 | 5.3 | Agg. | 1.6% |
| 1060 | 600 | 2000 | 750 | **480951** | 3324.1 | MB-I | 494025 | 4.6 | DB-Agg. | 2.7% |
| | 600 | 2000 | 1000 | **483617** | 1884.1 | MB-II | 495594 | 4.0 | DB-Agg. | 2.5% |
| | 600 | 5000 | 500 | **517134** | 1798.6 | MB-I, MB-II | 517161 | 4.9 | DB-Agg. | 0.0% |
| | 600 | 5000 | 750 | **687615** | 11068.8 | MB-I | 709067 | 33.7 | DB-KM | 3.1% |
| | 600 | 5000 | 1000 | **723707** | 11001.8 | MB-I | 764565 | 32.0 | DB-KM | 5.6% |
| | 800 | 1000 | 500 | **357837** | 484.7 | MB-I | 364831 | 6.8 | Agg., DB-Agg. | 2.0% |
| | 800 | 1000 | 750 | **361271** | 339.7 | MB-I | 365838 | 7.1 | Agg., DB-Agg. | 1.3% |
| | 800 | 1000 | 1000 | **362085** | 496.5 | MB-II, MB-III | 366588 | 7.9 | Agg., DB-Agg. | 1.2% |
| | 800 | 2000 | 500 | **457627** | 1878.3 | MB-I | 466317 | 5.1 | Agg. | 1.9% |
| | 800 | 2000 | 750 | **478960** | 11261.4 | MB-II | 487034 | 8.1 | DB-Agg. | 1.7% |
| | 800 | 2000 | 1000 | **480082** | 210.8 | MB-III | 487874 | 6.8 | Agg., DB-Agg. | 1.6% |
| | 800 | 5000 | 500 | **517134** | 2491.9 | MB-I, MB-II | 517692 | 28.5 | DB-KM | 0.1% |
| | 800 | 5000 | 750 | **689213** | 11180.8 | MB-I | 693024 | 6.2 | Agg., DB-Agg. | 0.6% |
| | 800 | 5000 | 1000 | **701761** | 11267.8 | MB-II | 722278 | 5.5 | Agg., DB-Agg. | 2.9% |
| | 1000 | 1000 | 500 | **357872** | 572.1 | MB-II | 364822 | 8.5 | Agg., DB-Agg. | 1.9% |
| | 1000 | 1000 | 750 | **361231** | 321.3 | MB-I | 365829 | 9.6 | Agg., DB-Agg. | 1.3% |
| | 1000 | 1000 | 1000 | **362078** | 223.0 | MB-III | 366579 | 8.7 | Agg., DB-Agg. | 1.2% |
| | 1000 | 2000 | 500 | **457613** | 3500.5 | MB-I | 466306 | 4.7 | Agg., DB-Agg. | 1.9% |
| | 1000 | 2000 | 750 | **479251** | 11253.8 | MB-II | 487158 | 5.5 | Agg., DB-Agg. | 1.6% |
| | 1000 | 2000 | 1000 | **480006** | 195.8 | MB-III | 488400 | 8.2 | Agg., DB-Agg. | 1.7% |
| | 1000 | 5000 | 500 | **517134** | 12158.9 | MB-I, MB-II | 518042 | 21.6 | DB-KM | 0.2% |
| | 1000 | 5000 | 750 | **686373** | 11220.8 | MB-I | 694215 | 5.2 | Agg., DB-Agg. | 1.1% |
| | 1000 | 5000 | 1000 | **697586** | 193.6 | MB-III | 710665 | 5.1 | Agg., DB-Agg. | 1.9% |

Table 5.5: Comparison of Heuristic Methods on 1060 (Variable Cost)

| | | | | Best Model-based Heuristic | | | Best Clustering-based Heuristic | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F3 | F2 | Cost | Time | Method | Cost | Time | Method | Diff. |
| 1060 | 200 | 500 | 1000 | **626676** | 778.6 | MB-II | 658971 | 4.7 | Agg. | 5.2% |
| | 200 | 500 | 2000 | **639552** | 773.3 | MB-II | 706732 | 5.1 | Agg. | 10.5% |
| | 200 | 500 | 5000 | **678552** | 773.0 | MB-II | 835732 | 4.8 | Agg. | 23.2% |
| | 200 | 750 | 1000 | **887279** | 805.7 | MB-II | 901399 | 5.6 | Agg. | 1.6% |
| | 200 | 750 | 2000 | **901302** | 772.3 | MB-II | 960982 | 4.9 | Agg. | 6.6% |
| | 200 | 750 | 5000 | **940302** | 773.3 | MB-II | 1089982 | 4.9 | Agg. | 15.9% |
| | 200 | 1000 | 1000 | **1060000** | 930.4 | MB-I, MB-II | **1060000** | 3.8 | Agg., DB-KM, DB-Agg. | 0.0% |
| | 200 | 1000 | 2000 | **1163052** | 774.3 | MB-II | 1215175 | 5.1 | Agg. | 4.5% |
| | 200 | 1000 | 5000 | **1202052** | 775.3 | MB-II | 1344232 | 5.5 | Agg. | 11.8% |
| | 400 | 500 | 1000 | **620652** | 724.1 | MB-II | 653781 | 1.8 | DB-Agg. | 5.3% |
| | 400 | 500 | 2000 | **623741** | 712.4 | MB-II | 674534 | 1.7 | DB-Agg. | 8.1% |
| | 400 | 500 | 5000 | **632733** | 738.4 | MB-II | 717790 | 5.9 | Agg. | 13.4% |
| | 400 | 750 | 1000 | **883060** | 776.8 | MB-II | 901296 | 6.3 | Agg. | 2.1% |
| | 400 | 750 | 2000 | **887991** | 710.4 | MB-II | 935034 | 1.2 | DB-Agg. | 5.3% |
| | 400 | 750 | 5000 | **896983** | 716.6 | MB-II | 980370 | 5.7 | Agg. | 9.3% |
| | 400 | 1000 | 1000 | **1060000** | 843.0 | MB-I, MB-II | **1060000** | 4.6 | Agg., DB-KM, DB-Agg. | 0.0% |
| | 400 | 1000 | 2000 | **1152241** | 710.8 | MB-II | 1195225 | 1.7 | DB-Agg. | 3.7% |
| | 400 | 1000 | 5000 | **1161233** | 722.8 | MB-II | 1242370 | 5.5 | Agg. | 7.0% |
| | 600 | 500 | 1000 | **620330** | 717.6 | MB-II | 647783 | 5.9 | DB-Agg. | 4.4% |
| | 600 | 500 | 2000 | **622337** | 509.5 | MB-I | 665789 | 5.7 | DB-Agg. | 7.0% |
| | 600 | 500 | 5000 | **628341** | 498.3 | MB-I | 705645 | 5.7 | DB-Agg. | 12.3% |
| | 600 | 750 | 1000 | **883057** | 721.2 | MB-II | 898725 | 5.9 | DB-Agg. | 1.8% |
| | 600 | 750 | 2000 | **886838** | 704.1 | MB-II | 926789 | 7.0 | DB-Agg. | 4.5% |
| | 600 | 750 | 5000 | **892841** | 498.7 | MB-I | 968395 | 6.1 | DB-Agg. | 8.5% |
| | 600 | 1000 | 1000 | **1060000** | 840.1 | MB-I, MB-II | **1060000** | 4.9 | Agg., DB-KM, DB-Agg. | 0.0% |
| | 600 | 1000 | 2000 | **1151338** | 724.5 | MB-II | 1187789 | 6.1 | DB-Agg. | 3.2% |
| | 600 | 1000 | 5000 | **1157341** | 498.5 | MB-I | 1231145 | 5.5 | DB-Agg. | 6.4% |
| | 800 | 500 | 1000 | **620287** | 585.6 | MB-I | 650830 | 9.6 | DB-Agg. | 4.9% |
| | 800 | 500 | 2000 | **622236** | 603.5 | MB-I | 670940 | 8.4 | DB-Agg. | 7.8% |
| | 800 | 500 | 5000 | **628230** | 731.0 | MB-I | 710901 | 9.8 | DB-Agg. | 13.2% |
| | 800 | 750 | 1000 | **883057** | 619.8 | MB-I, MB-II | 900131 | 8.5 | DB-Agg. | 1.9% |
| | 800 | 750 | 2000 | **886735** | 604.7 | MB-I | 931940 | 8.5 | DB-Agg. | 5.1% |
| | 800 | 750 | 5000 | **892730** | 731.7 | MB-I | 973986 | 8.0 | DB-Agg. | 9.1% |
| | 800 | 1000 | 1000 | **1060000** | 938.1 | MB-I, MB-II | **1060000** | 6.9 | Agg., DB-KM, DB-Agg. | 0.0% |
| | 800 | 1000 | 2000 | **1151824** | 787.1 | MB-II | 1192940 | 8.3 | DB-Agg. | 3.6% |
| | 800 | 1000 | 5000 | **1157230** | 730.5 | MB-I | 1236736 | 8.1 | DB-Agg. | 6.9% |
| | 1000 | 500 | 1000 | **620230** | 788.1 | MB-II | 652668 | 10.7 | DB-Agg. | 5.2% |
| | 1000 | 500 | 2000 | **622232** | 911.2 | MB-II | 674010 | 10.5 | DB-Agg. | 8.3% |
| | 1000 | 500 | 5000 | **622349** | 601.0 | MB-I | 713971 | 14.4 | DB-Agg. | 14.7% |
| | 1000 | 750 | 1000 | **883078** | 609.1 | MB-I | 900778 | 11.1 | DB-Agg. | 2.0% |
| | 1000 | 750 | 2000 | **886739** | 594.5 | MB-I | 935010 | 10.5 | DB-Agg. | 5.4% |
| | 1000 | 750 | 5000 | **887349** | 602.2 | MB-I | 977056 | 10.7 | DB-Agg. | 10.1% |
| | 1000 | 1000 | 1000 | **1060000** | 924.1 | MB-I, MB-II | **1060000** | 7.1 | Agg., DB-KM, DB-Agg. | 0.0% |
| | 1000 | 2000 | 665082.46 | **1151236** | 597.9 | MB-I | 1196010 | 11.8 | DB-Agg. | 3.9% |
| | 1000 | 5000 | 665082.46 | **1152349** | 601.4 | MB-I | 1239806 | 10.9 | DB-Agg. | 7.6% |

Table 5.6: Comparison of Heuristic Methods on 1060 (Fixed and Variable Costs)

| | | | | | Best Model-based Heuristic | | | Best Clustering-based Heuristic | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | F3 | Cost | Time | Method | Cost | Time | Method | Diff. |
| 1060 | 200 | 1000 | 1000 | 500 | **929356** | 728.3 | MB-II | 944687 | 8.2 | Agg. | 1.6% |
| | 200 | 1000 | 1000 | 750 | **1053886** | 1577.8 | MB-II | 1054001 | 5.3 | DB-KM | 0.0% |
| | 200 | 1000 | 2000 | 500 | **975954** | 402.3 | MB-I | 1011388 | 5.8 | Agg. | 3.6% |
| | 200 | 1000 | 2000 | 750 | **1235454** | 401.7 | MB-I | 1265638 | 5.9 | Agg. | 2.4% |
| | 200 | 1000 | 5000 | 500 | **1042095** | 238.4 | MB-I | 1140388 | 5.3 | Agg. | 9.4% |
| | 200 | 1000 | 5000 | 750 | **1301595** | 237.8 | MB-I | 1394638 | 5.3 | Agg. | 7.1% |
| | 400 | 1000 | 1000 | 500 | **890124** | 564.1 | MB-II | 898356 | 2.2 | DB-Agg. | 0.9% |
| | 400 | 1000 | 1000 | 750 | **1053770** | 1931.1 | MB-I, MB-II | 1055562 | 2.2 | DB-Agg. | 0.2% |
| | 400 | 1000 | 2000 | 500 | **903082** | 363.2 | MB-II | 911720 | 5.7 | Agg. | 1.0% |
| | 400 | 1000 | 2000 | 750 | **1166062** | 472.8 | MB-II | 1175220 | 5.8 | Agg. | 0.8% |
| | 400 | 1000 | 5000 | 500 | **921082** | 360.6 | MB-II | 929720 | 5.8 | Agg. | 0.9% |
| | 400 | 1000 | 5000 | 750 | **1184582** | 363.7 | MB-II | 1193220 | 6.2 | Agg. | 0.7% |
| | 600 | 1000 | 1000 | 500 | **887808** | 398.2 | MB-I | 894106 | 6.1 | Agg., DB-Agg. | 0.7% |
| | 600 | 1000 | 1000 | 750 | **1053789** | 2049.7 | MB-I | 1055562 | 3.7 | DB-Agg. | 0.2% |
| | 600 | 1000 | 2000 | 500 | **895855** | 174.1 | MB-I | 899007 | 6.1 | Agg. | 0.4% |
| | 600 | 1000 | 2000 | 750 | **1159507** | 386.5 | MB-II | 1163257 | 6.5 | Agg. | 0.3% |
| | 600 | 1000 | 5000 | 500 | 910855 | 175.2 | MB-I | **908007** | 7.3 | Agg. | -0.3% |
| | 600 | 1000 | 5000 | 750 | 1174605 | 174.1 | MB-I | **1172257** | 6.9 | Agg. | -0.2% |
| | 800 | 1000 | 1000 | 500 | **887837** | 488.1 | MB-I | 894831 | 6.6 | Agg., DB-Agg. | 0.8% |
| | 800 | 1000 | 1000 | 750 | **1053789** | 2480.1 | MB-II | 1057623 | 3.9 | DB-Agg. | 0.4% |
| | 800 | 1000 | 2000 | 500 | **893710** | 270.9 | MB-I | 898088 | 8.0 | Agg., DB-Agg. | 0.5% |
| | 800 | 1000 | 2000 | 750 | **1157835** | 497.0 | MB-II | 1162338 | 6.7 | Agg., DB-Agg. | 0.4% |
| | 800 | 1000 | 5000 | 500 | **902710** | 271.7 | MB-I | 907088 | 8.6 | Agg., DB-Agg. | 0.5% |
| | 800 | 1000 | 5000 | 750 | **1166960** | 274.7 | MB-I | 1171338 | 7.6 | Agg., DB-Agg. | 0.4% |
| | 1000 | 1000 | 1000 | 500 | **887872** | 576.5 | MB-II | 894822 | 8.1 | Agg., DB-Agg. | 0.8% |
| | 1000 | 1000 | 1000 | 750 | **1053789** | 1847.2 | MB-I, MB-II | 1057623 | 4.5 | DB-Agg. | 0.4% |
| | 1000 | 1000 | 2000 | 500 | **893701** | 455.8 | MB-II | 898079 | 9.2 | Agg., DB-Agg. | 0.5% |
| | 1000 | 1000 | 2000 | 750 | **1157828** | 288.8 | MB-I | 1162329 | 9.1 | Agg., DB-Agg. | 0.4% |
| | 1000 | 1000 | 5000 | 500 | **902701** | 460.0 | MB-II | 907079 | 8.3 | Agg., DB-Agg. | 0.5% |
| | 1000 | 1000 | 5000 | 750 | **1166951** | 454.3 | MB-II | 1171329 | 8.9 | Agg., DB-Agg. | 0.4% |

## 5.2 Computational Results on the Real Instances

In this section, we discuss the performances of the model-based and the clustering-based heuristics on the real instances having distinct settlement patterns. For this purpose, we first conducted a comparative analysis of the model-based and clustering-based methods individually, whose details can be found in Appendix F - H. Here, we summarize the best-performing model-based and clustering-based approaches and compare them based on the solutions' quality and the computational time for the real instances.

Based on the settlement patterns we encountered in different regions, we propose a new indicator metric called Household Coverage Index (HCI) to measure the dispersion of households and classify the spatial distribution of the sample populations. This metric represents the average number of demand nodes in the $distLim-$neighborhood of each household. In other words, we define HCI as the average number of demand nodes within $distLim$ distance from each demand location. The regions having a smaller HCI are considered as dispersed settlements, whereas higher HCI refers to densely populated structures in the given region. Therefore, all sample sites selected from Tiby and Potou-1 are considered as densely populated areas while Mbola and Ruhiira have dispersed settlement structures. The computational results in the following sections indicate that the solution time of the model-based heuristic methods for densely populated areas are significantly longer compared to the sites having dispersed settlements.

Table 5.7: Household Coverage Index for the Real Instances

| | Distance Limit | HCI |
|---|---|---|
| TIBY-1 | 30 | 4.6 |
| | 50 | 11.5 |
| | 100 | 41.4 |
| | 200 | 135.8 |
| TIBY-2 | 30 | 5.6 |
| | 50 | 14.3 |
| | 100 | 49.4 |
| | 200 | 147.9 |
| TIBY-3 | 30 | 4.1 |
| | 50 | 9.2 |
| | 100 | 29.1 |
| | 200 | 86.5 |
| TIBY-4 | 30 | 4.8 |
| | 50 | 11.6 |
| | 100 | 38.4 |
| | 200 | 114.5 |

| | Distance Limit | HCI |
|---|---|---|
| POTOU-1 | 30 | 10.4 |
| | 50 | 24.8 |
| | 100 | 73.9 |
| | 200 | 167.4 |
| POTOU-2 | 30 | 2.6 |
| | 50 | 3.6 |
| | 100 | 5.8 |
| | 200 | 12.1 |
| POTOU-3 | 30 | 3.5 |
| | 50 | 5.6 |
| | 100 | 7.8 |
| | 200 | 10.2 |
| POTOU-4 | 30 | 5.3 |
| | 50 | 11.2 |
| | 100 | 21.5 |
| | 200 | 31.2 |

| | Distance Limit | HCI |
|---|---|---|
| MBOLA-1 | 30 | 2.1 |
| | 50 | 3.1 |
| | 100 | 6.1 |
| | 200 | 18.8 |
| MBOLA-2 | 30 | 2.2 |
| | 50 | 2.7 |
| | 100 | 3.2 |
| | 200 | 4.5 |
| MBOLA-3 | 30 | 2.1 |
| | 50 | 2.4 |
| | 100 | 3.2 |
| | 200 | 4.2 |
| MBOLA-4 | 30 | 1.7 |
| | 50 | 2.8 |
| | 100 | 5.0 |
| | 200 | 8.9 |

| | Distance Limit | HCI |
|---|---|---|
| RUHIIRA-1 | 30 | 1.7 |
| | 50 | 2.4 |
| | 100 | 4.0 |
| | 200 | 8.7 |
| RUHIIRA-2 | 30 | 2.0 |
| | 50 | 2.7 |
| | 100 | 5.4 |
| | 200 | 13.6 |
| RUHIIRA-3 | 30 | 2.5 |
| | 50 | 3.8 |
| | 100 | 7.3 |
| | 200 | 16.2 |
| RUHIIRA-4 | 30 | 1.6 |
| | 50 | 2.2 |
| | 100 | 4.1 |
| | 200 | 10.8 |

### 5.2.1 Tiby

The sample sites selected from Tiby are considered as densely populated areas compared to the sample regions in Mbola and Ruhiira with a lower household coverage index (HCI). For the fixed cost formulation, Table F.1 shows that the extended version of the multi-stage heuristic approach (MB-II) outperforms the other model-based heuristics in Tiby-1, Tiby-2, and Tiby-4, when the distance threshold is less than or equal to 50 m. However, MB-I and MB-III perform more effectively than MB-II in terms of the total cost for the larger values of the distance threshold. Nevertheless, it is worth noticing that the CPU time limit of three hours is exceeded in the majority of instances, where the distance limit is enforced to be greater than 50 m.

Tiby-3 has a more dispersed structure compared to other sample sites selected from Tiby. Interestingly, MB-I is found to be effective in Tiby-3 under strict distance limitations. Although MB-II is expected to be the superior method, the best cost solution is attained by MB-I in 5 out of 8 instances for the 30 m and 50 m distance limits. However, it should be noted that the variance between MB-I and MB-II is less than 0.02% for these instances in terms of the objective value.

In the fixed and variable cost problem, we draw similar conclusions as in the fixed cost formulation. Table H.1 demonstrate that MB-I becomes the more prominent method when the other multi-stage heuristics violate the predetermined CPU time limit. However, as long as the problem is solved to optimality, MB-II can provide the best solution unless Cooper's algorithm falls into local optima traps in early iterations.

In the variable cost formulation, the best solutions are attained by MB-II in all the instances of Tiby-2 and Tiby-3 as shown in Table G.1. For Tiby-1 and Tiby-2, MB-I seems to perform better than the extended version of the heuristic under the 30 m distance limit. However, the most significant difference between these solutions is obtained as 0.02%. Similarly, the reasoning behind this negligible difference is that Cooper's algorithm may converge to a local optimum in the earlier iterations. Another point that should be noted that the solution time reduces significantly in the variable cost problems. Although most instances violate the time limit for the problems with the fixed cost component, the maximum running times of MB-I and MB-II are recorded as 120 and 270 CPU seconds, respectively.

On the contrary to the model-based approaches, clustering-based heuristics yield the final output within the significantly shorter computational time. The running time of the agglomerative clustering (Agg.) and the hybrid DBSCAN Agglomerative clustering approach (DB-Agg.) range between 0.2 to 4 CPU seconds for the fixed cost formulation. DB-KM, on the other hand, yields the final output in less than 31 seconds in all instances of Tiby. In Tiby-1, Tiby-2, and Tiby-3, DB-Agg. and agglomerative clustering methods outperform the hybrid DBSCAN & k-means (DB-KM) approach, particularly for 100 and 200 m distance limits. However, DB-KM is observed to perform better under relatively lower distance limits as shown in Table F.2. The clustering-based algorithms show the same characteristics in the variable cost formulation (see Table G.2). The only difference is that the DB-KM algorithm does not yield the best solution in any of the instances of Tiby. Agglomerative clustering dominates the DB-Agg. in almost all of the instances for the 30 m distance threshold. In the fixed and variable cost formulation, we observe a significant increase in the performance of the DB-KM algorithm. According to Table H.2, the algorithm finds the least-cost solution in 60 out of 128 instances of Tiby, and it dominates the other clustering-based algorithms in 19 instances.

### 5.2.2 Mbola

The sample sites selected from Mbola include a much smaller number of households with a dispersed population structure. The considerably lower HCI measures indicate that all these sample sites, except Mbola-1, have the most dispersed structures in the sixteen sample regions. As the areas in Mbola show a dispersed pattern of population, the frames of size 2 km x 2 km contain at most 145 households. Accordingly, due to the sparse population structure and the fewer households in each frame, the problem becomes more trivial to solve compared to the dense and crowded settlements in Tiby. Hence, even the model-based methods obtain the least-cost solution in seconds in all instances according to Table F.3, G.3 and H.3.

In the fixed cost formulation, the solution times of MB-I and MB-II generally range between 1 to 19 CPU seconds in Mbola as seen in Table F.3. However, in Mbola-1, the optimal solutions are attained in at most 32 CPU seconds for the coverage thresholds ranging between 30 to 100 meters, and the running time increases up to 686 seconds in the instances with a 200 m distance limit. Because all instances can be solved within the time limit, MB-II provides the least-cost configuration in Mbola for all distance thresholds and cost parameters. MB-I accompanies MB-II in 78% of instances by giving the best result simultaneously. Similarly, both multi-stage heuristics achieve the least-cost configuration in 46 out of 64 instances for the variable cost problem as shown in Table G.3. For the remaining 18 instances, it is found that MB-II outperforms MB-I in 17 solutions, whereas there is only a single case that MB-I performs better than MB-II. Finally, in the fixed and variable cost problems (Table H.3), the majority of the solutions can be obtained within 3 CPU seconds in Mbola-2, Mbola-3, and Mbola-4. However, the average running time of both heuristic methods increases in Mbola-1, where the maximum solution times are recorded as 88.2 and 174 CPU seconds for MB-I and MB-II, respectively. MB-I outperforms MB-II only in a single instance, whereas MB-II dominates the other in 12 instances.

The clustering-based approaches can find the best solution within a second in all instances of Mbola. This result can be associated with the fact that the algorithms prefer the nano-grid option more frequently in the dispersed settlements as the distance limit constraint restricts the available micro-grid connections. According to Table F.4 DBSCAN-based algorithms perform better than the agglomerative clustering in the majority of the instances. Although the agglomerative approach dominates the DBSCAN-based algorithms in densely populated areas, the situation is the opposite in Mbola, where the households are sparsely distributed. In the fixed cost formulation, DBSCAN based algorithms seem to outperform the agglomerative clustering approach, especially in the instances of Mbola-2. We also note that these algorithms create a higher number of micro-grid clusters, leading to significant cost reductions. For the methods that include the agglomeration steps (Agg. and DB-Agg), GeomDiff is observed to outperform Ward's variance and Complete measure in most instances. In fact, none of the least-cost solutions is attained by using Ward's variance method for the sample sites selected from Mbola. In the variable cost formulation, Table G.4 shows that agglomerative clustering dominates DBSCAN-based algorithms in all the instances of Mbola-3 and Mbola-4. While GeomDiff is the prominent dissimilarity measure in Mbola-2, Mbola-3, and Mbola-4, Ward's variance method dominates the other measures in the instances of the first sample site. Interestingly, it is observed that all clustering-based approaches can find the least-cost configuration in 71 out of 128 instances for the problems having fixed and variable cost components. In Table H.4, agglomerative clustering is shown to work effectively in terms the total cost as in the variable cost formulation. Similarly, GeomDiff performs better than the other two dissimilarity measures in approximately more than 87% of the instances.

### 5.2.3 Potou

Unlike Mbola and Tiby, the sample sites in Potou show diverse characteristics in terms of population density as can be observed from the HCI values. While Potou-1 is considered as the most densely populated area among all sample sites, Potou-2 and Potou-3 have dispersed settlement patterns as in the samples from Mbola. In Table F.5, we observe that the performance of MB-I surpasses that of the other two model-based heuristic methods for some instances having a strict distance limit constraint (i.e., 30 m, 50 m) in Potou-1 and Potou-2. While these instances in Potou-1 exceed the three hours limit, Table F.5 indicates that the instances in Potou-2 could be solved within 25 seconds. In Potou-3 and Potou-4, all model-based heuristic approaches can obtain the least-cost configuration for a 200 m distance limit. We also note that MB-III outperforms the other multi-stage heuristics in 3 out of 64 instances in Potou-1 and Potou-3. In the variable cost problem, the cost-efficient solution can be attained by MB-II in almost all instances except a single case, where MB-I performs better than the extended multi-stage heuristic method. Nevertheless, MB-I accompanies MB-II in 67% of the instances, where both methods achieve the least-cost solution. As in the previous analysis on the variable cost problems, the running time is relatively less than the fixed cost formulation according to Table G.5. While the solution time ranges between 1.6 to 11 seconds in Potou-2 - Potou-4, the solution time increases to over 100 seconds under the 200 m distance limit constraint. Lastly, in the fixed and variable cost problems, approximately 81% of the instances in Potou-1 are observed to exceed the given computational time limit. Accordingly, MB-I outperforms the extended method in 14 out of 32 instances as MB-II searches a larger feasible region. In the rest of the sample sites, both MB-I and MB-II provide the best cost solution simultaneously for the greater distance thresholds as shown in Table H.5.

According to Table F.6, the heuristics with the agglomeration steps become prominent in the fixed cost formulation, especially for the instances in Potou-1 and Potou-3. In the agglomeration steps, the Complete measure is observed to be the best-performing measure followed by GeomDiff, which we newly introduced in Section 4.2.1. For Potou-2 and Potou-4, DBSCAN-based algorithms work effectively for the distance thresholds less than or equal to 50 m. GeomDiff seems to be the dominating dissimilarity measure for the Potou-3 and Potou-4 instances. However, the Complete measure outperforms GeomDiff in Potou-3 for the distance limits ranging between 30 to 50 meters. The computational results of the variable cost problems (Table G.6) show that agglomerative clustering is effective not only on the instances of Potou-1 but also on the remaining sample sites, Potou-2, Potou-3, and Potou-4. Ward's variance method seems to perform successfully in Potou-1 and Potou-4, whereas the best-performing measure alternates between 'GeomDiff' and Complete measures in the instances of Potou-2 and Potou-3. Another observation is that the DB-KM yields the least-cost solution in all instances of Potou-4 within the 30 m distance limit in the fixed and variable cost problems. It is also worth noticing that all clustering-based approaches can find the best solution in 30 out of 64 instances in Potou-2 and Potou-3 as seen in Table H.6.

### 5.2.4 Ruhiira

As the sample sites in Ruhiira show a dispersed population structure, the model-based heuristics are observed to provide an output with higher computational efficiency. Hence, the model-based heuristics generally work faster in Ruhiira compared to all sample sites in Tiby and Potou-1. In the fixed cost formulation, Table F.7 demonstrates that MBI and MB-II achieve to find the least-cost solution for the majority of the instances. However, the performance of the MB-I is observed to decrease slightly, particularly for the instances with a 100 m distance limit. Similarly, in the variable cost formulation, MB-II performs effectively in the majority of instances. As demonstrated in Table G.7, MB-I performs better than MB-II only in 5 instances out of 64 solutions in total. The maximum solution times are reported approximately 23.5 seconds for both heuristic methods. Finally, the performances of these heuristic approaches are almost equal for the problems having fixed and variable cost components. According to Table H.7, both methods provide the exact solutions in 87% of the instances.

With regards to the performance of the clustering-based approaches, it is observed that the majority of the least-cost solutions can be obtained by using the DBSCAN-based heuristic algorithms for the fixed cost problem. However, in Ruhiira-3, Table F.8 shows that the performance of the agglomerative approach surpasses the other alternatives for 100 and 200 m distance limits. Another important observation is that the DB-KM approach provides the best solution in all instances having a 30 m distance limit.

While the least-cost configuration can be attained by the diverse methods in the fixed cost formulation, the agglomerative approach establishes an absolute superiority by dominating the other clustering techniques in 62 out of 64 instances in the variable cost formulation. According to Table G.8, Ward's variance method surpasses the GeomDiff and Complete measure in the agglomeration, especially for the instances subject to more than 100 m distance limit. For the distance thresholds lower than 100 m, it is observed that the Complete method may substitute Ward's method in some instances. Finally, similar outcomes to the Mbola case are obtained for the fixed and variable cost problems. The three of the clustering-based approaches yield the same configuration in 60 out of 128 instances. However, it should also be noted that most households are electrified by nano-grid facilities in these solutions, implying that none of the households join a micro-grid cluster (see Table H.8).

### 5.2.5 Discussion: Generalization of the Results

In Tables 5.9 - 5.20, we compare the performances of the model-based heuristic approaches with the faster clustering-based heuristic algorithms for different cost structures. In these tables, we summarize the solutions of the best performing model-based and clustering-based alternatives in terms of the running time and the objective value, where the cost-efficient solutions are indicated by the boldface letters.

The results for the fixed cost formulations demonstrate that the-model based heuristics achieves the majority of the least-cost solutions. Although the cost difference between the model-based and clustering-based methods generally ranges between 0% to 5%, this percentage is observed to increase in the densely populated regions with an HCI over 4 households within 30 meters. In fact, the cost difference between the heuristic approaches is observed to increase up to 20% in the instances with 30 m and 50 m distance limits for the dense sample sites. Because the model-based approaches can solve the discrete counterpart of the problem either to optimality or with the relative optimality gaps less than 2%, we observe such significant differences between the heuristics' performances for the given distance thresholds. However, this percentage difference reduces dramatically for the 100 and 200 m distance limits due to the increasing computational complexity and the optimality gaps. In the regions with the dispersed settlement pattern, the cost difference reduces below 0% for some instances, meaning that the clustering-based approach outperforms the model-based heuristics. Nevertheless, the model-based approaches dominate the other clustering techniques in the majority of instances.

In this study, we classify the sample sites with an HCI of lower than 2.5 households within 30 m radius as dispersed regions. The results indicate that DBSCAN-based algorithms perform better than the agglomerative clustering approach for 30 m and 50 m distance limits in the dispersed areas. We also note that DB-Agg. yields better results when the merging process is performed based on the GeomDiff dissimilarity measure. For the densely populated areas, on the other hand, we observe that agglomeration-based approaches (DB-Agg., Agg.) perform better than the DB-KM when the low voltage connections are restricted to 30-50 meters. Furthermore, the agglomeration step is found to be more effective when the most similar pair of clusters are identified based on the Complete measure.

Among the multiple alternatives, MB-II is expected to be the best performing model-based heuristic approach as the domain of the problem is enlarged with other feasible locations. While its superior performance in the dispersed areas validates the aforementioned expectation, the method can be dominated by the other model-based heuristics in densely populated regions due to the significant optimality gaps that we obtained at the end of three hours time limit. Additionally, Cooper's algorithm may converge to a local optimum in earlier iterations, which restricts the improvements in the continuous space.

As the running time of the model-based heuristics generally exceeds the given time limit, MB-III could be considered as a practical alternative to solve the fixed cost problems for larger distance limits. Unlike the other multi-stage heuristic approaches, the unicost assumption facilitates the decision-making in favor of micro-grids, leading to a higher number of micro-grid clusters in the final configuration. In other words, due to the assumption that both decentralized systems require identical fixed facility costs, micro-grids are more likely to be the cost-efficient option in the MB-III as long as the interhousehold distances conform to the distance limitation. However, as the unicost assumption is reverted to the original problem settings for nano-grid and micro-grid facilities, there could be a remarkable increase in the objective value at the end of the post-processing phase, specifically if there is a significant difference between nano-grid and micro-grid facility costs. As a result, while the unicost model performs effectively in dense areas with similar F1 and F2 costs, the algorithms' performance falls below the desired standards as the variation between F1 and F2 increases.

On the contrary to the previous results, Tables 5.13 - 5.16 which present the results for the variable cost problems demonstrate that the variance between the objective values is generally less than 4% in the variable cost problems even in the densely populated sample sites. Here, we also observe that the model-based and the clustering-based heuristics show similar performances. Nevertheless, the cost difference was observed to increase when the low voltage connections are longer than 100 m, as all the instances could be solved optimally in the second stage regardless of the settlement structure. Another observation is that the agglomerative clustering method dominates the other two clustering-based approaches in the majority of the instances. In the agglomeration steps, Ward's variance method is found to be the prominent measure for the densely populated settlements.

Finally, for the problems with fixed and variable cost components, we observe that the difference between the model-based and clustering-based methods decreases further as shown in Tables 5.17 - 5.20. The cost difference is observed to be higher than 2% only in 18 instances out of 512 solutions. Two main reasons could explain the reduction in the cost differences. Firstly, the model-based approach may not be able to obtain the optimal solution within the specified CPU time limit for the dense sample sites. Hence, as the optimal solution cannot be attained in three hours, the cost difference between the clustering algorithms and the optimization model-based heuristic decreases. Secondly, in the fixed and variable cost formulation, it is more challenging to create micro-grid clusters that can cover an ideal number of households within the distance limit. Given that the investment cost of deploying a micro-grid facility is composed of the fixed facility cost, cost of the low voltage connections, and a variable cost component, micro-grid clusters require to cover a higher number of households in order the nano-grid option to be discarded. However, only the minority of the potential micro-grid clusters can reach a sufficient number of households under the given distance thresholds. Accordingly, Tables 5.17 - 5.20 indicate that nano-grid option becomes a more prevalent choice as micro-grids are relatively expensive compared to fixed cost formulation. Hence, both model-based and clustering-based approaches are more likely to output similar configurations due to the decline in the solution diversity.

For the generality of the problem types, the reasoning behind the positive cost differences is that the model-based approaches are found to be more capable of capturing potential micro-grid clusters. Given that each household could be electrified by individual stand-alone systems (nano-grid) in the most trivial solution, the potential micro-grid clusters could lead to remarkable cost reductions based on the trade-off between the decentralized facilities. However, the bottom-up or top-down clustering approaches may overlook some of the possible micro-grid opportunities as they construct the final solutions iteratively. For instance, the agglomerative clustering selects the closest pair of clusters in the merging process and continues to form new clusters based on the decisions made in the previous iteration. However, it does not evaluate the cases where a cluster is agglomerated with the second or the third closest cluster; and thus, it can overlook such micro-grid clusters that could end up with a better configuration. While this iterative process can negatively impact the solutions' quality, it allows a faster computational time as the final solution can be attained in seconds.

In the computational experiments, we also increased the time limit to two days for some sample sites to observe if the instances with the positive optimality gaps could be solved optimally. However, we still observed solutions with up to 13% optimality gaps in the fixed cost solution of Tiby-1, and none of the instances with more than 100 m distance limit could be solved optimally. We also tested the performance of the continuous models (PFLAP-Fixed, PFLAP-Var, PFLAP-FixedVar) on the running example and another small-sized sample with 10 nodes, under the CPU time limit of one day. While the optimal solution could not be attained for the running example, only the fixed cost and variable cost models could be solved to optimality for the 10-node instance. The solutions are summarized in Table 5.8, and the resulting configurations of the continuous models are provided in Figure 5.7 - 5.8 for the running example.

In conclusion, since the continuous models can not be solved to optimality even for the small-sized samples, we propose six different heuristic approaches that the energy planners can benefit from different advantages. Although model-based algorithms are shown to provide closer estimates to the continuous model for all problem types regardless of the settlement structure, the clustering-based algorithms enable energy planners to evaluate the trade-off between two decentralized systems and make rapid assessments without the need of a commercial solver. Thus, energy planners could select the most convenient method that aligns with the user's needs, including the choice of the computational environment and the allocated computational time.

Table 5.8: The Results of the Continuous Model on Small-sized Examples

| **Running Example 10** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Continuous Model | Time | Gap | MB | Time | Diff | CB | Time | Diff |
| Fixed Cost | 3931.995634 | 10683.2 | 0% | 3932.03 | 1.34 | 0.001% | 4143.08 | 0.06 | 5.4% |
| Variable Cost | 2639.772264 | 15647.3 | 0% | 2643.08 | 0.61 | 0.125% | 2643.08 | 0.07 | 0.1% |
| Fixed and Variable Cost | 6149.589235 | 86413.11 | 17.8% | 6149.63 | 0.44 | 0.001% | 6571.88 | 0.06 | 6.9% |
| **Running Example 15** | | | | | | | | | |
| | Continuous Model | Time | Gap | MB | Time | Diff | CB | Time | Diff |
| Fixed Cost | 6214.108811 | 86418.1 | 48.6% | 6214.185 | 0.47 | 0.001% | 6214.185 | 0.03 | 0.001% |
| Variable Cost | 4504.802744 | 86424.75 | 83.3% | 4523.92 | 0.51 | 0.424% | 5924.67 | 0.03 | 31.519% |
| Fixed and Variable Cost | 8964.108801 | 86421.52 | 54.0% | 8964.19 | 0.6 | 0.001% | 8964.19 | 0.04 | 0.001% |

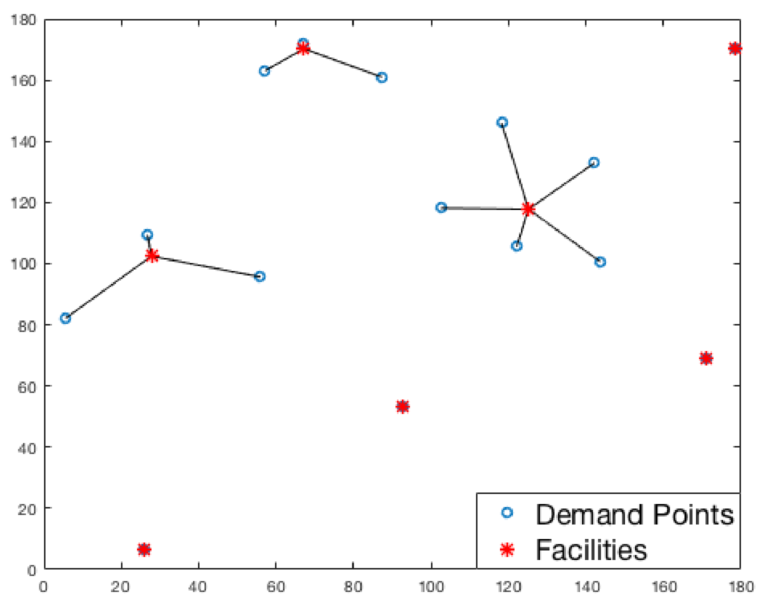



Figure 5.6: Fixed Cost Result, ($F1 = 1000$, $F2 = 750$)

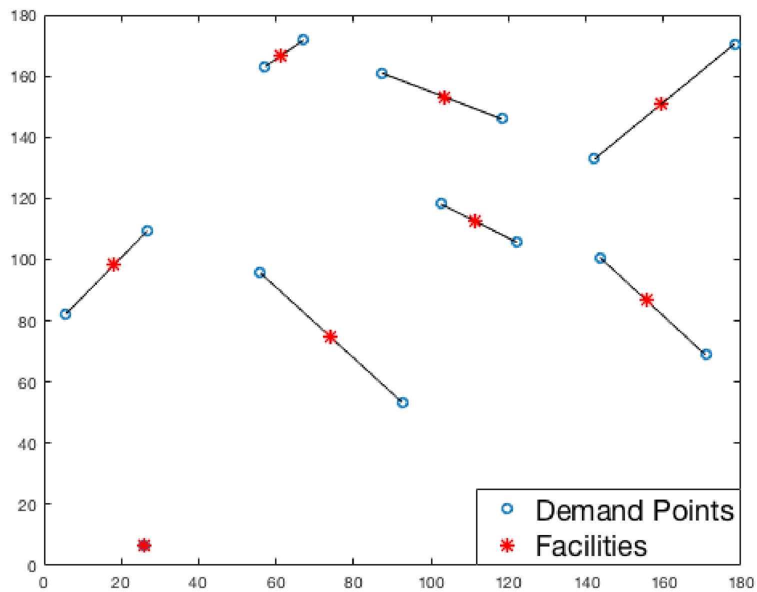



Figure 5.7: Variable Cost Result, ($F2 = 750$, $F3 = 250$)

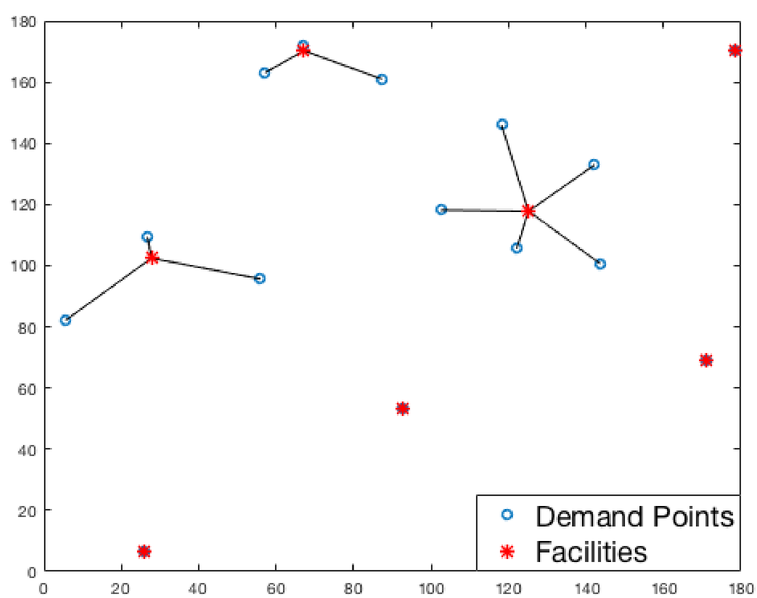



Figure 5.8: Fixed Variable Cost Result, ($F1 = 1000$, $F2 = 750$, $F3 = 250$)

Table 5.9: Comparison of Heuristic Methods with Fixed Facility Costs on Tiby

| | | | | Best Model-based Heuristic | | | Best Clustering-based Heuristic | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | Cost | Time | Method | Cost | Time | Method | Diff. |
| TIBY - 1 | 30 | 3000 | 750 | **236917** | 196.1 | MB-II | 267273 | 0.6 | DB-Agg. | 12.8% |
| | 30 | 3000 | 1000 | **251151** | 67.0 | MB-II | 301130 | 0.9 | Agg. | 19.9% |
| | 30 | 4000 | 750 | **279449** | 316.8 | MB-II | 295892 | 19.8 | DB-KM | 5.9% |
| | 30 | 4000 | 1000 | **306364** | 134.8 | MB-II | 350273 | 0.4 | DB-Agg. | 14.3% |
| | 50 | 3000 | 750 | **165901** | 10827.7 | MB-II | 189309 | 0.7 | Agg., DB-Agg. | 14.1% |
| | 50 | 3000 | 1000 | **169034** | 1871.8 | MB-I | 197992 | 0.7 | Agg., DB-Agg. | 17.1% |
| | 50 | 4000 | 750 | **197557** | 10824.0 | MB-I, MB-II | 224806 | 0.5 | Agg., DB-Agg. | 13.8% |
| | 50 | 4000 | 1000 | **203195** | 10835.1 | MB-II | 237809 | 0.6 | Agg., DB-Agg. | 17.0% |
| | 100 | 3000 | 750 | **140231** | 10829.0 | MB-II | 142957 | 1.1 | DB-Agg. | 1.9% |
| | 100 | 3000 | 1000 | **140696** | 10829.4 | MB-II | 144457 | 1.1 | DB-Agg. | 2.7% |
| | 100 | 4000 | 750 | **156298** | 10828.8 | MB-II | 163665 | 1.1 | DB-Agg. | 4.7% |
| | 100 | 4000 | 1000 | **158334** | 18.6 | MB-III | 165457 | 0.8 | DB-Agg. | 4.5% |
| | 200 | 3000 | 750 | **136219** | 132.8 | MB-III | 139323 | 2.1 | Agg., DB-Agg. | 2.3% |
| | 200 | 3000 | 1000 | **136469** | 133.9 | MB-III | 139573 | 1.8 | Agg., DB-Agg. | 2.3% |
| | 200 | 4000 | 750 | **150193** | 10904.8 | MB-I | 155608 | 1.7 | Agg., DB-Agg. | 3.6% |
| | 200 | 4000 | 1000 | **150862** | 132.9 | MB-III | 155858 | 1.7 | Agg., DB-Agg. | 3.3% |
| TIBY - 2 | 30 | 3000 | 750 | **205585** | 3581.6 | MB-II | 235208 | 23.4 | DB-KM | 14.4% |
| | 30 | 3000 | 1000 | **216927** | 456.3 | MB-II | 260529 | 0.6 | DB-Agg. | 20.1% |
| | 30 | 4000 | 750 | **241538** | 5741.1 | MB-II | 262455 | 17.8 | DB-KM | 8.7% |
| | 30 | 4000 | 1000 | **265085** | 4593.7 | MB-II | 307694 | 17.0 | DB-KM | 16.1% |
| | 50 | 3000 | 750 | **141503** | 10820.8 | MB-II | 164205 | 0.7 | Agg., DB-Agg. | 16.0% |
| | 50 | 3000 | 1000 | **143724** | 10820.3 | MB-II | 167945 | 0.7 | Agg. | 16.9% |
| | 50 | 4000 | 750 | **169584** | 10818.6 | MB-I | 197610 | 0.5 | Agg., DB-Agg. | 16.5% |
| | 50 | 4000 | 1000 | **171219** | 10821.1 | MB-II | 205205 | 0.7 | Agg., DB-Agg. | 19.8% |
| | 100 | 3000 | 750 | **118253** | 10818.8 | MB-III | 123130 | 0.8 | Agg., DB-Agg. | 4.1% |
| | 100 | 3000 | 1000 | **118253** | 10818.4 | MB-III | 124040 | 0.9 | Agg., DB-Agg. | 4.9% |
| | 100 | 4000 | 750 | **132372** | 10822.0 | MB-III | 137646 | 1.1 | Agg., DB-Agg. | 4.0% |
| | 100 | 4000 | 1000 | **132372** | 10817.3 | MB-III | 138646 | 0.5 | Agg., DB-Agg. | 4.7% |
| | 200 | 3000 | 750 | **116798** | 10886.1 | MB-III | 119889 | 1.3 | Agg., DB-Agg. | 2.6% |
| | 200 | 3000 | 1000 | **116798** | 94.4 | MB-III | 119889 | 1.8 | Agg., DB-Agg. | 2.6% |
| | 200 | 4000 | 750 | **129167** | 88.9 | MB-III | 132488 | 4.3 | Agg., DB-Agg. | 2.6% |
| | 200 | 4000 | 1000 | **129167** | 89.2 | MB-III | 132488 | 4.4 | Agg., DB-Agg. | 2.6% |
| TIBY - 3 | 30 | 3000 | 750 | **249306** | 67.5 | MB-II | 271895 | 0.3 | DB-Agg. | 9.1% |
| | 30 | 3000 | 1000 | **272153** | 25.3 | MB-I | 309715 | 0.4 | DB-Agg. | 13.8% |
| | 30 | 4000 | 750 | **280774** | 57.4 | MB-I | 294474 | 13.8 | DB-KM | 4.9% |
| | 30 | 4000 | 1000 | **324294** | 47.9 | MB-I | 358645 | 0.3 | DB-Agg. | 10.6% |
| | 50 | 3000 | 750 | **183257** | 10816.6 | MB-I | 210107 | 15.5 | DB-KM | 14.7% |
| | 50 | 3000 | 1000 | **188688** | 494.3 | MB-I | 225981 | 16.1 | DB-KM | 19.8% |
| | 50 | 4000 | 750 | **214852** | 10834.9 | MB-II | 238401 | 15.8 | DB-KM | 11.0% |
| | 50 | 4000 | 1000 | **227383** | 10822.6 | MB-II | 273327 | 0.9 | Agg., DB-Agg. | 20.2% |
| | 100 | 3000 | 750 | **147483** | 15.0 | MB-III | 152232 | 0.8 | Agg., DB-Agg. | 3.2% |
| | 100 | 3000 | 1000 | **147483** | 14.4 | MB-III | 153324 | 0.8 | Agg., DB-Agg. | 4.0% |
| | 100 | 4000 | 750 | **166741** | 10816.4 | MB-I | 174507 | 0.5 | Agg., DB-Agg. | 4.7% |
| | 100 | 4000 | 1000 | **169426** | 17.7 | MB-III | 176982 | 0.5 | Agg., DB-Agg. | 4.5% |
| | 200 | 3000 | 750 | **142641** | 37.0 | MB-III | 146273 | 2.9 | Agg., DB-Agg. | 2.5% |
| | 200 | 3000 | 1000 | **142641** | 37.2 | MB-III | 146273 | 3.1 | Agg., DB-Agg. | 2.5% |
| | 200 | 4000 | 750 | **158524** | 47.9 | MB-III | 160745 | 2.8 | Agg., DB-Agg. | 1.4% |
| | 200 | 4000 | 1000 | **158524** | 49.6 | MB-III | 161470 | 2.6 | Agg., DB-Agg. | 1.9% |

| | | | | Best Model-based Heuristic | | | Best Clustering-based Heuristic | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | Cost | Time | Method | Cost | Time | Method | Diff. |
| TIBY - 4 | 30 | 3000 | 750 | **122129** | 248.4 | MB-II | 134269 | 0.3 | Agg. | 9.9% |
| | 30 | 3000 | 1000 | **131038** | 198.1 | MB-II | 147284 | 0.2 | Agg. | 12.4% |
| | 30 | 4000 | 750 | **141847** | 59.8 | MB-II | 155522 | 0.4 | DB-KM | 9.6% |
| | 30 | 4000 | 1000 | **158109** | 203.4 | MB-II | 175269 | 0.2 | Agg. | 10.9% |
| | 50 | 3000 | 750 | **84799** | 10805.0 | MB-II | 95678 | 0.4 | Agg. | 12.8% |
| | 50 | 3000 | 1000 | **87610** | 10804.7 | MB-II | 98178 | 0.5 | Agg. | 12.1% |
| | 50 | 4000 | 750 | **100534** | 10804.3 | MB-II | 117678 | 0.4 | Agg. | 17.1% |
| | 50 | 4000 | 1000 | **103873** | 10817.7 | MB-II | 120178 | 0.3 | Agg. | 15.7% |
| | 100 | 3000 | 750 | **70953** | 10806.2 | MB-I | 72472 | 1.9 | Agg.DB-Agg. | 2.1% |
| | 100 | 3000 | 1000 | **72370** | 5162.0 | MB-I, MB-II | 74722 | 1.8 | Agg.DB-Agg. | 3.2% |
| | 100 | 4000 | 750 | **79458** | 10806.5 | MB-I | 81472 | 1.6 | Agg.DB-Agg. | 2.5% |
| | 100 | 4000 | 1000 | **81693** | 10807.4 | MB-II | 83722 | 0.9 | Agg.DB-Agg. | 2.5% |
| | 200 | 3000 | 750 | **71145** | 28.1 | MB-III | 71441 | 1.7 | Agg.DB-Agg. | 0.4% |
| | 200 | 3000 | 1000 | **70791** | 10818.8 | MB-I | 72191 | 1.4 | Agg.DB-Agg. | 2.0% |
| | 200 | 4000 | 750 | **78276** | 10818.7 | MB-I | 79870 | 1.4 | Agg.DB-Agg. | 2.0% |
| | 200 | 4000 | 1000 | **78962** | 10819.3 | MB-I | 80620 | 1.5 | Agg.DB-Agg. | 2.1% |

Table 5.10: Comparison of Heuristic Methods with Fixed Facility Costs on Mbola

| | | | | Best Model-based Heuristic | | | Best Clustering-based Heuristic | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | Cost | Time | Method | Cost | Time | Method | Diff. |
| MBOLA - 1 | 30 | 3000 | 750 | **107026** | 4.1 | MB-I, MB-II | 107581 | 0.3 | DB-KM, DB-Agg. | 0.5% |
| | 30 | 3000 | 1000 | **132626** | 4.3 | MB-I, MB-II | 139243 | 0.1 | DB-KM, DB-Agg. | 5.0% |
| | 30 | 4000 | 750 | **108581** | 3.6 | MB-I, MB-II | **108581** | 0.1 | DB-KM, DB-Agg. | 0.0% |
| | 30 | 4000 | 1000 | **142276** | 3.7 | MB-I, MB-II | 143331 | 0.1 | DB-KM, DB-Agg. | 0.7% |
| | 50 | 3000 | 750 | **100920** | 5.0 | MB-II | 102969 | 0.6 | DB-KM | 2.0% |
| | 50 | 3000 | 1000 | **117720** | 11.8 | MB-II | 120456 | 0.1 | Agg. | 2.3% |
| | 50 | 4000 | 750 | **106692** | 12.3 | MB-I, MB-II | 108410 | 0.2 | DB-KM | 1.6% |
| | 50 | 4000 | 1000 | **131784** | 5.0 | MB-II | 134484 | 0.4 | DB-KM | 2.0% |
| | 100 | 3000 | 750 | **88303** | 31.4 | MB-II | 93097 | 0.1 | DB-Agg. | 5.4% |
| | 100 | 3000 | 1000 | **95411** | 30.4 | MB-II | 102771 | 0.1 | Agg. | 7.7% |
| | 100 | 4000 | 750 | **96385** | 8.3 | MB-II | 99280 | 3.5 | DB-KM | 3.0% |
| | 100 | 4000 | 1000 | **108551** | 32.0 | MB-II | 115545 | 3.9 | DB-KM | 6.4% |
| | 200 | 3000 | 750 | **81715** | 410.8 | MB-I, MB-II | 84723 | 0.7 | Agg., DB-Agg. | 3.7% |
| | 200 | 3000 | 1000 | **85674** | 117.0 | MB-I, MB-II | 88182 | 0.7 | Agg., DB-Agg. | 2.9% |
| | 200 | 4000 | 750 | **90321** | 594.1 | MB-I, MB-II | 93782 | 0.7 | Agg., DB-Agg. | 3.8% |
| | 200 | 4000 | 1000 | **95701** | 606.9 | MB-I, MB-II | 98368 | 0.7 | Agg., DB-Agg. | 2.8% |
| MBOLA - 2 | 30 | 3000 | 750 | **55836** | 4.6 | MB-II | **55836** | 0.1 | DB-Agg. | 0.0% |
| | 30 | 3000 | 1000 | **70323** | 3.3 | MB-II | **70323** | 0.0 | DB-Agg. | 0.0% |
| | 30 | 4000 | 750 | **57642** | 3.2 | MB-I, MB-II | **57642** | 0.1 | DB-KM, DB-Agg. | 0.0% |
| | 30 | 4000 | 1000 | **74086** | 4.2 | MB-II | **74086** | 0.1 | DB-Agg. | 0.0% |
| | 50 | 3000 | 750 | **55272** | 1.9 | MB-I, MB-II | **55272** | 0.1 | DB-KM, DB-Agg. | 0.0% |
| | 50 | 3000 | 1000 | **68749** | 11.1 | MB-I, MB-II | 69510 | 0.0 | DB-KM, DB-Agg. | 1.1% |
| | 50 | 4000 | 750 | **57624** | 2.1 | MB-I, MB-II | **57624** | 0.0 | DB-KM, DB-Agg. | 0.0% |
| | 50 | 4000 | 1000 | **73272** | 1.3 | MB-I, MB-II | **73272** | 0.1 | DB-KM, DB-Agg. | 0.0% |
| | 100 | 3000 | 750 | **55272** | 5.7 | MB-I, MB-II | **55272** | 0.1 | DB-KM, DB-Agg. | 0.0% |
| | 100 | 3000 | 1000 | **66818** | 1.4 | MB-I, MB-II | 67952 | 0.1 | DB-KM | 1.7% |
| | 100 | 4000 | 750 | **57624** | 2.1 | MB-I, MB-II | **57624** | 0.0 | DB-KM, DB-Agg. | 0.0% |
| | 100 | 4000 | 1000 | **73272** | 2.8 | MB-I, MB-II | **73272** | 0.0 | DB-KM, DB-Agg. | 0.0% |
| | 200 | 3000 | 750 | **55121** | 2.9 | MB-I, MB-II | 55984 | 0.1 | DB-KM, DB-Agg. | 1.6% |
| | 200 | 3000 | 1000 | **64253** | 14.4 | MB-II | 64513 | 0.0 | DB-KM, DB-Agg. | 0.4% |
| | 200 | 4000 | 750 | **57527** | 3.0 | MB-I, MB-II | 57624 | 0.1 | DB-KM, DB-Agg. | 0.2% |

| | | | | Best Model-based Heuristic | | | Best Clustering-based Heuristic | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | Cost | Time | Method | Cost | Time | Method | Diff. |
| | 200 | 4000 | 1000 | **71267** | 2.4 | MB-II | 71527 | 0.0 | DB-KM, DB-Agg. | 0.4% |
| MBOLA - 3 | 30 | 3000 | 750 | **34967** | 2.9 | MB-I, MB-II | **35250** | 0.1 | All | 0.8% |
| | 30 | 3000 | 1000 | **44723** | 1.1 | MB-I, MB-II | 46256 | 0.0 | DB-KM, DB-Agg. | 3.4% |
| | 30 | 4000 | 750 | **35250** | 1.7 | MB-I, MB-II | **35250** | 0.0 | All | 0.0% |
| | 30 | 4000 | 1000 | **46467** | 1.6 | MB-I, MB-II | **47000** | 0.0 | All | 1.1% |
| | 50 | 3000 | 750 | **34369** | 1.7 | MB-I, MB-II | **34369** | 0.1 | DB-KM, DB-Agg. | 0.0% |
| | 50 | 3000 | 1000 | **43539** | 10.7 | MB-I, MB-II | 43875 | 0.0 | DB-KM, DB-Agg. | 0.8% |
| | 50 | 4000 | 750 | **35250** | 2.3 | MB-I, MB-II | **35250** | 0.1 | All | 0.0% |
| | 50 | 4000 | 1000 | **45619** | 2.0 | MB-I, MB-II | **45619** | 0.0 | DB-KM, DB-Agg. | 0.0% |
| | 100 | 3000 | 750 | **34369** | 1.3 | MB-I, MB-II | **34369** | 0.0 | DB-KM, DB-Agg. | 0.0% |
| | 100 | 3000 | 1000 | **42486** | 3.7 | MB-I, MB-II | **42486** | 0.1 | DB-KM, DB-Agg. | 0.0% |
| | 100 | 4000 | 750 | **35250** | 2.1 | MB-I, MB-II | **35250** | 0.1 | All | 0.0% |
| | 100 | 4000 | 1000 | **45619** | 1.2 | MB-I, MB-II | **45619** | 0.0 | DB-KM, DB-Agg. | 0.0% |
| | 200 | 3000 | 750 | **34110** | 1.3 | MB-I, MB-II | **34110** | 0.2 | DB-KM | 0.0% |
| | 200 | 3000 | 1000 | **40785** | 1.4 | MB-I, MB-II | **40785** | 0.1 | DB-KM | 0.0% |
| | 200 | 4000 | 750 | **35250** | 2.7 | MB-I, MB-II | **35250** | 0.1 | All | 0.0% |
| | 200 | 4000 | 1000 | **44360** | 5.0 | MB-I, MB-II | **44360** | 0.1 | DB-KM | 0.0% |
| MBOLA - 4 | 30 | 3000 | 750 | **46177** | 4.5 | MB-I, MB-II | 46500 | 0.2 | All | 0.7% |
| | 30 | 3000 | 1000 | **59772** | 2.3 | MB-I, MB-II | 62000 | 0.1 | All | 3.7% |
| | 30 | 4000 | 750 | **46500** | 1.7 | MB-I, MB-II | **46500** | 0.0 | All | 0.0% |
| | 30 | 4000 | 1000 | **61427** | 1.5 | MB-I, MB-II | 62000 | 0.0 | All | 0.9% |
| | 50 | 3000 | 750 | **43822** | 2.1 | MB-I, MB-II | 45207 | 0.3 | DB-Agg. | 3.2% |
| | 50 | 3000 | 1000 | **52680** | 10.9 | MB-I, MB-II | 54242 | 0.1 | Agg. | 3.0% |
| | 50 | 4000 | 750 | **45822** | 1.6 | MB-I, MB-II | 46500 | 0.0 | All | 1.5% |
| | 50 | 4000 | 1000 | **57530** | 1.6 | MB-I, MB-II | 59834 | 0.1 | DB-KM | 4.0% |
| | 100 | 3000 | 750 | **40322** | 2.5 | MB-II | 40416 | 0.1 | DB-Agg. | 0.2% |
| | 100 | 3000 | 1000 | **45245** | 3.4 | MB-II | 46143 | 0.0 | Agg., DB-Agg. | 2.0% |
| | 100 | 4000 | 750 | **43845** | 2.8 | MB-I, MB-II | 44246 | 0.8 | DB-KM | 0.9% |
| | 100 | 4000 | 1000 | **51322** | 5.2 | MB-I, MB-II | 51416 | 0.1 | DB-Agg. | 0.2% |
| | 200 | 3000 | 750 | **39471** | 7.1 | MB-I, MB-II | 39768 | 0.2 | Agg., DB-Agg. | 0.8% |
| | 200 | 3000 | 1000 | **42272** | 4.8 | MB-I, MB-II | **42272** | 0.2 | Agg., DB-Agg. | 0.0% |
| | 200 | 4000 | 750 | **43166** | 16.3 | MB-I, MB-II | 43893 | 0.8 | DB-KM | 1.7% |
| | 200 | 4000 | 1000 | **48441** | 10.0 | MB-I, MB-II | 48735 | 0.1 | Agg., DB-Agg. | 0.6% |

Table 5.11: Comparison of Heuristic Methods with Fixed Facility Costs on Potou

| | | | | Best Model-based Heuristic | | | Best Clustering-based Heuristic | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | Cost | Time | Method | Cost | Time | Method | Diff. |
| POTOU - 1 | 30 | 3000 | 750 | **173461** | 10856.0 | MB-II | 196767 | 1.6 | Agg. | 13.4% |
| | 30 | 3000 | 1000 | **186001** | 2243.6 | MB-II | 219641 | 1.4 | Agg. | 18.1% |
| | 30 | 4000 | 750 | **201827** | 10849.0 | MB-II | 222794 | 0.8 | Agg., DB-Agg. | 10.4% |
| | 30 | 4000 | 1000 | **221961** | 10831.3 | MB-II | 255267 | 0.9 | Agg. | 15.0% |
| | 50 | 3000 | 750 | **137204** | 10818.7 | MB-I | 146546 | 0.8 | Agg., DB-Agg. | 6.8% |
| | 50 | 3000 | 1000 | **141509** | 10832.8 | MB-II | 152583 | 0.9 | Agg. | 7.8% |
| | 50 | 4000 | 750 | **158240** | 10824.1 | MB-I | 169756 | 0.7 | Agg. | 7.3% |
| | 50 | 4000 | 1000 | **167153** | 10818.6 | MB-I | 181046 | 0.6 | Agg., DB-Agg. | 8.3% |
| | 100 | 3000 | 750 | **120795** | 10841.5 | MB-II | 123345 | 2.9 | DB-Agg. | 2.1% |
| | 100 | 3000 | 1000 | **123575** | 10841.1 | MB-II | 126121 | 2.9 | DB-Agg. | 2.1% |
| | 100 | 4000 | 750 | **133554** | 10842.1 | MB-II | 136797 | 3.7 | DB-KM | 2.4% |
| | 100 | 4000 | 1000 | **139417** | 10833.2 | MB-I | 140601 | 3.3 | DB-KM | 0.8% |
| | 200 | 3000 | 750 | 122470 | 116.3 | MB-III | **121999** | 1.5 | Agg. | -0.4% |
| | 200 | 3000 | 1000 | **122470** | 115.4 | MB-III | 123529 | 4.6 | Agg., DB-Agg. | 0.9% |

| | | | | Best Model-based Heuristic | | | Best Clustering-based Heuristic | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | Cost | Time | Method | Cost | Time | Method | Diff. |
| | 200 | 4000 | 750 | 138462 | 10877.8 | MB-I | **136755** | 1.6 | Agg., DB-Agg. | -1.2% |
| | 200 | 4000 | 1000 | **137451** | 10880.1 | MB-I | 138755 | 1.8 | Agg., DB-Agg. | 0.9% |
| POTOU - 2 | 30 | 3000 | 750 | **73833** | 19.7 | MB-I | 74517 | 0.2 | DB-KM | 0.9% |
| | 30 | 3000 | 1000 | **87929** | 2.1 | MB-I | 91391 | 0.1 | DB-Agg. | 3.9% |
| | 30 | 4000 | 750 | **77104** | 4.0 | MB-I | 77171 | 0.1 | DB-KM, DB-Agg. | 0.1% |
| | 30 | 4000 | 1000 | **97833** | 4.6 | MB-I | 99400 | 0.0 | DB-KM, DB-Agg. | 1.6% |
| | 50 | 3000 | 750 | **67892** | 2.1 | MB-I, MB-II | 70949 | 0.2 | DB-KM | 4.5% |
| | 50 | 3000 | 1000 | **77920** | 19.4 | MB-I, MB-II | 79505 | 0.1 | Agg. | 2.0% |
| | 50 | 4000 | 750 | **74355** | 5.5 | MB-II | 75940 | 0.3 | DB-KM, DB-Agg. | 2.1% |
| | 50 | 4000 | 1000 | **88392** | 3.9 | MB-I, MB-II | 93229 | 0.0 | DB-Agg. | 5.5% |
| | 100 | 3000 | 750 | **63810** | 13.1 | MB-II | 64491 | 0.0 | DB-KM | 1.1% |
| | 100 | 3000 | 1000 | **67846** | 9.9 | MB-I, MB-II | 69932 | 0.1 | Agg. | 3.1% |
| | 100 | 4000 | 750 | **70197** | 7.0 | MB-II | 70289 | 0.1 | DB-KM | 0.1% |
| | 100 | 4000 | 1000 | **79560** | 2.5 | MB-I, MB-II | 82189 | 0.1 | Agg. | 3.3% |
| | 200 | 3000 | 750 | **61364** | 23.5 | MB-I, MB-II | 62553 | 0.1 | DB-Agg. | 1.9% |
| | 200 | 3000 | 1000 | **63451** | 20.1 | MB-I, MB-II | 64100 | 0.1 | DB-Agg. | 1.0% |
| | 200 | 4000 | 750 | **68295** | 32.7 | MB-I, MB-II | 68874 | 0.1 | DB-Agg. | 0.8% |
| | 200 | 4000 | 1000 | **73176** | 26.8 | MB-I, MB-II | 73663 | 0.1 | DB-Agg. | 0.7% |
| POTOU - 3 | 30 | 3000 | 750 | 41857 | 18.4 | MB-II | **41191** | 0.1 | DB-Agg. | -1.6% |
| | 30 | 3000 | 1000 | **46875** | 2.8 | MB-II | 47185 | 0.2 | DB-Agg. | 0.7% |
| | 30 | 4000 | 750 | **47201** | 5.9 | MB-II | **46707** | 0.1 | DB-KM | -1.0% |
| | 30 | 4000 | 1000 | 54857 | 2.4 | MB-II | **53941** | 0.0 | DB-Agg. | -1.7% |
| | 50 | 3000 | 750 | **36472** | 0.9 | MB-I, MB-II | **36472** | 0.1 | Agg. | 0.0% |
| | 50 | 3000 | 1000 | **37732** | 8.0 | MB-I, MB-II | **37732** | 0.0 | Agg. | 0.0% |
| | 50 | 4000 | 750 | **42664** | 1.2 | MB-I, MB-II | **42664** | 0.1 | Agg. | 0.0% |
| | 50 | 4000 | 1000 | **46487** | 1.0 | MB-I, MB-II | **46487** | 0.0 | Agg. | 0.0% |
| | 100 | 3000 | 750 | **33736** | 0.9 | MB-I, MB-II | 34286 | 0.1 | All | 1.6% |
| | 100 | 3000 | 1000 | **33986** | 1.0 | MB-I, MB-II | 34905 | 0.1 | All | 2.7% |
| | 100 | 4000 | 750 | **39974** | 1.2 | MB-I, MB-II | 40524 | 0.1 | Agg., DB-KM | 1.4% |
| | 100 | 4000 | 1000 | **41986** | 0.7 | MB-I, MB-II | 43036 | 0.1 | All | 2.5% |
| | 200 | 3000 | 750 | **33309** | 8.3 | MB-I, MB-II, MB-III | **33309** | 0.1 | Agg. | 0.0% |
| | 200 | 3000 | 1000 | **33309** | 4.6 | MB-I, MB-II, MB-III | **33309** | 0.1 | Agg. | 0.0% |
| | 200 | 4000 | 750 | 38943 | 4.1 | MB-I, MB-II | **38910** | 0.2 | Agg. | -0.1% |
| | 200 | 4000 | 1000 | **40474** | 0.9 | MB-III | **40474** | 0.1 | Agg. | 0.0% |
| POTOU - 4 | 30 | 3000 | 750 | **71176** | 28.7 | MB-I, MB-II | 72606 | 2.1 | DB-KM | 2.0% |
| | 30 | 3000 | 1000 | **78058** | 87.2 | MB-II | 80902 | 1.8 | DB-KM | 3.6% |
| | 30 | 4000 | 750 | **79691** | 27.1 | MB-I, MB-II | 84955 | 2.8 | DB-KM | 6.6% |
| | 30 | 4000 | 1000 | **92426** | 45.5 | MB-I, MB-II | 96156 | 2.1 | DB-KM | 4.0% |
| | 50 | 3000 | 750 | **53900** | 58.8 | MB-I | 59411 | 2.3 | DB-KM | 10.2% |
| | 50 | 3000 | 1000 | **57518** | 37.6 | MB-I, MB-II | 61456 | 0.2 | DB-Agg. | 6.8% |
| | 50 | 4000 | 750 | **63218** | 118.8 | MB-I | 67253 | 0.1 | DB-Agg. | 6.4% |
| | 50 | 4000 | 1000 | **67518** | 59.1 | MB-I, MB-II | 75456 | 0.1 | DB-Agg. | 11.8% |
| | 100 | 3000 | 750 | **43018** | 33.1 | MB-I, MB-II | 43633 | 0.3 | Agg., DB-Agg. | 1.4% |
| | 100 | 3000 | 1000 | **43628** | 31.1 | MB-II | 43883 | 0.3 | Agg., DB-Agg. | 0.6% |
| | 100 | 4000 | 750 | **49774** | 77.2 | MB-I, MB-II | 51393 | 1.2 | DB-KM | 3.3% |
| | 100 | 4000 | 1000 | **50702** | 41.0 | MB-I, MB-II | 51643 | 0.7 | DB-KM | 1.9% |
| | 200 | 3000 | 750 | **42049** | 52.6 | MB-I, MB-II, MB-III | **42049** | 0.5 | Agg., DB-Agg. | 0.0% |
| | 200 | 3000 | 1000 | **42049** | 33.7 | MB-I, MB-II, MB-III | **42049** | 0.5 | Agg., DB-Agg. | 0.0% |
| | 200 | 4000 | 750 | **48049** | 66.5 | MB-I, MB-II, MB-III | **48049** | 0.5 | Agg., DB-Agg. | 0.0% |
| | 200 | 4000 | 1000 | **48049** | 68.5 | MB-I, MB-II, MB-III | **48049** | 0.5 | Agg., DB-Agg. | 0.0% |

Table 5.12: Comparison of Heuristic Methods with Fixed Facility Costs on Ruhiira

| | | | | Best Model-based Heuristic | | | Best Clustering-based Heuristic | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | Cost | Time | Method | Cost | Time | Method | Diff. |
| RUHIIRA - 1 | 30 | 3000 | 750 | 100374 | 6.0 | MB-I, MB-II | **99717** | 0.2 | DB-KM, DB-Agg. | -0.7% |
| | 30 | 3000 | 1000 | 131233 | 4.3 | MB-I, MB-II | **130979** | 0.1 | DB-KM | -0.2% |
| | 30 | 4000 | 750 | 101374 | 5.3 | MB-I, MB-II | **100717** | 0.1 | DB-KM, DB-Agg. | -0.6% |
| | 30 | 4000 | 1000 | 133624 | 4.0 | MB-I, MB-II | **132717** | 0.0 | DB-KM, DB-Agg. | -0.7% |
| | 50 | 3000 | 750 | **98577** | 5.3 | MB-I, MB-II | 98643 | 0.2 | DB-Agg. | 0.1% |
| | 50 | 3000 | 1000 | **124062** | 12.4 | MB-I, MB-II | 125493 | 0.0 | DB-KM | 1.2% |
| | 50 | 4000 | 750 | **100110** | 4.2 | MB-I, MB-II | 100110 | 0.1 | DB-Agg. | 0.0% |
| | 50 | 4000 | 1000 | **130577** | 8.4 | MB-I, MB-II | 130893 | 0.1 | DB-Agg. | 0.2% |
| | 100 | 3000 | 750 | **95059** | 19.4 | MB-II | 96640 | 0.4 | DB-KM | 1.7% |
| | 100 | 3000 | 1000 | **110838** | 6.0 | MB-II | 113086 | 0.1 | Agg. | 2.0% |
| | 100 | 4000 | 750 | **99315** | 4.6 | MB-I, MB-II | 99463 | 0.9 | DB-KM, DB-Agg. | 0.1% |
| | 100 | 4000 | 1000 | **122757** | 8.6 | MB-II | 126038 | 1.0 | DB-KM | 2.7% |
| | 200 | 3000 | 750 | **91594** | 12.1 | MB-I, MB-II | 92295 | 0.3 | DB-Agg. | 0.8% |
| | 200 | 3000 | 1000 | **100348** | 19.4 | MB-II | 100871 | 0.3 | DB-Agg. | 0.5% |
| | 200 | 4000 | 750 | **97637** | 20.3 | MB-I, MB-II | 99782 | 3.3 | DB-KM | 2.2% |
| | 200 | 4000 | 1000 | **111010** | 13.0 | MB-II | 113435 | 0.3 | DB-Agg. | 2.2% |
| RUHIIRA - 2 | 30 | 3000 | 750 | **176463** | 34.7 | MB-I, MB-II | 177523 | 0.2 | DB-KM, DB-Agg. | 0.6% |
| | 30 | 3000 | 1000 | **226282** | 20.9 | MB-II | 231029 | 0.1 | DB-KM, DB-Agg. | 2.1% |
| | 30 | 4000 | 750 | **179924** | 16.7 | MB-I, MB-II | 180634 | 0.1 | DB-KM, DB-Agg. | 0.4% |
| | 30 | 4000 | 1000 | **234713** | 13.2 | MB-I, MB-II | 236273 | 0.1 | DB-KM, DB-Agg. | 0.7% |
| | 50 | 3000 | 750 | **171425** | 21.6 | MB-II | 171782 | 0.0 | DB-Agg. | 0.2% |
| | 50 | 3000 | 1000 | **209818** | 13.7 | MB-I, MB-II | 214962 | 0.1 | DB-Agg. | 2.5% |
| | 50 | 4000 | 750 | **176947** | 14.0 | MB-I, MB-II | 180633 | 0.5 | DB-KM | 2.1% |
| | 50 | 4000 | 1000 | **225536** | 12.0 | MB-I, MB-II | 227032 | 0.1 | DB-Agg. | 0.7% |
| | 100 | 3000 | 750 | **159153** | 34.7 | MB-I, MB-II | 161434 | 4.2 | DB-KM | 1.4% |
| | 100 | 3000 | 1000 | **178618** | 27.5 | MB-II | 184552 | 0.3 | DB-Agg. | 3.3% |
| | 100 | 4000 | 750 | **168884** | 16.9 | MB-I, MB-II | 171799 | 4.0 | DB-KM | 1.7% |
| | 100 | 4000 | 1000 | **202298** | 80.2 | MB-II | 208275 | 0.2 | DB-Agg. | 3.0% |
| | 200 | 3000 | 750 | **151140** | 165.3 | MB-I, MB-II | 154768 | 1.2 | Agg., DB-Agg. | 2.4% |
| | 200 | 3000 | 1000 | **158852** | 40.8 | MB-I, MB-II | 162285 | 0.3 | DB-Agg. | 2.2% |
| | 200 | 4000 | 750 | **163071** | 236.7 | MB-I, MB-II | 169017 | 4.9 | DB-KM | 3.6% |
| | 200 | 4000 | 1000 | **179623** | 226.6 | MB-I, MB-II | 185642 | 0.2 | DB-Agg. | 3.4% |
| RUHIIRA - 3 | 30 | 3000 | 750 | **188616** | 18.5 | MB-I, MB-II | 191733 | 0.7 | DB-KM | 1.7% |
| | 30 | 3000 | 1000 | **232482** | 15.8 | MB-I, MB-II | 240455 | 0.5 | DB-KM | 3.4% |
| | 30 | 4000 | 750 | **197850** | 16.4 | MB-I, MB-II | 199568 | 0.5 | DB-KM | 0.9% |
| | 30 | 4000 | 1000 | **249616** | 15.5 | MB-I, MB-II | 252829 | 0.3 | DB-KM | 1.3% |
| | 50 | 3000 | 750 | **176412** | 38.7 | MB-II | 181787 | 1.3 | DB-KM | 3.0% |
| | 50 | 3000 | 1000 | **206097** | 36.6 | MB-II | 211374 | 0.4 | Agg. | 2.6% |
| | 50 | 4000 | 750 | **188699** | 17.3 | MB-I, MB-II | 193087 | 0.5 | DB-KM | 2.3% |
| | 50 | 4000 | 1000 | **229275** | 78.4 | MB-II | 239260 | 0.1 | DB-Agg. | 4.4% |
| | 100 | 3000 | 750 | **156564** | 69.7 | MB-II | 159899 | 0.4 | Agg. | 2.1% |
| | 100 | 3000 | 1000 | **172028** | 67.2 | MB-II | 176054 | 0.4 | Agg. | 2.3% |
| | 100 | 4000 | 750 | **173082** | 77.2 | MB-II | 176194 | 3.5 | DB-KM | 1.8% |
| | 100 | 4000 | 1000 | **195443** | 86.6 | MB-II | 200649 | 0.3 | Agg. | 2.7% |
| | 200 | 3000 | 750 | **148939** | 186.1 | MB-I, MB-II | 152707 | 0.4 | Agg. | 2.5% |
| | 200 | 3000 | 1000 | **155652** | 140.3 | MB-I, MB-II | 157451 | 0.4 | Agg. | 1.2% |
| | 200 | 4000 | 750 | **164533** | 228.4 | MB-I, MB-II | 168074 | 0.4 | Agg. | 2.2% |
| | 200 | 4000 | 1000 | **173975** | 155.7 | MB-I | 178648 | 0.2 | Agg. | 2.7% |

| | | | | Best Model-based Heuristic | | | Best Clustering-based Heuristic | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | Cost | Time | Method | Cost | Time | Method | Diff. |
| RUHIIRA - 4 | 30 | 3000 | 750 | **180546** | 13.4 | MB-I, MB-II | 181500 | 0.6 | All | 0.5% |
| | 30 | 3000 | 1000 | **236606** | 14.6 | MB-I, MB-II | 238892 | 0.1 | DB-KM, DB-Agg. | 1.0% |
| | 30 | 4000 | 750 | **181500** | 12.7 | MB-I, MB-II | **181500** | 0.2 | All | 0.0% |
| | 30 | 4000 | 1000 | **240546** | 12.1 | MB-I, MB-II | 242000 | 0.3 | All | 0.6% |
| | 50 | 3000 | 750 | **179133** | 23.2 | MB-II | 179163 | 0.4 | DB-KM, DB-Agg. | 0.0% |
| | 50 | 3000 | 1000 | **223482** | 19.6 | MB-II | 229579 | 0.2 | DB-KM | 2.7% |
| | 50 | 4000 | 750 | **180424** | 10.5 | MB-I, MB-II | **180424** | 0.0 | DB-KM, DB-Agg. | 0.0% |
| | 50 | 4000 | 1000 | **237421** | 13.7 | MB-I, MB-II | 238163 | 0.1 | DB-KM, DB-Agg. | 0.3% |
| | 100 | 3000 | 750 | **166795** | 15.6 | MB-II | 172616 | 2.9 | DB-KM | 3.5% |
| | 100 | 3000 | 1000 | **193327** | 22.7 | MB-II | 200908 | 0.1 | DB-Agg. | 3.9% |
| | 100 | 4000 | 750 | **174337** | 12.8 | MB-I, MB-II | 177931 | 2.6 | DB-KM | 2.1% |
| | 100 | 4000 | 1000 | **212728** | 14.7 | MB-II | 224000 | 0.2 | DB-Agg. | 5.3% |
| | 200 | 3000 | 750 | **160430** | 42.4 | MB-I, MB-II | 168541 | 9.4 | DB-KM | 5.1% |
| | 200 | 3000 | 1000 | **172532** | 33.5 | MB-I, MB-II | 176329 | 0.5 | Agg., DB-Agg. | 2.2% |
| | 200 | 4000 | 750 | **170253** | 35.7 | MB-I, MB-II | 175506 | 8.6 | DB-KM | 3.1% |
| | 200 | 4000 | 1000 | **192816** | 91.2 | MB-I, MB-II | 196440 | 0.3 | Agg., DB-Agg. | 1.9% |

Table 5.13: Comparison of Heuristic Methods with Variable Facility Costs on Tiby

| | | | | Best Model-based Heuristic | | | Best Clustering-based Heuristic | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F3 | F2 | Cost | Time | Method | Cost | Time | Method | Diff. |
| TIBY - 1 | 30 | 500 | 750 | **229381** | 38.4 | MB-I | 233840 | 1.9 | Agg. | 1.9% |
| | 30 | 500 | 1000 | **230499** | 39.1 | MB-I | 236754 | 1.4 | Agg. | 2.7% |
| | 30 | 600 | 750 | **271113** | 33.4 | MB-I | 274521 | 0.8 | Agg. | 1.3% |
| | 30 | 600 | 1000 | **272499** | 35.3 | MB-I | 278154 | 1.2 | Agg. | 2.1% |
| | 50 | 500 | 750 | **228586** | 40.5 | MB-II | 233839 | 1.1 | Agg., DB-Agg. | 2.3% |
| | 50 | 500 | 1000 | **229331** | 41.9 | MB-II | 236754 | 0.8 | Agg., DB-Agg. | 3.2% |
| | 50 | 600 | 750 | **270675** | 34.2 | MB-I, MB-II | 274439 | 1.0 | DB-Agg. | 1.4% |
| | 50 | 600 | 1000 | **271531** | 40.7 | MB-II | 278154 | 1.0 | Agg., DB-Agg. | 2.4% |
| | 100 | 500 | 750 | **228522** | 41.6 | MB-I, MB-II | 233839 | 1.3 | Agg., DB-Agg. | 2.3% |
| | 100 | 500 | 1000 | **229133** | 52.9 | MB-II | 236754 | 1.2 | Agg., DB-Agg. | 3.3% |
| | 100 | 600 | 750 | **270619** | 48.8 | MB-I, MB-II | 274521 | 1.6 | Agg., DB-Agg. | 1.4% |
| | 100 | 600 | 1000 | **271472** | 39.8 | MB-I, MB-II | 278154 | 1.7 | Agg., DB-Agg. | 2.5% |
| | 200 | 500 | 750 | **228522** | 133.5 | MB-I, MB-II | 233839 | 1.9 | Agg., DB-Agg. | 2.3% |
| | 200 | 500 | 1000 | **229133** | 130.2 | MB-I, MB-II | 236754 | 2.1 | Agg., DB-Agg. | 3.3% |
| | 200 | 600 | 750 | **270619** | 126.2 | MB-I, MB-II | 274521 | 1.6 | Agg., DB-Agg. | 1.4% |
| | 200 | 600 | 1000 | **271433** | 128.6 | MB-I, MB-II | 278154 | 1.9 | Agg., DB-Agg. | 2.5% |
| TIBY - 2 | 30 | 500 | 750 | **212862** | 34.1 | MB-I, MB-II | 218417 | 1.8 | Agg. | 2.6% |
| | 30 | 500 | 1000 | **212819** | 31.6 | MB-I, MB-II | 220737 | 1.3 | Agg. | 3.7% |
| | 30 | 600 | 750 | **252442** | 40.9 | MB-II | 256122 | 0.6 | DB-Agg. | 1.5% |
| | 30 | 600 | 1000 | **252519** | 31.3 | MB-I, MB-II | 259770 | 0.6 | Agg. | 2.9% |
| | 50 | 500 | 750 | **212395** | 27.8 | MB-I, MB-II | 218114 | 0.7 | DB-Agg. | 2.7% |
| | 50 | 500 | 1000 | **212395** | 27.6 | MB-I, MB-II | 220067 | 0.9 | DB-Agg. | 3.6% |
| | 50 | 600 | 750 | **252050** | 27.4 | MB-I, MB-II | 256330 | 0.9 | DB-Agg. | 1.7% |
| | 50 | 600 | 1000 | **252095** | 27.9 | MB-I, MB-II | 259167 | 0.9 | DB-Agg. | 2.8% |
| | 100 | 500 | 750 | **212367** | 37.8 | MB-I, MB-II | 218417 | 1.4 | Agg., DB-Agg. | 2.8% |
| | 100 | 500 | 1000 | **212367** | 37.0 | MB-I, MB-II | 220702 | 1.3 | Agg., DB-Agg. | 3.9% |
| | 100 | 600 | 750 | **252050** | 40.1 | MB-I, MB-II | 256433 | 1.1 | Agg., DB-Agg. | 1.7% |
| | 100 | 600 | 1000 | **252067** | 40.2 | MB-I, MB-II | 259769 | 1.4 | Agg., DB-Agg. | 3.1% |
| | 200 | 500 | 750 | **212367** | 118.0 | MB-I, MB-II | 218417 | 1.8 | Agg., DB-Agg. | 2.8% |

| | DLim | F3 | F2 | Best Model-based Heuristic Cost | Time | Method | Best Clustering-based Heuristic Cost | Time | Method | Diff. |
|---|---|---|---|---|---|---|---|---|---|---|
| | 200 | 500 | 1000 | **212367** | 115.0 | MB-I, MB-II | 220702 | 2.1 | Agg., DB-Agg. | 3.9% |
| | 200 | 600 | 750 | **252050** | 115.3 | MB-I, MB-II | 256433 | 1.6 | Agg., DB-Agg. | 1.7% |
| | 200 | 600 | 1000 | **252067** | 117.2 | MB-I, MB-II | 259769 | 1.8 | Agg., DB-Agg. | 3.1% |
| TIBY - 3 | 30 | 500 | 750 | **222269** | 39.4 | MB-II | 227366 | 1.4 | Agg. | 2.3% |
| | 30 | 500 | 1000 | **223153** | 37.6 | MB-II | 231045 | 1.1 | Agg. | 3.5% |
| | 30 | 600 | 750 | **262947** | 39.1 | MB-II | 265581 | 1.2 | Agg. | 1.0% |
| | 30 | 600 | 1000 | **263753** | 37.1 | MB-II | 270516 | 0.5 | Agg. | 2.6% |
| | 50 | 500 | 750 | **221809** | 32.9 | MB-II | 227305 | 1.0 | Agg. | 2.5% |
| | 50 | 500 | 1000 | **222048** | 34.6 | MB-II | 230841 | 2.0 | Agg. | 4.0% |
| | 50 | 600 | 750 | **262389** | 24.6 | MB-I, MB-II | 265581 | 0.6 | Agg. | 1.2% |
| | 50 | 600 | 1000 | **262941** | 33.7 | MB-II | 270455 | 0.7 | Agg. | 2.9% |
| | 100 | 500 | 750 | **221730** | 28.8 | MB-I, MB-II | 227059 | 1.9 | DB-Agg. | 2.4% |
| | 100 | 500 | 1000 | **221830** | 31.6 | MB-I, MB-II | 230519 | 1.9 | DB-Agg. | 3.9% |
| | 100 | 600 | 750 | **262334** | 32.4 | MB-I, MB-II | 265525 | 0.7 | DB-Agg. | 1.2% |
| | 100 | 600 | 1000 | **262730** | 31.7 | MB-I, MB-II | 270209 | 1.0 | DB-Agg. | 2.8% |
| | 200 | 500 | 750 | **221723** | 57.0 | MB-I, MB-II | 227305 | 1.3 | Agg. | 2.5% |
| | 200 | 500 | 1000 | **221723** | 56.3 | MB-I, MB-II | 230841 | 3.0 | Agg. | 4.1% |
| | 200 | 600 | 750 | **262334** | 57.4 | MB-I, MB-II | 265581 | 1.6 | Agg. | 1.2% |
| | 200 | 600 | 1000 | **262623** | 56.0 | MB-I, MB-II | 270455 | 1.1 | Agg. | 3.0% |
| TIBY - 4 | 30 | 500 | 750 | **118009** | 8.1 | MB-I | 120272 | 0.4 | Agg. | 1.9% |
| | 30 | 500 | 1000 | **118759** | 5.8 | MB-I | 122954 | 0.4 | Agg. | 3.5% |
| | 30 | 600 | 750 | **139555** | 7.0 | MB-I, MB-II | 140972 | 0.4 | Agg. | 1.0% |
| | 30 | 600 | 1000 | **140259** | 6.3 | MB-I | 143722 | 0.4 | Agg. | 2.5% |
| | 50 | 500 | 750 | **117751** | 6.2 | MB-I, MB-II | 120035 | 0.4 | DB-Agg. | 1.9% |
| | 50 | 500 | 1000 | **117954** | 9.4 | MB-II | 122285 | 0.5 | DB-Agg. | 3.7% |
| | 50 | 600 | 750 | **139378** | 5.2 | MB-I, MB-II | 140935 | 0.2 | DB-Agg. | 1.1% |
| | 50 | 600 | 1000 | **139654** | 9.2 | MB-II | 143185 | 0.1 | DB-Agg. | 2.5% |
| | 100 | 500 | 750 | **117704** | 8.0 | MB-I, MB-II | 120170 | 0.3 | DB-Agg. | 2.1% |
| | 100 | 500 | 1000 | **117954** | 10.4 | MB-I, MB-II | 122603 | 0.8 | DB-Agg. | 3.9% |
| | 100 | 600 | 750 | **139353** | 11.1 | MB-I, MB-II | 140970 | 0.3 | DB-Agg. | 1.2% |
| | 100 | 600 | 1000 | **139654** | 12.2 | MB-I, MB-II | 143470 | 0.4 | DB-Agg. | 2.7% |
| | 200 | 500 | 750 | **117704** | 27.0 | MB-I, MB-II | 120272 | 0.4 | Agg., DB-Agg. | 2.2% |
| | 200 | 500 | 1000 | **117954** | 26.6 | MB-I, MB-II | 122954 | 0.6 | Agg., DB-Agg. | 4.2% |
| | 200 | 600 | 750 | **139353** | 26.7 | MB-I, MB-II | 140972 | 0.5 | Agg., DB-Agg. | 1.2% |
| | 200 | 600 | 1000 | **139654** | 28.1 | MB-I, MB-II | 143722 | 0.4 | Agg., DB-Agg. | 2.9% |

Table 5.14: Comparison of Heuristic Methods with Variable Facility Costs on Mbola

| | | | | Best Model-based Heuristic | | | Best Clustering-based Heuristic | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F3 | F2 | Cost | Time | Method | Cost | Time | Method | Diff. |
| MBOLA - 1 | 30 | 500 | 750 | **85083** | 6.9 | MB-II | 85809 | 0.1 | Agg. | 0.9% |
| | 30 | 500 | 1000 | **90604** | 4.3 | MB-II | 92309 | 0.1 | Agg. | 1.9% |
| | 30 | 600 | 750 | **97278** | 4.4 | MB-II | 97633 | 0.1 | Agg. | 0.4% |
| | 30 | 600 | 1000 | **102904** | 4.6 | MB-II | 104209 | 0.1 | Agg. | 1.3% |
| | 50 | 500 | 750 | **84116** | 5.3 | MB-II | 85027 | 0.1 | Agg. | 1.1% |
| | 50 | 500 | 1000 | **85737** | 19.5 | MB-II | 88275 | 0.1 | Agg. | 3.0% |
| | 50 | 600 | 750 | **97143** | 7.5 | MB-II | 97565 | 0.1 | Agg. | 0.4% |
| | 50 | 600 | 1000 | **99786** | 4.9 | MB-II | 101575 | 0.1 | Agg. | 1.8% |
| | 100 | 500 | 750 | **83539** | 7.1 | MB-I, MB-II | 84521 | 0.1 | DB-Agg. | 1.2% |
| | 100 | 500 | 1000 | **84867** | 3.9 | MB-II | 86955 | 0.1 | DB-Agg. | 2.5% |
| | 100 | 600 | 750 | **96845** | 2.9 | MB-II | 97452 | 0.1 | DB-Agg. | 0.6% |
| | 100 | 600 | 1000 | **98954** | 2.8 | MB-I, MB-II | 100555 | 0.1 | DB-Agg. | 1.6% |
| | 200 | 500 | 750 | **83539** | 6.8 | MB-I, MB-II | 84996 | 0.3 | DB-Agg. | 1.7% |
| | 200 | 500 | 1000 | **84810** | 3.1 | MB-I, MB-II | 88246 | 0.3 | DB-Agg. | 4.1% |
| | 200 | 600 | 750 | **96872** | 2.6 | MB-I, MB-II | 97565 | 0.3 | Agg. | 0.7% |
| | 200 | 600 | 1000 | **98910** | 3.2 | MB-I, MB-II | 101446 | 0.3 | DB-Agg. | 2.6% |
| MBOLA - 2 | 30 | 500 | 750 | **45926** | 1.6 | MB-I, MB-II | 46327 | 0.2 | Agg., DB-Agg. | 0.9% |
| | 30 | 500 | 1000 | **50926** | 1.2 | MB-I, MB-II | 51327 | 0.1 | Agg., DB-Agg. | 0.8% |
| | 30 | 600 | 750 | **51626** | 1.1 | MB-I, MB-II | 51902 | 0.0 | Agg. | 0.5% |
| | 30 | 600 | 1000 | **56626** | 0.8 | MB-I, MB-II | 57027 | 0.1 | Agg., DB-Agg. | 0.7% |
| | 50 | 500 | 750 | **45463** | 1.2 | MB-I, MB-II | 46145 | 0.1 | Agg. | 1.5% |
| | 50 | 500 | 1000 | **49102** | 11.2 | MB-II | 49642 | 0.0 | Agg. | 1.1% |
| | 50 | 600 | 750 | **51626** | 1.3 | MB-I, MB-II | 51902 | 0.1 | Agg. | 0.5% |
| | 50 | 600 | 1000 | **55413** | 1.5 | MB-I, MB-II | 56042 | 0.0 | Agg. | 1.1% |
| | 100 | 500 | 750 | **45314** | 2.2 | MB-I, MB-II | 46116 | 0.1 | Agg. | 1.8% |
| | 100 | 500 | 1000 | **47850** | 3.4 | MB-II | 49359 | 0.0 | Agg. | 3.2% |
| | 100 | 600 | 750 | **51626** | 1.0 | MB-I, MB-II | 51902 | 0.0 | Agg. | 0.5% |
| | 100 | 600 | 1000 | **54833** | 1.1 | MB-I | 56216 | 0.1 | Agg. | 2.5% |
| | 200 | 500 | 750 | **45314** | 1.5 | MB-I, MB-II | 46116 | 0.1 | Agg. | 1.8% |
| | 200 | 500 | 1000 | **47850** | 8.4 | MB-I, MB-II | 49305 | 0.1 | Agg. | 3.0% |
| | 200 | 600 | 750 | **51626** | 1.3 | MB-I, MB-II | 51902 | 0.1 | Agg. | 0.5% |
| | 200 | 600 | 1000 | **54770** | 1.1 | MB-I, MB-II | 56205 | 0.1 | Agg. | 2.6% |
| MBOLA - 3 | 30 | 500 | 750 | **27584** | 1.9 | MB-I, MB-II | 27680 | 0.1 | Agg. | 0.3% |
| | 30 | 500 | 1000 | **30084** | 0.7 | MB-I, MB-II | 30180 | 0.0 | Agg. | 0.3% |
| | 30 | 600 | 750 | **31284** | 1.1 | MB-I, MB-II | 31380 | 0.0 | Agg. | 0.3% |
| | 30 | 600 | 1000 | **33784** | 1.2 | MB-I, MB-II | 33880 | 0.0 | Agg. | 0.3% |
| | 50 | 500 | 750 | **27410** | 1.1 | MB-I, MB-II | 27506 | 0.1 | Agg. | 0.4% |
| | 50 | 500 | 1000 | **29046** | 9.4 | MB-II | 29225 | 0.0 | Agg. | 0.6% |
| | 50 | 600 | 750 | **31284** | 0.6 | MB-I, MB-II | 31380 | 0.0 | Agg. | 0.3% |
| | 50 | 600 | 1000 | **33167** | 1.0 | MB-I, MB-II | 33325 | 0.1 | Agg. | 0.5% |
| | 100 | 500 | 750 | **27410** | 1.1 | MB-I, MB-II | 27506 | 0.1 | Agg. | 0.4% |
| | 100 | 500 | 1000 | **28227** | 1.0 | MB-I, MB-II | 28653 | 0.0 | Agg. | 1.5% |
| | 100 | 600 | 750 | **31284** | 0.8 | MB-I, MB-II | 31380 | 0.1 | Agg. | 0.3% |
| | 100 | 600 | 1000 | **32727** | 1.0 | MB-I, MB-II | 33053 | 0.0 | Agg. | 1.0% |
| | 200 | 500 | 750 | **27410** | 1.1 | MB-I, MB-II | 27506 | 0.1 | Agg. | 0.4% |
| | 200 | 500 | 1000 | **28227** | 1.2 | MB-I, MB-II | 28653 | 0.1 | Agg. | 1.5% |
| | 200 | 600 | 750 | **31284** | 0.9 | MB-I, MB-II | 31380 | 0.1 | Agg. | 0.3% |
| | 200 | 600 | 1000 | **32727** | 2.3 | MB-I, MB-II | 33053 | 0.1 | Agg. | 1.0% |

| | DLim | F3 | F2 | Best Model-based Heuristic Cost | Time | Method | Best Clustering-based Heuristic Cost | Time | Method | Diff. |
|---|---|---|---|---|---|---|---|---|---|---|
| MBOLA - 4 | 30 | 500 | 750 | **36715** | 1.8 | MB-I, MB-II | 36801 | 0.1 | Agg. | 0.2% |
| | 30 | 500 | 1000 | **39465** | 1.0 | MB-I, MB-II | 39572 | 0.0 | Agg. | 0.3% |
| | 30 | 600 | 750 | 41805 | 1.4 | MB-I, MB-II | **41770** | 0.0 | Agg. | -0.1% |
| | 30 | 600 | 1000 | **44565** | 1.1 | MB-I, MB-II | 44672 | 0.0 | Agg. | 0.2% |
| | 50 | 500 | 750 | **36214** | 1.5 | MB-II | 36596 | 0.1 | Agg. | 1.1% |
| | 50 | 500 | 1000 | **37472** | 8.7 | MB-II | 38729 | 0.0 | Agg. | 3.4% |
| | 50 | 600 | 750 | **41657** | 1.1 | MB-II | 41770 | 0.0 | Agg. | 0.3% |
| | 50 | 600 | 1000 | **43172** | 1.4 | MB-II | 44296 | 0.0 | Agg. | 2.6% |
| | 100 | 500 | 750 | **36186** | 1.2 | MB-I, MB-II | 36596 | 0.1 | Agg. | 1.1% |
| | 100 | 500 | 1000 | **37445** | 1.2 | MB-I, MB-II | 38523 | 0.1 | Agg. | 2.9% |
| | 100 | 600 | 750 | **41657** | 1.6 | MB-I, MB-II | 41770 | 0.0 | Agg. | 0.3% |
| | 100 | 600 | 1000 | **43145** | 2.4 | MB-I, MB-II | 44223 | 0.1 | Agg. | 2.5% |
| | 200 | 500 | 750 | **36186** | 0.8 | MB-I, MB-II | 36596 | 0.1 | Agg. | 1.1% |
| | 200 | 500 | 1000 | **37445** | 0.8 | MB-I, MB-II | 38523 | 0.2 | Agg. | 2.9% |
| | 200 | 600 | 750 | **41657** | 1.0 | MB-I, MB-II | 41770 | 0.1 | Agg. | 0.3% |
| | 200 | 600 | 1000 | **43145** | 0.8 | MB-I, MB-II | 44223 | 0.2 | Agg. | 2.5% |

Table 5.15: Comparison of Heuristic Methods with Variable Facility Costs on Potou

| | DLim | F3 | F2 | Best Model-based Heuristic Cost | Time | Method | Best Clustering-based Heuristic Cost | Time | Method | Diff. |
|---|---|---|---|---|---|---|---|---|---|---|
| POTOU - 1 | 30 | 500 | 750 | **223160** | 38.9 | MB-II | 229744 | 1.4 | DB-Agg | 3.0% |
| | 30 | 500 | 1000 | **224910** | 30.1 | MB-I, MB-II | 234068 | 0.7 | Agg | 4.1% |
| | 30 | 600 | 750 | **264356** | 35.3 | MB-I, MB-II | 268714 | 1.2 | Agg | 1.6% |
| | 30 | 600 | 1000 | **266210** | 28.1 | MB-I, MB-II | 274968 | 0.9 | Agg | 3.3% |
| | 50 | 500 | 750 | **223135** | 35.3 | MB-I, MB-II | 229914 | 0.8 | Agg | 3.0% |
| | 50 | 500 | 1000 | **224637** | 37.8 | MB-I, MB-II | 233461 | 1.2 | Agg | 3.9% |
| | 50 | 600 | 750 | **264338** | 32.5 | MB-I, MB-II | 268714 | 1.6 | Agg | 1.7% |
| | 50 | 600 | 1000 | **266295** | 45.2 | MB-II | 274613 | 1.1 | Agg | 3.1% |
| | 100 | 500 | 750 | **223007** | 49.5 | MB-I, MB-II | 229914 | 1.6 | Agg | 3.1% |
| | 100 | 500 | 1000 | **223867** | 48.3 | MB-I, MB-II | 233461 | 3.5 | Agg | 4.3% |
| | 100 | 600 | 750 | **264297** | 48.6 | MB-I, MB-II | 268714 | 1.2 | Agg | 1.7% |
| | 100 | 600 | 1000 | **265635** | 48.7 | MB-I | 274613 | 3.1 | Agg | 3.4% |
| | 200 | 500 | 750 | **223007** | 104.9 | MB-I, MB-II | 227792 | 1.4 | DB-Agg | 2.1% |
| | 200 | 500 | 1000 | **223681** | 105.3 | MB-I | 233274 | 4.4 | DB-Agg | 4.3% |
| | 200 | 600 | 750 | **264297** | 99.0 | MB-I, MB-II | 268255 | 1.1 | DB-Agg | 1.5% |
| | 200 | 600 | 1000 | **265549** | 100.6 | MB-I | 274612 | 1.8 | DB-Agg | 3.4% |
| POTOU - 2 | 30 | 500 | 750 | **58581** | 3.4 | MB-II | 59789 | 0.1 | Agg | 2.1% |
| | 30 | 500 | 1000 | **61331** | 2.3 | MB-II | 63039 | 0.0 | Agg | 2.8% |
| | 30 | 600 | 750 | **67781** | 2.1 | MB-II | 68495 | 0.1 | Agg | 1.1% |
| | 30 | 600 | 1000 | **70531** | 2.3 | MB-II | 72039 | 0.1 | Agg | 2.1% |
| | 50 | 500 | 750 | **58240** | 3.1 | MB-II | 59673 | 0.1 | Agg | 2.5% |
| | 50 | 500 | 1000 | **59742** | 8.7 | MB-II | 62262 | 0.1 | Agg | 4.2% |
| | 50 | 600 | 750 | **68032** | 1.8 | MB-I, MB-II | 68495 | 0.0 | Agg | 0.7% |
| | 50 | 600 | 1000 | **69590** | 2.7 | MB-II | 71611 | 0.1 | Agg | 2.9% |
| | 100 | 500 | 750 | **58220** | 9.2 | MB-I, MB-II | 59673 | 0.1 | Agg | 2.5% |
| | 100 | 500 | 1000 | **59399** | 6.9 | MB-II | 61952 | 0.1 | Agg | 4.3% |
| | 100 | 600 | 750 | **67740** | 1.9 | MB-I, MB-II | 68495 | 0.1 | Agg | 1.1% |
| | 100 | 600 | 1000 | **69293** | 2.3 | MB-II | 71509 | 0.1 | Agg | 3.2% |
| | 200 | 500 | 750 | **58220** | 2.8 | MB-I, MB-II | 59433 | 0.1 | DB-Agg | 2.1% |

| | | | | Best Model-based Heuristic | | | Best Clustering-based Heuristic | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F3 | F2 | Cost | Time | Method | Cost | Time | Method | Diff. |
| | 200 | 500 | 1000 | **59269** | 1.6 | MB-I, MB-II | 61346 | 0.1 | DB-Agg | 3.5% |
| | 200 | 600 | 750 | **67740** | 1.3 | MB-I, MB-II | 68495 | 0.1 | Agg | 1.1% |
| | 200 | 600 | 1000 | **69293** | 1.7 | MB-I, MB-II | 70946 | 0.1 | DB-Agg | 2.4% |
| POTOU - 3 | 30 | 500 | 750 | **36268** | 2.6 | MB-I, MB-II | 37180 | 0.3 | Agg | 2.5% |
| | 30 | 500 | 1000 | **36307** | 1.6 | MB-I, MB-II | 38185 | 0.1 | Agg | 5.2% |
| | 30 | 600 | 750 | **42615** | 1.1 | MB-I, MB-II | 43121 | 0.0 | Agg | 1.2% |
| | 30 | 600 | 1000 | **42907** | 1.8 | MB-I, MB-II | 44485 | 0.1 | Agg | 3.7% |
| | 50 | 500 | 750 | **36232** | 2.0 | MB-I, MB-II | 37180 | 0.1 | Agg | 2.6% |
| | 50 | 500 | 1000 | **36243** | 8.6 | MB-I, MB-II | 38015 | 0.1 | Agg | 4.9% |
| | 50 | 600 | 750 | **42579** | 0.6 | MB-I, MB-II | 43121 | 0.1 | Agg | 1.3% |
| | 50 | 600 | 1000 | **42843** | 1.4 | MB-I, MB-II | 44315 | 0.1 | Agg | 3.4% |
| | 100 | 500 | 750 | **36195** | 1.6 | MB-I, MB-II | 37180 | 0.1 | Agg | 2.7% |
| | 100 | 500 | 1000 | **36195** | 1.8 | MB-I, MB-II | 37988 | 0.1 | Agg | 5.0% |
| | 100 | 600 | 750 | **42579** | 0.8 | MB-I, MB-II | 43121 | 0.0 | Agg | 1.3% |
| | 100 | 600 | 1000 | **42795** | 1.6 | MB-I, MB-II | 44315 | 0.1 | Agg | 3.6% |
| | 200 | 500 | 750 | **36195** | 1.7 | MB-I, MB-II | 37180 | 0.2 | Agg | 2.7% |
| | 200 | 500 | 1000 | **36195** | 0.8 | MB-I, MB-II | 37988 | 0.1 | Agg | 5.0% |
| | 200 | 600 | 750 | **42579** | 0.7 | MB-I, MB-II | 43121 | 0.1 | Agg | 1.3% |
| | 200 | 600 | 1000 | **42795** | 3.4 | MB-I, MB-II | 44315 | 0.1 | Agg | 3.6% |
| POTOU - 4 | 30 | 500 | 750 | **69693** | 6.1 | MB-II | 72400 | 0.4 | Agg | 3.9% |
| | 30 | 500 | 1000 | **70193** | 4.2 | MB-II | 74549 | 0.1 | Agg | 6.2% |
| | 30 | 600 | 750 | **82267** | 2.9 | MB-II | 83584 | 0.1 | Agg | 1.6% |
| | 30 | 600 | 1000 | **82793** | 4.4 | MB-II | 86649 | 0.1 | Agg | 4.7% |
| | 50 | 500 | 750 | **69683** | 5.4 | MB-II | 72005 | 0.2 | DB-Agg | 3.3% |
| | 50 | 500 | 1000 | **69628** | 10.7 | MB-II | 74110 | 0.1 | Agg | 6.4% |
| | 50 | 600 | 750 | **82166** | 2.8 | MB-II | 83473 | 0.1 | DB-Agg | 1.6% |
| | 50 | 600 | 1000 | **82428** | 7.0 | MB-II | 86300 | 0.3 | DB-Agg | 4.7% |
| | 100 | 500 | 750 | **69509** | 3.9 | MB-I, MB-II | 72400 | 0.3 | Agg | 4.2% |
| | 100 | 500 | 1000 | **69544** | 2.2 | MB-I, MB-II | 74110 | 0.2 | Agg | 6.6% |
| | 100 | 600 | 750 | **82117** | 2.3 | MB-I, MB-II | 83584 | 0.1 | Agg | 1.8% |
| | 100 | 600 | 1000 | **82344** | 1.8 | MB-I, MB-II | 86310 | 0.2 | Agg | 4.8% |
| | 200 | 500 | 750 | **69509** | 6.6 | MB-I, MB-II | 72400 | 0.5 | Agg | 4.2% |
| | 200 | 500 | 1000 | **69544** | 3.5 | MB-I, MB-II | 74110 | 0.2 | Agg | 6.6% |
| | 200 | 600 | 750 | **82117** | 2.3 | MB-I, MB-II | 83584 | 0.2 | Agg | 1.8% |
| | 200 | 600 | 1000 | **82344** | 3.6 | MB-I, MB-II | 86310 | 0.3 | Agg | 4.8% |

Table 5.16: Comparison of Heuristic Methods with Variable Facility Costs on Ruhiira

| | DLim | F3 | F2 | Best Model-based Heuristic Cost | Time | Method | Best Clustering-based Heuristic Cost | Time | Method | Diff. |
|---|---|---|---|---|---|---|---|---|---|---|
| RUHIIRA - 1 | 30 | 500 | 750 | **83489** | 10.0 | MB-II | 83833 | 0.1 | Agg | 0.4% |
| | 30 | 500 | 1000 | **91767** | 3.5 | MB-II | 93586 | 0.1 | Agg | 2.0% |
| | 30 | 600 | 750 | **93329** | 2.8 | MB-I | 93333 | 0.1 | Agg | 0.0% |
| | 30 | 600 | 1000 | **101967** | 4.3 | MB-II | 103286 | 0.1 | Agg | 1.3% |
| | 50 | 500 | 750 | **81739** | 11.1 | MB-II | 82863 | 0.1 | Agg | 1.4% |
| | 50 | 500 | 1000 | **85802** | 10.5 | MB-I, MB-II | 87275 | 0.1 | Agg | 1.7% |
| | 50 | 600 | 750 | **93250** | 2.4 | MB-I, MB-II | 93261 | 0.1 | Agg | 0.0% |
| | 50 | 600 | 1000 | **98039** | 4.7 | MB-I, MB-II | 99175 | 0.1 | Agg | 1.2% |
| | 100 | 500 | 750 | **81612** | 3.0 | MB-I, MB-II | 82861 | 0.1 | Agg | 1.5% |
| | 100 | 500 | 1000 | **83757** | 4.3 | MB-II | 86894 | 0.1 | Agg | 3.7% |
| | 100 | 600 | 750 | **93001** | 3.6 | MB-I, MB-II | 93261 | 0.1 | Agg | 0.3% |
| | 100 | 600 | 1000 | **96909** | 2.9 | MB-I | 99011 | 0.1 | Agg | 2.2% |
| | 200 | 500 | 750 | **81553** | 2.1 | MB-I, MB-II | 82861 | 0.1 | Agg | 1.6% |
| | 200 | 500 | 1000 | **83367** | 2.3 | MB-I, MB-II | 86894 | 0.1 | Agg | 4.2% |
| | 200 | 600 | 750 | **93001** | 2.4 | MB-I, MB-II | 93261 | 0.1 | Agg | 0.3% |
| | 200 | 600 | 1000 | **96491** | 2.9 | MB-I, MB-II | 99011 | 0.3 | Agg | 2.6% |
| RUHIIRA - 2 | 30 | 500 | 750 | **144774** | 16.3 | MB-I | 146154 | 0.3 | Agg | 1.0% |
| | 30 | 500 | 1000 | **157328** | 9.4 | MB-I | 161154 | 0.5 | Agg | 2.4% |
| | 30 | 600 | 750 | **163545** | 12.9 | MB-II | 164254 | 0.1 | Agg | 0.4% |
| | 30 | 600 | 1000 | **176656** | 10.1 | MB-I | 179454 | 0.2 | Agg | 1.6% |
| | 50 | 500 | 750 | **143368** | 11.9 | MB-I, MB-II | 145968 | 0.3 | Agg | 1.8% |
| | 50 | 500 | 1000 | **149668** | 15.3 | MB-II | 155485 | 0.2 | Agg | 3.9% |
| | 50 | 600 | 750 | **163590** | 12.8 | MB-II | 164177 | 0.2 | Agg | 0.4% |
| | 50 | 600 | 1000 | **171692** | 11.8 | MB-II | 176679 | 0.3 | Agg | 2.9% |
| | 100 | 500 | 750 | **142863** | 12.9 | MB-I, MB-II | 145968 | 0.4 | Agg | 2.2% |
| | 100 | 500 | 1000 | **146642** | 10.8 | MB-II | 153510 | 0.4 | Agg | 4.7% |
| | 100 | 600 | 750 | **163105** | 7.2 | MB-I, MB-II | 164177 | 0.4 | Agg | 0.7% |
| | 100 | 600 | 1000 | **169934** | 10.8 | MB-II | 175810 | 0.2 | Agg | 3.5% |
| | 200 | 500 | 750 | **142744** | 7.8 | MB-I, MB-II | 145968 | 0.2 | Agg | 2.3% |
| | 200 | 500 | 1000 | **145962** | 7.8 | MB-I, MB-II | 153510 | 0.4 | Agg | 5.2% |
| | 200 | 600 | 750 | **163105** | 6.7 | MB-I, MB-II | 164177 | 0.3 | Agg | 0.7% |
| | 200 | 600 | 1000 | **169517** | 6.2 | MB-I, MB-II | 175810 | 0.3 | Agg | 3.7% |
| RUHIIRA - 3 | 30 | 500 | 750 | **158327** | 23.6 | MB-II | 161353 | 0.6 | Agg | 1.9% |
| | 30 | 500 | 1000 | **169777** | 18.1 | MB-II | 174882 | 0.4 | Agg | 3.0% |
| | 30 | 600 | 750 | **180541** | 12.2 | MB-I, MB-II | 181697 | 0.4 | Agg | 0.6% |
| | 30 | 600 | 1000 | **192360** | 18.9 | MB-II | 196582 | 0.5 | Agg | 2.2% |
| | 50 | 500 | 750 | **156811** | 16.4 | MB-II | 160445 | 0.4 | Agg | 2.3% |
| | 50 | 500 | 1000 | **162916** | 15.7 | MB-II | 169547 | 0.3 | Agg | 4.1% |
| | 50 | 600 | 750 | **180282** | 15.0 | MB-II | 181697 | 0.4 | Agg | 0.8% |
| | 50 | 600 | 1000 | **187816** | 10.0 | MB-I | 193447 | 0.6 | Agg | 3.0% |
| | 100 | 500 | 750 | **156135** | 11.4 | MB-I, MB-II | 160445 | 0.3 | Agg | 2.8% |
| | 100 | 500 | 1000 | **159246** | 12.3 | MB-II | 168426 | 0.2 | Agg | 5.8% |
| | 100 | 600 | 750 | **179896** | 9.5 | MB-I, MB-II | 181697 | 0.3 | Agg | 1.0% |
| | 100 | 600 | 1000 | **185493** | 12.5 | MB-II | 193166 | 0.4 | Agg | 4.1% |
| | 200 | 500 | 750 | **156111** | 8.2 | MB-I, MB-II | 160445 | 0.3 | Agg | 2.8% |
| | 200 | 500 | 1000 | **158570** | 8.5 | MB-I, MB-II | 168426 | 0.4 | Agg | 6.2% |
| | 200 | 600 | 750 | **179896** | 9.7 | MB-I, MB-II | 181697 | 0.2 | Agg | 1.0% |
| | 200 | 600 | 1000 | **185141** | 9.4 | MB-I, MB-II | 193166 | 0.3 | Agg | 4.3% |

| | DLim | F3 | F2 | Best Model-based Heuristic Cost | Time | Method | Best Clustering-based Heuristic Cost | Time | Method | Diff. |
|---|---|---|---|---|---|---|---|---|---|---|
| RUHIIRA - 4 | 30 | 500 | 750 | **150506** | 13.1 | MB-II | 151810 | 0.1 | Agg | 0.9% |
| | 30 | 500 | 1000 | **168541** | 13.0 | MB-II | 171560 | 0.1 | Agg | 1.8% |
| | 30 | 600 | 750 | **167316** | 13.1 | MB-II | 167949 | 0.4 | Agg | 0.4% |
| | 30 | 600 | 1000 | **185541** | 12.8 | MB-II | 187860 | 0.1 | Agg | 1.2% |
| | 50 | 500 | 750 | **148151** | 13.4 | MB-II | 149626 | 0.3 | Agg | 1.0% |
| | 50 | 500 | 1000 | **156899** | 14.9 | MB-II | 160895 | 0.3 | Agg | 2.5% |
| | 50 | 600 | 750 | **167086** | 8.0 | MB-I, MB-II | 167862 | 0.4 | Agg | 0.5% |
| | 50 | 600 | 1000 | **178009** | 11.5 | MB-II | 180695 | 0.4 | Agg | 1.5% |
| | 100 | 500 | 750 | **147498** | 10.6 | MB-II | 149513 | 0.3 | Agg | 1.4% |
| | 100 | 500 | 1000 | **151356** | 9.6 | MB-II | 157777 | 0.3 | Agg | 4.2% |
| | 100 | 600 | 750 | **166752** | 7.2 | MB-I, MB-II | 167862 | 0.3 | Agg | 0.7% |
| | 100 | 600 | 1000 | **174765** | 7.1 | MB-I | 179434 | 0.7 | Agg | 2.7% |
| | 200 | 500 | 750 | **147205** | 6.6 | MB-I, MB-II | 149513 | 0.4 | Agg | 1.6% |
| | 200 | 500 | 1000 | **150196** | 6.1 | MB-I, MB-II | 157231 | 0.4 | DB-Agg | 4.7% |
| | 200 | 600 | 750 | **166752** | 6.9 | MB-I, MB-II | 167862 | 0.3 | Agg | 0.7% |
| | 200 | 600 | 1000 | **173695** | 6.3 | MB-I, MB-II | 179197 | 0.3 | DB-Agg | 3.2% |

Table 5.17: Comparison of Heuristic Methods with Fixed and Variable Facility Costs on Tiby

| | DLim | F1 | F2 | F3 | Best Model-based Heuristic Cost | Time | Method | Best Clustering-based Heuristic Cost | Time | Method | Diff. |
|---|---|---|---|---|---|---|---|---|---|---|---|
| TIBY - 1 | 30 | 1000 | 750 | 500 | **308975** | 183.5 | MB-II | 312116 | 19.5 | DB-KM | 1.0% |
| | 30 | 1000 | 750 | 600 | **318750** | 35.6 | MB-I, MB-II | **318750** | 1.5 | All | 0.0% |
| | 30 | 1000 | 1000 | 500 | **323074** | 49.3 | MB-II | 338047 | 0.6 | Agg. | 4.6% |
| | 30 | 1000 | 1000 | 600 | **363494** | 86.3 | MB-II | 375810 | 1 | Agg. | 3.4% |
| | 30 | 2000 | 750 | 500 | **318750** | 41 | MB-I, MB-II | 318750 | 0.8 | All | 0.0% |
| | 30 | 2000 | 750 | 600 | **318750** | 37 | MB-I, MB-II | **318750** | 0.6 | All | 0.0% |
| | 30 | 2000 | 1000 | 500 | **380167** | 317.8 | MB-II | 396773 | 0.2 | DB-Agg. | 4.4% |
| | 30 | 2000 | 1000 | 600 | **409655** | 317.7 | MB-II | 415923 | 18.8 | DB-KM | 1.5% |
| | 50 | 1000 | 750 | 500 | **299833** | 8213.1 | MB-I | 302958 | 0.7 | Agg., DB-Agg. | 1.0% |
| | 50 | 1000 | 750 | 600 | **318750** | 69.7 | MB-I, MB-II | **318750** | 0.8 | All | 0.0% |
| | 50 | 1000 | 1000 | 500 | **305536** | 4311.7 | MB-II | 310282 | 1 | Agg. | 1.6% |
| | 50 | 1000 | 1000 | 600 | **346878** | 10828.8 | MB-II | 351492 | 0.4 | Agg., DB-Agg. | 1.3% |
| | 50 | 2000 | 750 | 500 | **316511** | 1563.4 | MB-I, MB-II | 318602 | 17.2 | DB-KM | 0.7% |
| | 50 | 2000 | 750 | 600 | **318750** | 51.8 | MB-I, MB-II | **318750** | 0.8 | All | 0.0% |
| | 50 | 2000 | 1000 | 500 | **341145** | 10827 | MB-II | 353231 | 0.7 | Agg., DB-Agg. | 3.5% |
| | 50 | 2000 | 1000 | 600 | **380791** | 10828.5 | MB-II | 389049 | 0.9 | Agg., DB-Agg. | 2.2% |
| | 100 | 1000 | 750 | 500 | **299295** | 10828 | MB-I | 302008 | 0.8 | Agg., DB-Agg. | 0.9% |
| | 100 | 1000 | 750 | 600 | **318750** | 608.3 | MB-I, MB-II | **318750** | 2 | All | 0.0% |
| | 100 | 1000 | 1000 | 500 | **302118** | 6612 | MB-I, MB-II | 304932 | 3 | Agg., DB-Agg. | 0.9% |
| | 100 | 1000 | 1000 | 600 | **344191** | 10830.6 | MB-II | 346934 | 2.4 | Agg., DB-Agg. | 0.8% |
| | 100 | 2000 | 750 | 500 | **316302** | 10838.4 | MB-I | 318750 | 1.9 | All | 0.8% |
| | 100 | 2000 | 750 | 600 | **318750** | 321.7 | MB-I, MB-II | **318750** | 2.2 | All | 0.0% |
| | 100 | 2000 | 1000 | 500 | **330067** | 10823.9 | MB-I | 332860 | 1.1 | DB-Agg. | 0.8% |
| | 100 | 2000 | 1000 | 600 | **371161** | 10831.1 | MB-II | 374368 | 1.6 | DB-Agg. | 0.9% |
| | 200 | 1000 | 750 | 500 | **299930** | 10919.8 | MB-II | 302008 | 1.4 | Agg., DB-Agg. | 0.7% |
| | 200 | 1000 | 750 | 600 | **318750** | 2076.2 | MB-I, MB-II | **318750** | 4.7 | All | 0.0% |
| | 200 | 1000 | 1000 | 500 | **302892** | 10920.8 | MB-II | 304944 | 5.6 | Agg., DB-Agg. | 0.7% |
| | 200 | 1000 | 1000 | 600 | **344802** | 10923.7 | MB-II | 347244 | 5 | Agg., DB-Agg. | 0.7% |
| | 200 | 2000 | 750 | 500 | **316354** | 10928.7 | MB-I | 318750 | 4.7 | All | 0.8% |

| | DLim | F1 | F2 | F3 | Best Model-based Heuristic Cost | Time | Method | Best Clustering-based Heuristic Cost | Time | Method | Diff. |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 200 | 2000 | 750 | 600 | **318750** | 1246.3 | MB-I, MB-II | **318750** | 5.5 | All | 0.0% |
| | 200 | 2000 | 1000 | 500 | **329739** | 10921 | MB-II | 333580 | 1.9 | Agg., DB-Agg. | 1.2% |
| | 200 | 2000 | 1000 | 600 | **372130** | 10912.7 | MB-I | 374990 | 1.7 | Agg., DB-Agg. | 0.8% |
| TIBY - 2 | 30 | 1000 | 750 | 500 | **283456** | 241.4 | MB-I | 287375 | 17.8 | DB-KM | 1.4% |
| | 30 | 1000 | 750 | 600 | **297596** | 44.6 | MB-I, MB-II | 297750 | 1.6 | All | 0.1% |
| | 30 | 1000 | 1000 | 500 | **294551** | 61.8 | MB-II | 308113 | 1.3 | DB-Agg. | 4.6% |
| | 30 | 1000 | 1000 | 600 | **332473** | 271 | MB-II | 343743 | 0.6 | DB-Agg. | 3.4% |
| | 30 | 2000 | 750 | 500 | **296831** | 42.6 | MB-I, MB-II | 297750 | 0.8 | All | 0.3% |
| | 30 | 2000 | 750 | 600 | **297750** | 31.3 | MB-I, MB-II | **297750** | 0.8 | All | 0.0% |
| | 30 | 2000 | 1000 | 500 | **344543** | 1940 | MB-II | 361208 | 16.9 | DB-KM | 4.8% |
| | 30 | 2000 | 1000 | 600 | **372987** | 945.4 | MB-II | 381327 | 16.4 | DB-KM | 2.2% |
| | 50 | 1000 | 750 | 500 | **275648** | 10822.6 | MB-II | 279162 | 1 | Agg., DB-Agg. | 1.3% |
| | 50 | 1000 | 750 | 600 | **297530** | 358.4 | MB-I, MB-II | **297634** | 13.5 | DB-KM | 0.0% |
| | 50 | 1000 | 1000 | 500 | **278931** | 1444.4 | MB-I | 283584 | 0.5 | Agg. | 1.7% |
| | 50 | 1000 | 1000 | 600 | **318134** | 9482.1 | MB-I | 322545 | 0.9 | Agg. | 1.4% |
| | 50 | 2000 | 750 | 500 | **291638** | 10829.3 | MB-I, MB-II | 293930 | 13.8 | DB-KM | 0.8% |
| | 50 | 2000 | 750 | 600 | **297750** | 48.9 | MB-I, MB-II | **297750** | 1 | All | 0.0% |
| | 50 | 2000 | 1000 | 500 | **309375** | 10817 | MB-I | 321775 | 0.9 | Agg., DB-Agg. | 4.0% |
| | 50 | 2000 | 1000 | 600 | **347682** | 10817.5 | MB-I | 357191 | 0.7 | Agg., DB-Agg. | 2.7% |
| | 100 | 1000 | 750 | 500 | **275199** | 10827 | MB-II | 276737 | 1.8 | Agg., DB-Agg. | 0.6% |
| | 100 | 1000 | 750 | 600 | **297530** | 2126.9 | MB-I, MB-II | 297750 | 1.7 | All | 0.1% |
| | 100 | 1000 | 1000 | 500 | **276644** | 8439.1 | MB-I, MB-II | 278329 | 1.5 | Agg., DB-Agg. | 0.6% |
| | 100 | 1000 | 1000 | 600 | **316202** | 10824.7 | MB-II | 317674 | 1.7 | Agg., DB-Agg. | 0.5% |
| | 100 | 2000 | 750 | 500 | **291944** | 10833.4 | MB-I | 294902 | 6.4 | DB-KM | 1.0% |
| | 100 | 2000 | 750 | 600 | **297750** | 849.5 | MB-I, MB-II | **297750** | 1.7 | All | 0.0% |
| | 100 | 2000 | 1000 | 500 | **302135** | 10821 | MB-I | 302713 | 0.8 | Agg., DB-Agg. | 0.2% |
| | 100 | 2000 | 1000 | 600 | **339618** | 10825 | MB-I | 341119 | 1.3 | Agg., DB-Agg. | 0.4% |
| | 200 | 1000 | 750 | 500 | **275735** | 10960.6 | MB-II | 276933 | 4.2 | Agg., DB-Agg. | 0.4% |
| | 200 | 1000 | 750 | 600 | **297530** | 5463.2 | MB-I | 297750 | 4.2 | All | 0.1% |
| | 200 | 1000 | 1000 | 500 | **276782** | 10897.3 | MB-I | 278149 | 4.1 | Agg., DB-Agg. | 0.5% |
| | 200 | 1000 | 1000 | 600 | **316774** | 10893.3 | MB-I | 317849 | 4.2 | Agg., DB-Agg. | 0.3% |
| | 200 | 2000 | 750 | 500 | **293034** | 10908.9 | MB-I | 297750 | 4.6 | All | 1.6% |
| | 200 | 2000 | 750 | 600 | **297750** | 4117 | MB-I, MB-II | **297750** | 3.8 | All | 0.0% |
| | 200 | 2000 | 1000 | 500 | **301370** | 10953.2 | MB-II | 302525 | 1.6 | Agg., DB-Agg. | 0.4% |
| | 200 | 2000 | 1000 | 600 | **340595** | 10898.5 | MB-I | 341052 | 1.8 | Agg., DB-Agg. | 0.1% |

| | DLim | F1 | F2 | F3 | Best Model-based Heuristic Cost | Time | Method | Best Clustering-based Heuristic Cost | Time | Method | Diff. |
|---|---|---|---|---|---|---|---|---|---|---|---|
| TIBY - 3 | 30 | 1000 | 750 | 500 | **300218** | 250.3 | MB-II | 303338 | 13.6 | DB-KM | 1.0% |
| | 30 | 1000 | 750 | 600 | **306750** | 36.6 | MB-I, MB-II | **306750** | 1.5 | All | 0.0% |
| | 30 | 1000 | 1000 | 500 | **323289** | 82 | MB-II | 334504 | 0.8 | Agg. | 3.5% |
| | 30 | 1000 | 1000 | 600 | **359826** | 185.2 | MB-II | 369754 | 0.7 | Agg. | 2.8% |
| | 30 | 2000 | 750 | 500 | **306750** | 37.5 | MB-I, MB-II | **306750** | 1.4 | All | 0.0% |
| | 30 | 2000 | 750 | 600 | **306750** | 37.6 | MB-I, MB-II | **306750** | 1.1 | All | 0.0% |
| | 30 | 2000 | 1000 | 500 | **378667** | 293.2 | MB-II | 389645 | 0.4 | DB-Agg. | 2.9% |
| | 30 | 2000 | 1000 | 600 | **398286** | 61.8 | MB-I, MB-II | 404530 | 13.1 | DB-KM | 1.6% |
| | 50 | 1000 | 750 | 500 | **292701** | 1219.6 | MB-II | 296317 | 15.4 | DB-KM | 1.2% |
| | 50 | 1000 | 750 | 600 | **306750** | 35.2 | MB-I, MB-II | **306750** | 0.8 | All | 0.0% |
| | 50 | 1000 | 1000 | 500 | **302955** | 663.5 | MB-II | 308839 | 0.7 | Agg. | 1.9% |
| | 50 | 1000 | 1000 | 600 | **342312** | 1585.9 | MB-II | 348282 | 0.7 | Agg. | 1.7% |
| | 50 | 2000 | 750 | 500 | **305291** | 261.6 | MB-II | 306357 | 14.8 | DB-KM | 0.3% |
| | 50 | 2000 | 750 | 600 | **306750** | 29 | MB-I, MB-II | 306750 | 0.9 | All | 0.0% |
| | 50 | 2000 | 1000 | 500 | **342073** | 10822.4 | MB-II | 357826 | 15.3 | DB-KM | 4.6% |
| | 50 | 2000 | 1000 | 600 | **375503** | 9658.6 | MB-II | 387058 | 17.5 | DB-KM | 3.1% |
| | 100 | 1000 | 750 | 500 | **291818** | 3506.2 | MB-I, MB-II | 293726 | 1.1 | Agg., DB-Agg. | 0.7% |
| | 100 | 1000 | 750 | 600 | **306750** | 300.5 | MB-I, MB-II | **306750** | 1 | All | 0.0% |
| | 100 | 1000 | 1000 | 500 | **297107** | 992.1 | MB-I, MB-II | 298790 | 1.3 | Agg., DB-Agg. | 0.6% |
| | 100 | 1000 | 1000 | 600 | **337596** | 3757.8 | MB-I, MB-II | 339382 | 1.1 | Agg., DB-Agg. | 0.5% |
| | 100 | 2000 | 750 | 500 | **304922** | 10835.2 | MB-I | 306151 | 8.6 | DB-KM | 0.4% |
| | 100 | 2000 | 750 | 600 | **306750** | 149 | MB-I, MB-II | **306750** | 1.3 | All | 0.0% |
| | 100 | 2000 | 1000 | 500 | **326917** | 10815.4 | MB-I | 329678 | 0.9 | Agg., DB-Agg. | 0.8% |
| | 100 | 2000 | 1000 | 600 | **365096** | 10822.4 | MB-II | 367432 | 0.9 | Agg., DB-Agg. | 0.6% |
| | 200 | 1000 | 750 | 500 | **291833** | 10847.2 | MB-II | 293801 | 1.3 | Agg. | 0.7% |
| | 200 | 1000 | 750 | 600 | **306750** | 899.7 | MB-I, MB-II | **306750** | 2.9 | All | 0.0% |
| | 200 | 1000 | 1000 | 500 | **296782** | 5430.8 | MB-I, MB-II | 298690 | 2.6 | Agg. | 0.6% |
| | 200 | 1000 | 1000 | 600 | **337596** | 8926.7 | MB-I, MB-II | 339590 | 2.5 | Agg. | 0.6% |
| | 200 | 2000 | 750 | 500 | **305140** | 10874.5 | MB-II | 306750 | 2.8 | All | 0.5% |
| | 200 | 2000 | 750 | 600 | **306750** | 484.5 | MB-I, MB-II | **306750** | 3 | All | 0.0% |
| | 200 | 2000 | 1000 | 500 | **326618** | 10838.2 | MB-I | 328427 | 2.8 | Agg. | 0.6% |
| | 200 | 2000 | 1000 | 600 | **365287** | 10848.4 | MB-II | 367932 | 3 | Agg. | 0.7% |

| | | | | | Best Model-based Heuristic | | | Best Clustering-based Heuristic | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | F3 | Cost | Time | Method | Cost | Time | Method | Diff. |
| TIBY - 4 | 30 | 1000 | 750 | 500 | **158296** | 82.7 | MB-II | 161288 | 11.1 | DB-KM | 1.9% |
| | 30 | 1000 | 750 | 600 | **163500** | 6.4 | MB-I, MB-II | **163500** | 0.4 | All | 0.0% |
| | 30 | 1000 | 1000 | 500 | **166140** | 24 | MB-I | 171227 | 0.1 | Agg. | 3.1% |
| | 30 | 1000 | 1000 | 600 | **186924** | 107.1 | MB-II | 191755 | 0.2 | Agg. | 2.6% |
| | 30 | 2000 | 750 | 500 | **163500** | 6.9 | MB-I, MB-II | **163500** | 0.4 | All | 0.0% |
| | 30 | 2000 | 750 | 600 | **163500** | 7.1 | MB-I, MB-II | **163500** | 0.3 | All | 0.0% |
| | 30 | 2000 | 1000 | 500 | **195129** | 211.4 | MB-II | 203447 | 0.1 | DB-Agg. | 4.3% |
| | 30 | 2000 | 1000 | 600 | **209197** | 63.4 | MB-II | 214865 | 9.6 | DB-KM | 2.7% |
| | 50 | 1000 | 750 | 500 | **153883** | 8092.3 | MB-II | 155377 | 0.1 | Agg., DB-Agg. | 1.0% |
| | 50 | 1000 | 750 | 600 | **163500** | 21.2 | MB-I, MB-II | **163500** | 0.6 | All | 0.0% |
| | 50 | 1000 | 1000 | 500 | **156301** | 404.7 | MB-II | 158059 | 0.1 | Agg. | 1.1% |
| | 50 | 1000 | 1000 | 600 | **177614** | 681 | MB-II | 178969 | 0.2 | Agg. | 0.8% |
| | 50 | 2000 | 750 | 500 | **162078** | 335.8 | MB-I, MB-II | 163072 | 7.5 | DB-KM | 0.6% |
| | 50 | 2000 | 750 | 600 | **163500** | 5.9 | MB-I, MB-II | **163500** | 0.4 | All | 0.0% |
| | 50 | 2000 | 1000 | 500 | **174142** | 10805.9 | MB-II | 180178 | 0.1 | Agg. | 3.5% |
| | 50 | 2000 | 1000 | 600 | **194830** | 10803.6 | MB-I | 200501 | 0.1 | Agg. | 2.9% |
| | 100 | 1000 | 750 | 500 | **153390** | 6743.7 | MB-I, MB-II | 154736 | 0.3 | Agg., DB-Agg. | 0.9% |
| | 100 | 1000 | 750 | 600 | **163500** | 249.8 | MB-I, MB-II | **163500** | 0.6 | All | 0.0% |
| | 100 | 1000 | 1000 | 500 | **155353** | 1241.5 | MB-I, MB-II | 156488 | 0.3 | Agg., DB-Agg. | 0.7% |
| | 100 | 1000 | 1000 | 600 | **176767** | 2043.9 | MB-I, MB-II | 177902 | 0.3 | Agg., DB-Agg. | 0.6% |
| | 100 | 2000 | 750 | 500 | **161753** | 10811.7 | MB-II | 163500 | 0.5 | All | 1.1% |
| | 100 | 2000 | 750 | 600 | **163500** | 88 | MB-I, MB-II | **163500** | 0.6 | All | 0.0% |
| | 100 | 2000 | 1000 | 500 | **167943** | 10805.8 | MB-I | 169903 | 0.5 | Agg., DB-Agg. | 1.2% |
| | 100 | 2000 | 1000 | 600 | **188845** | 10806.8 | MB-II | 190803 | 0.7 | Agg., DB-Agg. | 1.0% |
| | 200 | 1000 | 750 | 500 | **153407** | 10821 | MB-II | 154736 | 0.4 | Agg., DB-Agg. | 0.9% |
| | 200 | 1000 | 750 | 600 | **163500** | 948.2 | MB-I, MB-II | **163500** | 1.2 | All | 0.0% |
| | 200 | 1000 | 1000 | 500 | **155318** | 3756 | MB-II | 156462 | 0.7 | Agg., DB-Agg. | 0.7% |
| | 200 | 1000 | 1000 | 600 | **176767** | 7974.5 | MB-I | 177902 | 0.4 | Agg., DB-Agg. | 0.6% |
| | 200 | 2000 | 750 | 500 | **161993** | 10820.7 | MB-II | 163500 | 1.3 | All | 0.9% |
| | 200 | 2000 | 750 | 600 | **163500** | 549.9 | MB-I, MB-II | **163500** | 1.2 | All | 0.0% |
| | 200 | 2000 | 1000 | 500 | **168450** | 10817.8 | MB-I | 170399 | 1.2 | Agg., DB-Agg. | 1.2% |
| | 200 | 2000 | 1000 | 600 | **188885** | 10819.2 | MB-I | 191692 | 0.3 | Agg., DB-Agg. | 1.5% |

Table 5.18: Comparison of Heuristic Methods with Fixed and Variable Facility Costs on Mbola

| | | | | | Best Model-based Heuristic | | | Best Clustering-based Heuristic | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | F3 | Cost | Time | Method | Cost | Time | Method | Diff. |
| MBOLA - 1 | 30 | 1000 | 750 | 500 | **108581** | 5.5 | MB-I, MB-II | **108581** | 0.7 | DB-KM, DB-Agg. | 0.0% |
| | 30 | 1000 | 750 | 600 | **108750** | 2.7 | MB-I, MB-II | **108750** | 0 | All | 0.0% |
| | 30 | 1000 | 1000 | 500 | **132331** | 3.6 | MB-I, MB-II | 133528 | 0.1 | Agg. | 0.9% |
| | 30 | 1000 | 1000 | 600 | **140016** | 2.5 | MB-I, MB-II | 141353 | 0 | DB-Agg. | 1.0% |
| | 30 | 2000 | 750 | 500 | **108750** | 4 | MB-I, MB-II | **108750** | 0 | All | 0.0% |
| | 30 | 2000 | 750 | 600 | **108750** | 11.1 | MB-I, MB-II | **108750** | 0 | All | 0.0% |
| | 30 | 2000 | 1000 | 500 | **144250** | 13.4 | MB-I, MB-II | 144331 | 0 | DB-KM, DB-Agg. | 0.1% |
| | 30 | 2000 | 1000 | 600 | **144931** | 3.6 | MB-I, MB-II | **144931** | 0 | DB-KM, DB-Agg. | 0.0% |
| | 50 | 1000 | 750 | 500 | **108520** | 3.2 | MB-I, MB-II | 108581 | 0.5 | DB-KM | 0.1% |
| | 50 | 1000 | 750 | 600 | **108750** | 3 | MB-I, MB-II | **108750** | 0.1 | All | 0.0% |
| | 50 | 1000 | 1000 | 500 | **127247** | 2.3 | MB-II | 127748 | 0 | Agg. | 0.4% |
| | 50 | 1000 | 1000 | 600 | **136969** | 3.7 | MB-II | 137160 | 0 | Agg. | 0.1% |
| | 50 | 2000 | 750 | 500 | **108750** | 3.2 | MB-I, MB-II | **108750** | 0.1 | All | 0.0% |
| | 50 | 2000 | 750 | 600 | **108750** | 3.1 | MB-I, MB-II | **108750** | 0.1 | All | 0.0% |
| | 50 | 2000 | 1000 | 500 | **142050** | 5.1 | MB-II | 142827 | 0.3 | DB-KM | 0.5% |
| | 50 | 2000 | 1000 | 600 | **144537** | 10.6 | MB-I, MB-II | 144931 | 0.5 | DB-KM | 0.3% |
| | 100 | 1000 | 750 | 500 | **108511** | 5.4 | MB-I, MB-II | 108750 | 0.1 | All | 0.2% |
| | 100 | 1000 | 750 | 600 | **108750** | 2 | MB-I, MB-II | **108750** | 0.1 | All | 0.0% |
| | 100 | 1000 | 1000 | 500 | **124047** | 6.3 | MB-I | 124537 | 0.3 | Agg. | 0.4% |
| | 100 | 1000 | 1000 | 600 | **135419** | 6.2 | MB-I, MB-II | 135592 | 0.2 | Agg. | 0.1% |
| | 100 | 2000 | 750 | 500 | **108750** | 2.3 | MB-I, MB-II | **108750** | 0.1 | All | 0.0% |
| | 100 | 2000 | 750 | 600 | **108750** | 2.2 | MB-I, MB-II | **108750** | 0.1 | All | 0.0% |
| | 100 | 2000 | 1000 | 500 | **138105** | 17.5 | MB-II | 139886 | 3.1 | DB-KM | 1.3% |
| | 100 | 2000 | 1000 | 600 | **144057** | 7.5 | MB-I, MB-II | 144842 | 3.6 | DB-KM | 0.5% |
| | 200 | 1000 | 750 | 500 | **108511** | 5.5 | MB-I, MB-II | 108750 | 0.6 | All | 0.2% |
| | 200 | 1000 | 750 | 600 | **108750** | 3.1 | MB-I, MB-II | **108750** | 0.5 | All | 0.0% |
| | 200 | 1000 | 1000 | 500 | **123818** | 17.8 | MB-II | 124381 | 0.2 | Agg., DB-Agg. | 0.5% |
| | 200 | 1000 | 1000 | 600 | **135419** | 10.3 | MB-I, MB-II | 135851 | 0.2 | Agg., DB-Agg. | 0.3% |
| | 200 | 2000 | 750 | 500 | **108750** | 5.2 | MB-I, MB-II | **108750** | 0.5 | All | 0.0% |
| | 200 | 2000 | 750 | 600 | **108750** | 1.9 | MB-I, MB-II | **108750** | 0.5 | All | 0.0% |
| | 200 | 2000 | 1000 | 500 | **137603** | 88.2 | MB-I, MB-II | 139907 | 0.3 | DB-Agg. | 1.7% |
| | 200 | 2000 | 1000 | 600 | **144057** | 32.2 | MB-I, MB-II | 145000 | 0.5 | All | 0.7% |

| | | | | | Best Model-based Heuristic | | | Best Clustering-based Heuristic | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | F3 | Cost | Time | Method | Cost | Time | Method | Diff. |
| MBOLA - 2 | 30 | 1000 | 750 | 500 | **57642** | 8.2 | MB-I, MB-II | **57642** | 0.1 | DB-KM, DB-Agg. | 0.0% |
| | 30 | 1000 | 750 | 600 | **57750** | 1.7 | MB-I, MB-II | **57750** | 0 | All | 0.0% |
| | 30 | 1000 | 1000 | 500 | **71628** | 0.8 | MB-II | **71628** | 0 | Agg., DB-Agg. | 0.0% |
| | 30 | 1000 | 1000 | 600 | **74228** | 3.2 | MB-II | **74228** | 0 | DB-KM, DB-Agg. | 0.0% |
| | 30 | 2000 | 750 | 500 | **57750** | 2.2 | MB-I, MB-II | **57750** | 0 | All | 0.0% |
| | 30 | 2000 | 750 | 600 | **57750** | 4.5 | MB-I, MB-II | **57750** | 0.1 | All | 0.0% |
| | 30 | 2000 | 1000 | 500 | **76086** | 3.4 | MB-II | **76086** | 0 | DB-Agg. | 0.0% |
| | 30 | 2000 | 1000 | 600 | **77000** | 2.8 | MB-I, MB-II | **76992** | 0 | DB-KM, DB-Agg. | 0.0% |
| | 50 | 1000 | 750 | 500 | **57624** | 1.6 | MB-I, MB-II | **57624** | 0 | DB-KM, DB-Agg. | 0.0% |
| | 50 | 1000 | 750 | 600 | **57750** | 1.5 | MB-I, MB-II | **57750** | 0 | All | 0.0% |
| | 50 | 1000 | 1000 | 500 | 70303 | 0.6 | MB-I, MB-II | **70217** | 0 | Agg. | -0.1% |
| | 50 | 1000 | 1000 | 600 | **73908** | 1.7 | MB-II | 74014 | 0 | DB-KM, DB-Agg. | 0.1% |
| | 50 | 2000 | 750 | 500 | **57750** | 2.5 | MB-I, MB-II | **57750** | 0 | All | 0.0% |
| | 50 | 2000 | 750 | 600 | **57750** | 1.4 | MB-I, MB-II | **57750** | 0 | All | 0.0% |
| | 50 | 2000 | 1000 | 500 | **75772** | 1.8 | MB-I, MB-II | **75772** | 0 | DB-KM, DB-Agg. | 0.0% |
| | 50 | 2000 | 1000 | 600 | **76974** | 1.7 | MB-I, MB-II | **76974** | 0 | DB-KM, DB-Agg. | 0.0% |
| | 100 | 1000 | 750 | 500 | **57624** | 1.2 | MB-I, MB-II | **57624** | 0.2 | DB-KM, DB-Agg. | 0.0% |
| | 100 | 1000 | 750 | 600 | **57750** | 1.7 | MB-I, MB-II | **57750** | 0 | All | 0.0% |
| | 100 | 1000 | 1000 | 500 | **69848** | 0.8 | MB-I, MB-II | **69835** | 0 | Agg. | 0.0% |
| | 100 | 1000 | 1000 | 600 | **73891** | 1.2 | MB-I, MB-II | **73891** | 0 | DB-KM, DB-Agg. | 0.0% |
| | 100 | 2000 | 750 | 500 | **57750** | 2.4 | MB-I, MB-II | **57750** | 0 | All | 0.0% |
| | 100 | 2000 | 750 | 600 | **57750** | 1 | MB-I, MB-II | **57750** | 0 | All | 0.0% |
| | 100 | 2000 | 1000 | 500 | **75772** | 2 | MB-I, MB-II | **75772** | 0 | DB-KM, DB-Agg. | 0.0% |
| | 100 | 2000 | 1000 | 600 | **76974** | 1.9 | MB-I, MB-II | **76974** | 0 | DB-KM, DB-Agg. | 0.0% |
| | 200 | 1000 | 750 | 500 | **57624** | 1.7 | MB-I, MB-II | **57624** | 0 | DB-KM, DB-Agg. | 0.0% |
| | 200 | 1000 | 750 | 600 | **57750** | 1 | MB-I, MB-II | **57750** | 0.1 | All | 0.0% |
| | 200 | 1000 | 1000 | 500 | **69701** | 1.5 | MB-I, MB-II | **69731** | 0 | Agg. | 0.0% |
| | 200 | 1000 | 1000 | 600 | **73891** | 1.8 | MB-I, MB-II | 75277 | 0 | DB-KM, DB-Agg. | 1.9% |
| | 200 | 2000 | 750 | 500 | **57750** | 0.8 | MB-I, MB-II | **57750** | 0.1 | All | 0.0% |
| | 200 | 2000 | 750 | 600 | **57750** | 1.2 | MB-I, MB-II | **57750** | 0.1 | All | 0.0% |
| | 200 | 2000 | 1000 | 500 | **75772** | 2.1 | MB-I, MB-II | 76219 | 0 | DB-KM, DB-Agg. | 0.6% |
| | 200 | 2000 | 1000 | 600 | **76974** | 2.3 | MB-I, MB-II | **76974** | 0 | DB-KM, DB-Agg. | 0.0% |

| | DLim | F1 | F2 | F3 | Best Model-based Heuristic Cost | Time | Method | Best Clustering-based Heuristic Cost | Time | Method | Diff. |
|---|---|---|---|---|---|---|---|---|---|---|---|
| MBOLA - 3 | 30 | 1000 | 750 | 500 | **35250** | 4.4 | MB-I, MB-II | **35250** | 0.1 | All | 0.0% |
| | 30 | 1000 | 750 | 600 | **35250** | 1.7 | MB-I, MB-II | **35250** | 0 | All | 0.0% |
| | 30 | 1000 | 1000 | 500 | **44131** | 0.4 | MB-I, MB-II | 44377 | 0 | All | 0.6% |
| | 30 | 1000 | 1000 | 600 | **45931** | 0.7 | MB-I, MB-II | 46277 | 0 | DB-KM, DB-Agg. | 0.8% |
| | 30 | 2000 | 750 | 500 | **35250** | 1.5 | MB-I, MB-II | **35250** | 0 | All | 0.0% |
| | 30 | 2000 | 750 | 600 | **35250** | 1.3 | MB-I, MB-II | **35250** | 0 | All | 0.0% |
| | 30 | 2000 | 1000 | 500 | **46967** | 2.4 | MB-II | 47000 | 0 | All | 0.1% |
| | 30 | 2000 | 1000 | 600 | **47000** | 0.8 | MB-I, MB-II | **47000** | 0 | All | 0.0% |
| | 50 | 1000 | 750 | 500 | **35250** | 1.2 | MB-I, MB-II | **35250** | 0 | All | 0.0% |
| | 50 | 1000 | 750 | 600 | **35250** | 1 | MB-I, MB-II | **35250** | 0 | All | 0.0% |
| | 50 | 1000 | 1000 | 500 | 43783 | 0.3 | MB-I, MB-II | **43592** | 0 | Agg. | -0.4% |
| | 50 | 1000 | 1000 | 600 | **45683** | 0.6 | MB-I, MB-II | **45683** | 0 | DB-KM, DB-Agg. | 0.0% |
| | 50 | 2000 | 750 | 500 | **35250** | 1.7 | MB-I, MB-II | **35250** | 0 | All | 0.0% |
| | 50 | 2000 | 750 | 600 | **35250** | 1 | MB-I, MB-II | **35250** | 0 | All | 0.0% |
| | 50 | 2000 | 1000 | 500 | **46619** | 9.2 | MB-I, MB-II | **46619** | 0 | DB-KM, DB-Agg. | 0.0% |
| | 50 | 2000 | 1000 | 600 | **47000** | 6.4 | MB-I, MB-II | **47000** | 0 | All | 0.0% |
| | 100 | 1000 | 750 | 500 | **35250** | 1 | MB-I, MB-II | **35250** | 0 | All | 0.0% |
| | 100 | 1000 | 750 | 600 | **35250** | 1.2 | MB-I, MB-II | **35250** | 0 | All | 0.0% |
| | 100 | 1000 | 1000 | 500 | **42943** | 0.5 | MB-I, MB-II | **42943** | 0 | All | 0.0% |
| | 100 | 1000 | 1000 | 600 | **45618** | 1.4 | MB-I, MB-II | **45618** | 0 | DB-KM, DB-Agg. | 0.0% |
| | 100 | 2000 | 750 | 500 | **35250** | 1.2 | MB-I, MB-II | **35250** | 0 | All | 0.0% |
| | 100 | 2000 | 750 | 600 | **35250** | 1.3 | MB-I, MB-II | **35250** | 0 | All | 0.0% |
| | 100 | 2000 | 1000 | 500 | **46619** | 15 | MB-I, MB-II | **46619** | 0 | DB-KM, DB-Agg. | 0.0% |
| | 100 | 2000 | 1000 | 600 | **47000** | 1.5 | MB-I, MB-II | **47000** | 0 | All | 0.0% |
| | 200 | 1000 | 750 | 500 | **35250** | 1.1 | MB-I, MB-II | **35250** | 0 | All | 0.0% |
| | 200 | 1000 | 750 | 600 | **35250** | 0.6 | MB-I, MB-II | **35250** | 0 | All | 0.0% |
| | 200 | 1000 | 1000 | 500 | **42943** | 1 | MB-I, MB-II | **42943** | 0 | Agg., DB-Agg. | 0.0% |
| | 200 | 1000 | 1000 | 600 | **45618** | 1.1 | MB-I, MB-II | **45618** | 0 | DB-Agg. | 0.0% |
| | 200 | 2000 | 750 | 500 | **35250** | 0.9 | MB-I, MB-II | **35250** | 0 | All | 0.0% |
| | 200 | 2000 | 750 | 600 | **35250** | 0.7 | MB-I, MB-II | **35250** | 0 | All | 0.0% |
| | 200 | 2000 | 1000 | 500 | **46619** | 1.1 | MB-I, MB-II | **46619** | 0 | DB-KM, DB-Agg. | 0.0% |
| | 200 | 2000 | 1000 | 600 | **47000** | 1 | MB-I, MB-II | **47000** | 0 | All | 0.0% |

| | | | | | Best Model-based Heuristic | | | Best Clustering-based Heuristic | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | F3 | Cost | Time | Method | Cost | Time | Method | Diff. |
| MBOLA - 4 | 30 | 1000 | 750 | 500 | **46500** | 2 | MB-I, MB-II | **46500** | 0 | All | 0.0% |
| | 30 | 1000 | 750 | 600 | **46500** | 1.3 | MB-I, MB-II | **46500** | 0.1 | All | 0.0% |
| | 30 | 1000 | 1000 | 500 | **57955** | 0.5 | MB-I, MB-II | 58434 | 0 | Agg. | 0.8% |
| | 30 | 1000 | 1000 | 600 | **61050** | 13.5 | MB-I, MB-II | 61835 | 0 | DB-KM, DB-Agg. | 1.3% |
| | 30 | 2000 | 750 | 500 | **46500** | 1.4 | MB-I, MB-II | **46500** | 0 | All | 0.0% |
| | 30 | 2000 | 750 | 600 | **46500** | 1.6 | MB-I, MB-II | **46500** | 0 | All | 0.0% |
| | 30 | 2000 | 1000 | 500 | **61927** | 2.1 | MB-I, MB-II | 62000 | 0 | All | 0.1% |
| | 30 | 2000 | 1000 | 600 | **62000** | 0.9 | MB-I, MB-II | **62000** | 0 | All | 0.0% |
| | 50 | 1000 | 750 | 500 | **46500** | 0.8 | MB-I, MB-II | **46500** | 0 | All | 0.0% |
| | 50 | 1000 | 750 | 600 | **46500** | 2.7 | MB-I, MB-II | **46500** | 0 | All | 0.0% |
| | 50 | 1000 | 1000 | 500 | **55268** | 0.7 | MB-II | 55575 | 0 | Agg. | 0.6% |
| | 50 | 1000 | 1000 | 600 | **59527** | 0.9 | MB-II | 59848 | 0 | Agg. | 0.5% |
| | 50 | 2000 | 750 | 500 | **46500** | 1.9 | MB-I, MB-II | **46500** | 0 | All | 0.0% |
| | 50 | 2000 | 750 | 600 | **46500** | 1.2 | MB-I, MB-II | **46500** | 0.1 | All | 0.0% |
| | 50 | 2000 | 1000 | 500 | **60822** | 1.3 | MB-I, MB-II | 61626 | 0 | DB-KM | 1.3% |
| | 50 | 2000 | 1000 | 600 | **62000** | 1.4 | MB-I, MB-II | **62000** | 0.1 | All | 0.0% |
| | 100 | 1000 | 750 | 500 | **46500** | 1.7 | MB-I, MB-II | **46500** | 0 | All | 0.0% |
| | 100 | 1000 | 750 | 600 | **46500** | 0.7 | MB-I, MB-II | **46500** | 0 | All | 0.0% |
| | 100 | 1000 | 1000 | 500 | **54424** | 2.1 | MB-I, MB-II | 54525 | 0 | All | 0.2% |
| | 100 | 1000 | 1000 | 600 | **58968** | 1.5 | MB-I, MB-II | 59100 | 0 | Agg. | 0.2% |
| | 100 | 2000 | 750 | 500 | **46500** | 1.2 | MB-I, MB-II | **46500** | 0 | All | 0.0% |
| | 100 | 2000 | 750 | 600 | **46500** | 0.9 | MB-I, MB-II | **46500** | 0 | All | 0.0% |
| | 100 | 2000 | 1000 | 500 | **60194** | 2.2 | MB-I, MB-II | 60246 | 0.8 | DB-KM | 0.1% |
| | 100 | 2000 | 1000 | 600 | **61934** | 2.3 | MB-I, MB-II | **61934** | 0.8 | DB-KM | 0.0% |
| | 200 | 1000 | 750 | 500 | **46500** | 4.9 | MB-I, MB-II | **46500** | 0.1 | All | 0.0% |
| | 200 | 1000 | 750 | 600 | **46500** | 1 | MB-I, MB-II | **46500** | 0.1 | All | 0.0% |
| | 200 | 1000 | 1000 | 500 | **54307** | 2.8 | MB-I, MB-II | 54397 | 0 | DB-Agg. | 0.2% |
| | 200 | 1000 | 1000 | 600 | **58968** | 3.6 | MB-I, MB-II | 59058 | 0 | Agg. | 0.2% |
| | 200 | 2000 | 750 | 500 | **46500** | 1 | MB-I, MB-II | **46500** | 0.1 | All | 0.0% |
| | 200 | 2000 | 750 | 600 | **46500** | 0.7 | MB-I, MB-II | **46500** | 0.1 | All | 0.0% |
| | 200 | 2000 | 1000 | 500 | **60100** | 4.3 | MB-I, MB-II | 61094 | 0.5 | DB-KM, DB-Agg. | 1.7% |
| | 200 | 2000 | 1000 | 600 | **61934** | 3.5 | MB-I, MB-II | 62000 | 0.1 | All | 0.1% |

Table 5.19: Comparison of Heuristic Methods with Fixed and Variable Facility Costs on Potou

| | | | | | Best Model-based Heuristic | | | Best Clustering-based Heuristic | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | F3 | Cost | Time | Method | Cost | Time | Method | Diff. |
| POTOU - 1 | 30 | 1000 | 750 | 500 | **285107** | 10829 | MB-I | 288293 | 0.7 | Agg., DB-Agg. | 1.1% |
| | 30 | 1000 | 750 | 600 | **310238** | 2559.7 | MB-I, MB-II | 311257 | 12.3 | DB-KM | 0.3% |
| | 30 | 1000 | 1000 | 500 | **297618** | 1261.9 | MB-II | 306318 | 0.5 | Agg. | 2.9% |
| | 30 | 1000 | 1000 | 600 | **337048** | 8370.5 | MB-II | 344848 | 0.4 | Agg. | 2.3% |
| | 30 | 2000 | 750 | 500 | **301323** | 10840.1 | MB-II | 304657 | 11.7 | DB-KM | 1.1% |
| | 30 | 2000 | 750 | 600 | **315000** | 105.1 | MB-I, MB-II | **315000** | 1.1 | All | 0.0% |
| | 30 | 2000 | 1000 | 500 | **335013** | 10826.3 | MB-II | 348267 | 0.8 | Agg. | 4.0% |
| | 30 | 2000 | 1000 | 600 | **368005** | 10841.4 | MB-II | 376045 | 0.6 | Agg., DB-Agg. | 2.2% |
| | 50 | 1000 | 750 | 500 | **281825** | 10830.5 | MB-I | 283058 | 0.9 | DB-Agg. | 0.4% |
| | 50 | 1000 | 750 | 600 | **309978** | 10837.9 | MB-I | 312301 | 8.6 | DB-KM | 0.7% |
| | 50 | 1000 | 1000 | 500 | **288498** | 2083 | MB-I | 289787 | 1.5 | DB-Agg. | 0.4% |
| | 50 | 1000 | 1000 | 600 | **328615** | 8607.7 | MB-I | 330186 | 1.5 | DB-Agg. | 0.5% |
| | 50 | 2000 | 750 | 500 | **295477** | 10845.1 | MB-II | 297611 | 0.8 | DB-Agg. | 0.7% |
| | 50 | 2000 | 750 | 600 | **315000** | 10844.5 | MB-I, MB-II | **315000** | 1.1 | All | 0.0% |
| | 50 | 2000 | 1000 | 500 | **316334** | 10830 | MB-II | 321505 | 1.1 | DB-Agg. | 1.6% |
| | 50 | 2000 | 1000 | 600 | **354073** | 10830.6 | MB-II | 357487 | 8.5 | DB-KM | 1.0% |
| | 100 | 1000 | 750 | 500 | **282070** | 10841.6 | MB-II | 282601 | 0.8 | Agg. | 0.2% |
| | 100 | 1000 | 750 | 600 | **310429** | 10849.3 | MB-I | 315000 | 3 | All | 1.5% |
| | 100 | 1000 | 1000 | 500 | **286015** | 10837.1 | MB-I | 287824 | 1.2 | Agg. | 0.6% |
| | 100 | 1000 | 1000 | 600 | **326942** | 10837.2 | MB-I | 328676 | 2.9 | Agg. | 0.5% |
| | 100 | 2000 | 750 | 500 | **295529** | 10853.5 | MB-II | 297089 | 1.6 | DB-Agg. | 0.5% |
| | 100 | 2000 | 750 | 600 | 316454 | 10853.8 | MB-I | **315000** | 3.1 | All | -0.5% |
| | 100 | 2000 | 1000 | 500 | **310561** | 10838.5 | MB-I | 313424 | 1.3 | DB-Agg. | 0.9% |
| | 100 | 2000 | 1000 | 600 | **350448** | 10838.7 | MB-I | 352127 | 1 | Agg. | 0.5% |
| | 200 | 1000 | 750 | 500 | **281916** | 10886.2 | MB-II | 282601 | 1.5 | Agg. | 0.2% |
| | 200 | 1000 | 750 | 600 | **310485** | 10897.8 | MB-II | 315000 | 3.8 | All | 1.5% |
| | 200 | 1000 | 1000 | 500 | **286108** | 10881.4 | MB-I | 287705 | 2.5 | DB-Agg. | 0.6% |
| | 200 | 1000 | 1000 | 600 | **327074** | 10883.2 | MB-I | 328614 | 2.1 | DB-Agg. | 0.5% |
| | 200 | 2000 | 750 | 500 | **294686** | 10898 | MB-II | 296202 | 1.9 | DB-Agg. | 0.5% |
| | 200 | 2000 | 750 | 600 | 315264 | 10910 | MB-II | **315000** | 3.7 | All | -0.1% |
| | 200 | 2000 | 1000 | 500 | **312066** | 10883 | MB-II | 312222 | 1.5 | Agg., DB-Agg. | 0.1% |
| | 200 | 2000 | 1000 | 600 | **348588** | 10883.7 | MB-I | 351077 | 1.3 | Agg. | 0.7% |

| | DLim | F1 | F2 | F3 | Best Model-based Heuristic Cost | Time | Method | Best Clustering-based Heuristic Cost | Time | Method | Diff. |
|---|---|---|---|---|---|---|---|---|---|---|---|
| POTOU - 2 | 30 | 1000 | 750 | 500 | **77092** | 12 | MB-I | 77159 | 0 | DB-KM, DB-Agg. | 0.1% |
| | 30 | 1000 | 750 | 600 | **77250** | 8.4 | MB-I, MB-II | **77250** | 0 | All | 0.0% |
| | 30 | 1000 | 1000 | 500 | **90536** | 1.1 | MB-I, MB-II | 91111 | 0.1 | Agg. | 0.6% |
| | 30 | 1000 | 1000 | 600 | **96846** | 2.3 | MB-I | 97511 | 0.1 | Agg. | 0.7% |
| | 30 | 2000 | 750 | 500 | **77250** | 5.8 | MB-I, MB-II | **77250** | 0.1 | All | 0.0% |
| | 30 | 2000 | 750 | 600 | **77250** | 7.6 | MB-I, MB-II | **77250** | 0.1 | All | 0.0% |
| | 30 | 2000 | 1000 | 500 | **101333** | 7.4 | MB-I | 101767 | 0 | DB-KM | 0.4% |
| | 30 | 2000 | 1000 | 600 | **103000** | 10.4 | MB-I, MB-II | **103000** | 0 | All | 0.0% |
| | 50 | 1000 | 750 | 500 | **76927** | 3.5 | MB-I, MB-II | **76927** | 0.6 | DB-KM, DB-Agg. | 0.0% |
| | 50 | 1000 | 750 | 600 | **77250** | 4.4 | MB-I, MB-II | **77250** | 0 | All | 0.0% |
| | 50 | 1000 | 1000 | 500 | 87738 | 1.5 | MB-II | **87636** | 0 | Agg. | -0.1% |
| | 50 | 1000 | 1000 | 600 | **94990** | 2.5 | MB-I, MB-II | 95314 | 0 | Agg. | 0.3% |
| | 50 | 2000 | 750 | 500 | **77250** | 8 | MB-I, MB-II | **77250** | 0 | All | 0.0% |
| | 50 | 2000 | 750 | 600 | **77250** | 6.9 | MB-I, MB-II | **77250** | 0 | All | 0.0% |
| | 50 | 2000 | 1000 | 500 | **98892** | 2.5 | MB-II | **99886** | 0 | DB-Agg. | 1.0% |
| | 50 | 2000 | 1000 | 600 | **102402** | 4.1 | MB-I, MB-II | **102568** | 0.4 | DB-KM, DB-Agg. | 0.2% |
| | 100 | 1000 | 750 | 500 | **76927** | 7.3 | MB-I, MB-II | 77171 | 0.2 | DB-KM, DB-Agg. | 0.3% |
| | 100 | 1000 | 750 | 600 | **77250** | 2.6 | MB-I, MB-II | **77250** | 0.1 | All | 0.0% |
| | 100 | 1000 | 1000 | 500 | **85895** | 2.3 | MB-I, MB-II | **85885** | 0 | Agg. | 0.0% |
| | 100 | 1000 | 1000 | 600 | **94382** | 3.3 | MB-I, MB-II | 94482 | 0 | Agg. | 0.1% |
| | 100 | 2000 | 750 | 500 | **77250** | 3.2 | MB-I, MB-II | **77250** | 0.1 | All | 0.0% |
| | 100 | 2000 | 750 | 600 | **77250** | 4.4 | MB-I, MB-II | **77250** | 0.1 | All | 0.0% |
| | 100 | 2000 | 1000 | 500 | **97617** | 5.4 | MB-I, MB-II | 97677 | 0 | DB-Agg. | 0.1% |
| | 100 | 2000 | 1000 | 600 | **101911** | 8.2 | MB-I, MB-II | 102630 | 0 | DB-KM, DB-Agg. | 0.7% |
| | 200 | 1000 | 750 | 500 | **76927** | 8.1 | MB-I, MB-II | 77250 | 0.3 | All | 0.4% |
| | 200 | 1000 | 750 | 600 | **77250** | 4.5 | MB-I, MB-II | **77250** | 0.2 | All | 0.0% |
| | 200 | 1000 | 1000 | 500 | **85727** | 9.6 | MB-I, MB-II | **85751** | 0.1 | Agg., DB-Agg. | 0.0% |
| | 200 | 1000 | 1000 | 600 | **94382** | 13 | MB-I, MB-II | 94482 | 0.1 | Agg. | 0.1% |
| | 200 | 2000 | 750 | 500 | **77250** | 4.1 | MB-I, MB-II | **77250** | 0.2 | All | 0.0% |
| | 200 | 2000 | 750 | 600 | **77250** | 1.2 | MB-I, MB-II | **77250** | 0.2 | All | 0.0% |
| | 200 | 2000 | 1000 | 500 | **97469** | 12.5 | MB-I, MB-II | 98238 | 0.1 | DB-Agg. | 0.8% |
| | 200 | 2000 | 1000 | 600 | **101911** | 10.2 | MB-I, MB-II | 103000 | 0.2 | All | 1.1% |

| | | | | | Best Model-based Heuristic | | | Best Clustering-based Heuristic | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | F3 | Cost | Time | Method | Cost | Time | Method | Diff. |
| POTOU - 3 | 30 | 1000 | 750 | 500 | **48701** | 2.5 | MB-II | 49104 | 0 | DB-KM, DB-Agg. | 0.8% |
| | 30 | 1000 | 750 | 600 | **49500** | 3.3 | MB-I, MB-II | **49500** | 0 | All | 0.0% |
| | 30 | 1000 | 1000 | 500 | **53475** | 1.1 | MB-II | 54652 | 0 | DB-Agg. | 2.2% |
| | 30 | 1000 | 1000 | 600 | **58775** | 2.2 | MB-II | 59352 | 0 | DB-KM, DB-Agg. | 1.0% |
| | 30 | 2000 | 750 | 500 | **49500** | 7.1 | MB-I, MB-II | **49500** | 0.1 | All | 0.0% |
| | 30 | 2000 | 750 | 600 | **49500** | 7.5 | MB-I, MB-II | **49500** | 0 | All | 0.0% |
| | 30 | 2000 | 1000 | 500 | 61857 | 2.4 | MB-II | **61441** | 0 | DB-Agg. | -0.7% |
| | 30 | 2000 | 1000 | 600 | 65052 | 3 | MB-II | **64921** | 0 | DB-KM | -0.2% |
| | 50 | 1000 | 750 | 500 | **48139** | 2 | MB-II | **48139** | 0 | DB-KM, DB-Agg. | 0.0% |
| | 50 | 1000 | 750 | 600 | **49500** | 2.6 | MB-I, MB-II | **49500** | 0.1 | All | 0.0% |
| | 50 | 1000 | 1000 | 500 | 50747 | 0.7 | MB-I, MB-II | **50732** | 0 | Agg. | 0.0% |
| | 50 | 1000 | 1000 | 600 | **56847** | 0.8 | MB-II | **56847** | 0 | Agg. | 0.0% |
| | 50 | 2000 | 750 | 500 | **49500** | 8.2 | MB-I, MB-II | **49500** | 0 | All | 0.0% |
| | 50 | 2000 | 750 | 600 | **49500** | 7 | MB-I, MB-II | **49500** | 0 | All | 0.0% |
| | 50 | 2000 | 1000 | 500 | **59237** | 1.5 | MB-I, MB-II | **59222** | 0 | Agg. | 0.0% |
| | 50 | 2000 | 1000 | 600 | **63712** | 2 | MB-I, MB-II | **63712** | 0 | DB-KM, DB-Agg. | 0.0% |
| | 100 | 1000 | 750 | 500 | **48136** | 7.2 | MB-I, MB-II | 48334 | 0 | DB-KM | 0.4% |
| | 100 | 1000 | 750 | 600 | **49500** | 2.4 | MB-I, MB-II | **49500** | 0 | All | 0.0% |
| | 100 | 1000 | 1000 | 500 | **49864** | 0.9 | MB-I, MB-II | 49905 | 0 | All | 0.1% |
| | 100 | 1000 | 1000 | 600 | **56264** | 2.7 | MB-I, MB-II | 56505 | 0 | All | 0.4% |
| | 100 | 2000 | 750 | 500 | **49500** | 3.8 | MB-I, MB-II | **49500** | 0 | All | 0.0% |
| | 100 | 2000 | 750 | 600 | **49500** | 6.5 | MB-I, MB-II | **49500** | 0 | All | 0.0% |
| | 100 | 2000 | 1000 | 500 | **58241** | 3.2 | MB-I, MB-II | 58332 | 0 | All | 0.2% |
| | 100 | 2000 | 1000 | 600 | **63232** | 8.2 | MB-I, MB-II | 63423 | 0 | Agg., DB-KM | 0.3% |
| | 200 | 1000 | 750 | 500 | **48136** | 14.7 | MB-I, MB-II | 49073 | 0 | DB-KM, DB-Agg. | 1.9% |
| | 200 | 1000 | 750 | 600 | **49500** | 1.5 | MB-I, MB-II | **49500** | 0.1 | All | 0.0% |
| | 200 | 1000 | 1000 | 500 | **49787** | 2.2 | MB-I, MB-II | **49787** | 0.1 | Agg. | 0.0% |
| | 200 | 1000 | 1000 | 600 | **56264** | 5 | MB-I, MB-II | 56387 | 0.1 | Agg. | 0.2% |
| | 200 | 2000 | 750 | 500 | **49500** | 2.1 | MB-I, MB-II | **49500** | 0.1 | All | 0.0% |
| | 200 | 2000 | 750 | 600 | **49500** | 4.7 | MB-I, MB-II | **49500** | 0.1 | All | 0.0% |
| | 200 | 2000 | 1000 | 500 | **58105** | 8.9 | MB-I, MB-II | **58105** | 0.1 | Agg. | 0.0% |
| | 200 | 2000 | 1000 | 600 | **63232** | 16.3 | MB-I, MB-II | 63547 | 0.2 | Agg. | 0.5% |

| | | | | | Best Model-based Heuristic | | | Best Clustering-based Heuristic | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | F3 | Cost | Time | Method | Cost | Time | Method | Diff. |
| POTOU - 4 | 30 | 1000 | 750 | 500 | **91674** | 16.1 | MB-I, MB-II | 92018 | 1.3 | DB-KM | 0.4% |
| | 30 | 1000 | 750 | 600 | **95792** | 7 | MB-I, MB-II | 96000 | 0.2 | All | 0.2% |
| | 30 | 1000 | 1000 | 500 | **98395** | 5.3 | MB-II | 100596 | 1.1 | DB-KM | 2.2% |
| | 30 | 1000 | 1000 | 600 | **109595** | 11.3 | MB-II | 110565 | 1.3 | DB-KM | 0.9% |
| | 30 | 2000 | 750 | 500 | **95192** | 9.7 | MB-I, MB-II | 95694 | 1 | DB-KM | 0.5% |
| | 30 | 2000 | 750 | 600 | **96000** | 8.6 | MB-I, MB-II | **96000** | 0.1 | All | 0.0% |
| | 30 | 2000 | 1000 | 500 | **113717** | 78.4 | MB-I, MB-II | 114302 | 0.9 | DB-KM | 0.5% |
| | 30 | 2000 | 1000 | 600 | **120785** | 41.3 | MB-I, MB-II | 122203 | 1.1 | DB-KM | 1.2% |
| | 50 | 1000 | 750 | 500 | **89754** | 45.9 | MB-II | 91015 | 0.1 | Agg. | 1.4% |
| | 50 | 1000 | 750 | 600 | **95776** | 44 | MB-I, MB-II | 96000 | 0.1 | All | 0.2% |
| | 50 | 1000 | 1000 | 500 | **93345** | 21.7 | MB-I, MB-II | 93748 | 0 | Agg. | 0.4% |
| | 50 | 1000 | 1000 | 600 | **105345** | 32.2 | MB-I | 106056 | 0.2 | DB-Agg. | 0.7% |
| | 50 | 2000 | 750 | 500 | **93726** | 23.6 | MB-I, MB-II | 95377 | 0.2 | DB-Agg. | 1.8% |
| | 50 | 2000 | 750 | 600 | **96000** | 18.4 | MB-I, MB-II | **96000** | 0.1 | All | 0.0% |
| | 50 | 2000 | 1000 | 500 | **104289** | 152.7 | MB-I, MB-II | 107167 | 0.2 | DB-Agg. | 2.8% |
| | 50 | 2000 | 1000 | 600 | **115008** | 117.4 | MB-I, MB-II | 116800 | 1.4 | DB-KM | 1.6% |
| | 100 | 1000 | 750 | 500 | **89609** | 139.2 | MB-I, MB-II | 90546 | 0.1 | Agg. | 1.0% |
| | 100 | 1000 | 750 | 600 | **95776** | 112.9 | MB-I, MB-II | 96000 | 0.2 | All | 0.2% |
| | 100 | 1000 | 1000 | 500 | **90940** | 29.5 | MB-II | 91143 | 1 | DB-KM | 0.2% |
| | 100 | 1000 | 1000 | 600 | **103584** | 36.6 | MB-I, MB-II | 103917 | 0.2 | Agg. | 0.3% |
| | 100 | 2000 | 750 | 500 | **93543** | 273.6 | MB-I, MB-II | 93900 | 1 | DB-KM | 0.4% |
| | 100 | 2000 | 750 | 600 | **96000** | 17.3 | MB-I, MB-II | **96000** | 0.2 | All | 0.0% |
| | 100 | 2000 | 1000 | 500 | **99018** | 73.1 | MB-I, MB-II | 99143 | 1.4 | DB-KM | 0.1% |
| | 100 | 2000 | 1000 | 600 | **111455** | 206.7 | MB-I | 112083 | 0.1 | Agg., DB-Agg. | 0.6% |
| | 200 | 1000 | 750 | 500 | **89609** | 122.9 | MB-I, MB-II | 90546 | 0.1 | Agg., DB-Agg. | 1.0% |
| | 200 | 1000 | 750 | 600 | **95776** | 258.5 | MB-I, MB-II | 96000 | 0.1 | All | 0.2% |
| | 200 | 1000 | 1000 | 500 | **90905** | 40.4 | MB-I, MB-II | 91314 | 0.1 | Agg., DB-Agg. | 0.5% |
| | 200 | 1000 | 1000 | 600 | **103584** | 83.4 | MB-I, MB-II | 104059 | 0.2 | Agg., DB-Agg. | 0.5% |
| | 200 | 2000 | 750 | 500 | **93543** | 302.8 | MB-I, MB-II | 95592 | 0.9 | DB-KM | 2.2% |
| | 200 | 2000 | 750 | 600 | **96000** | 26 | MB-I, MB-II | **96000** | 0.1 | All | 0.0% |
| | 200 | 2000 | 1000 | 500 | **98973** | 189.7 | MB-I, MB-II | 99341 | 0.1 | Agg., DB-Agg. | 0.4% |
| | 200 | 2000 | 1000 | 600 | **111455** | 325.7 | MB-I, MB-II | 112141 | 0.1 | Agg., DB-Agg. | 0.6% |

Table 5.20: Comparison of Heuristic Methods with Fixed and Variable Facility Costs on Ruhiira

| | DLim | F1 | F2 | F3 | Best Model-based Heuristic Cost | Time | Method | Best Clustering-based Heuristic Cost | Time | Method | Diff. |
|---|---|---|---|---|---|---|---|---|---|---|---|
| RUHIIRA - 1 | 30 | 1000 | 750 | 500 | 101874 | 4.7 | MB-I, MB-II | 101717 | 0.2 | DB-KM, DB-Agg. | -0.2% |
| | 30 | 1000 | 750 | 600 | **102000** | 2.9 | MB-I, MB-II | 102000 | 0 | All | 0.0% |
| | 30 | 1000 | 1000 | 500 | **129636** | 2.1 | MB-II | 131832 | 0 | DB-KM, DB-Agg. | 1.7% |
| | 30 | 1000 | 1000 | 600 | **133916** | 4.1 | MB-I, MB-II | 134132 | 0 | DB-KM, DB-Agg. | 0.2% |
| | 30 | 2000 | 750 | 500 | **102000** | 2.8 | MB-I, MB-II | **102000** | 0.1 | All | 0.0% |
| | 30 | 2000 | 750 | 600 | **102000** | 2.6 | MB-I, MB-II | **102000** | 0.1 | All | 0.0% |
| | 30 | 2000 | 1000 | 500 | 135124 | 3.5 | MB-I, MB-II | **134717** | 0 | DB-KM, DB-Agg. | -0.3% |
| | 30 | 2000 | 1000 | 600 | 135824 | 3.2 | MB-I, MB-II | **135517** | 0 | DB-KM, DB-Agg. | -0.2% |
| | 50 | 1000 | 750 | 500 | **101610** | 4 | MB-I, MB-II | **101610** | 0 | DB-KM, DB-Agg. | 0.0% |
| | 50 | 1000 | 750 | 600 | **102000** | 2.2 | MB-I, MB-II | **102000** | 0.1 | All | 0.0% |
| | 50 | 1000 | 1000 | 500 | 125865 | 1.8 | MB-II | **125799** | 0 | Agg. | -0.1% |
| | 50 | 1000 | 1000 | 600 | **132087** | 2.8 | MB-I, MB-II | 132469 | 0 | DB-KM | 0.3% |
| | 50 | 2000 | 750 | 500 | **102000** | 4 | MB-I, MB-II | **102000** | 0.1 | All | 0.0% |
| | 50 | 2000 | 750 | 600 | **102000** | 2.9 | MB-I, MB-II | **102000** | 0 | All | 0.0% |
| | 50 | 2000 | 1000 | 500 | **134360** | 2.8 | MB-I, MB-II | **134356** | 0 | DB-Agg. | 0.0% |
| | 50 | 2000 | 1000 | 600 | **135260** | 2.9 | MB-I, MB-II | **135260** | 0 | DB-Agg. | 0.0% |
| | 100 | 1000 | 750 | 500 | **101610** | 3 | MB-I, MB-II | 101963 | 0.5 | DB-KM, DB-Agg. | 0.3% |
| | 100 | 1000 | 750 | 600 | **102000** | 1.9 | MB-I, MB-II | **102000** | 0.1 | All | 0.0% |
| | 100 | 1000 | 1000 | 500 | **123294** | 2.3 | MB-I, MB-II | 123644 | 0.5 | DB-KM | 0.3% |
| | 100 | 1000 | 1000 | 600 | **131203** | 2.9 | MB-I, MB-II | 131537 | 0.5 | DB-KM | 0.3% |
| | 100 | 2000 | 750 | 500 | **102000** | 2.4 | MB-I, MB-II | **102000** | 0.1 | All | 0.0% |
| | 100 | 2000 | 750 | 600 | **102000** | 2.5 | MB-I, MB-II | **102000** | 0.1 | All | 0.0% |
| | 100 | 2000 | 1000 | 500 | **133551** | 4.1 | MB-I, MB-II | 133621 | 0.6 | DB-KM | 0.1% |
| | 100 | 2000 | 1000 | 600 | **135175** | 3.9 | MB-I, MB-II | 135313 | 0.8 | DB-KM, DB-Agg. | 0.1% |
| | 200 | 1000 | 750 | 500 | **101610** | 4.1 | MB-I, MB-II | 102000 | 0.3 | All | 0.4% |
| | 200 | 1000 | 750 | 600 | **102000** | 2.7 | MB-I, MB-II | **102000** | 0.2 | All | 0.0% |
| | 200 | 1000 | 1000 | 500 | **123052** | 7.2 | MB-I, MB-II | 123282 | 0 | Agg. | 0.2% |
| | 200 | 1000 | 1000 | 600 | **131203** | 5.7 | MB-I, MB-II | 135899 | 0.2 | DB-Agg. | 3.6% |
| | 200 | 2000 | 750 | 500 | **102000** | 4.4 | MB-I, MB-II | **102000** | 0.2 | All | 0.0% |
| | 200 | 2000 | 750 | 600 | **102000** | 2 | MB-I, MB-II | **102000** | 0.2 | All | 0.0% |
| | 200 | 2000 | 1000 | 500 | **133512** | 7 | MB-I, MB-II | 136000 | 0.2 | All | 1.9% |
| | 200 | 2000 | 1000 | 600 | **135175** | 5.7 | MB-I, MB-II | 136000 | 0.2 | All | 0.6% |

| | DLim | F1 | F2 | F3 | Best Model-based Heuristic | | | Best Clustering-based Heuristic | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Cost | Time | Method | Cost | Time | Method | Diff. |
| RUHIIRA - 2 | 30 | 1000 | 750 | 500 | **181424** | 11.5 | MB-I, MB-II | 181634 | 0 | DB-KM, DB-Agg. | 0.1% |
| | 30 | 1000 | 750 | 600 | **182250** | 8.9 | MB-I, MB-II | **182250** | 0.2 | All | 0.0% |
| | 30 | 1000 | 1000 | 500 | **226490** | 8.5 | MB-II | 228384 | 0.2 | Agg. | 0.8% |
| | 30 | 1000 | 1000 | 600 | **236288** | 13 | MB-II | 237394 | 0 | DB-KM, DB-Agg. | 0.5% |
| | 30 | 2000 | 750 | 500 | **182250** | 8.6 | MB-I, MB-II | **182250** | 0.2 | All | 0.0% |
| | 30 | 2000 | 750 | 600 | **182250** | 8.8 | MB-I, MB-II | **182250** | 0.1 | All | 0.0% |
| | 30 | 2000 | 1000 | 500 | **239713** | 8.7 | MB-I, MB-II | 240273 | 0 | DB-KM, DB-Agg. | 0.2% |
| | 30 | 2000 | 1000 | 600 | **242009** | 10.4 | MB-I, MB-II | 242270 | 0 | DB-KM, DB-Agg. | 0.1% |
| | 50 | 1000 | 750 | 500 | **181243** | 10.5 | MB-I, MB-II | 181634 | 0.5 | DB-KM | 0.2% |
| | 50 | 1000 | 750 | 600 | **182250** | 8.8 | MB-I, MB-II | **182250** | 0.2 | All | 0.0% |
| | 50 | 1000 | 1000 | 500 | 220412 | 8.1 | MB-II | 221462 | 0 | Agg. | 0.5% |
| | 50 | 1000 | 1000 | 600 | **232978** | 10.7 | MB-II | 233557 | 0.2 | DB-KM | 0.2% |
| | 50 | 2000 | 750 | 500 | **182250** | 8.1 | MB-I, MB-II | **182250** | 0.1 | All | 0.0% |
| | 50 | 2000 | 750 | 600 | **182250** | 9.5 | MB-I, MB-II | **182250** | 0.2 | All | 0.0% |
| | 50 | 2000 | 1000 | 500 | **237907** | 8.3 | MB-I, MB-II | **237876** | 0 | DB-Agg. | 0.0% |
| | 50 | 2000 | 1000 | 600 | **241255** | 8.3 | MB-I, MB-II | 241916 | 0.2 | DB-KM | 0.3% |
| | 100 | 1000 | 750 | 500 | **181266** | 12.1 | MB-I, MB-II | 182226 | 2.1 | DB-KM | 0.5% |
| | 100 | 1000 | 750 | 600 | **182250** | 8.7 | MB-I, MB-II | **182250** | 0.2 | All | 0.0% |
| | 100 | 1000 | 1000 | 500 | **213350** | 6.6 | MB-I | 213772 | 0.2 | DB-Agg. | 0.2% |
| | 100 | 1000 | 1000 | 600 | **230247** | 14.1 | MB-I, MB-II | 231071 | 0.3 | Agg. | 0.4% |
| | 100 | 2000 | 750 | 500 | **182250** | 10.9 | MB-I, MB-II | **182250** | 0.3 | All | 0.0% |
| | 100 | 2000 | 750 | 600 | **182250** | 6.1 | MB-I, MB-II | **182250** | 0.4 | All | 0.0% |
| | 100 | 2000 | 1000 | 500 | **233606** | 13.2 | MB-I, MB-II | 234839 | 0.1 | DB-Agg. | 0.5% |
| | 100 | 2000 | 1000 | 600 | **240321** | 20.7 | MB-I, MB-II | 241705 | 2.9 | DB-KM | 0.6% |
| | 200 | 1000 | 750 | 500 | **181266** | 22.7 | MB-I, MB-II | 182250 | 0.3 | All | 0.5% |
| | 200 | 1000 | 750 | 600 | **182250** | 9.8 | MB-I, MB-II | **182250** | 0.2 | All | 0.0% |
| | 200 | 1000 | 1000 | 500 | **212623** | 19.4 | MB-I, MB-II | 214047 | 0.2 | DB-Agg. | 0.7% |
| | 200 | 1000 | 1000 | 600 | **230247** | 17.9 | MB-I, MB-II | 230874 | 0.2 | Agg. | 0.3% |
| | 200 | 2000 | 750 | 500 | **182250** | 24.2 | MB-I, MB-II | **182250** | 0.2 | All | 0.0% |
| | 200 | 2000 | 750 | 600 | **182250** | 5.9 | MB-I, MB-II | **182250** | 0.3 | All | 0.0% |
| | 200 | 2000 | 1000 | 500 | **233033** | 43.8 | MB-I, MB-II | 236588 | 0.1 | DB-Agg. | 1.5% |
| | 200 | 2000 | 1000 | 600 | **240321** | 42 | MB-I, MB-II | 243000 | 0.3 | All | 1.1% |

| | DLim | F1 | F2 | F3 | Best Model-based Heuristic Cost | Time | Method | Best Clustering-based Heuristic Cost | Time | Method | Diff. |
|---|---|---|---|---|---|---|---|---|---|---|---|
| RUHIIRA - 3 | 30 | 1000 | 750 | 500 | **201328** | 17.8 | MB-II | **201419** | 0.4 | DB-KM | 0.0% |
| | 30 | 1000 | 750 | 600 | **203250** | 9.8 | MB-I, MB-II | **203250** | 0.2 | All | 0.0% |
| | 30 | 1000 | 1000 | 500 | **242448** | 7.2 | MB-I | 244710 | 0.1 | Agg. | 0.9% |
| | 30 | 1000 | 1000 | 600 | **256278** | 9.8 | MB-I, MB-II | 257779 | 0.3 | Agg. | 0.6% |
| | 30 | 2000 | 750 | 500 | **203250** | 11.8 | MB-I, MB-II | **203250** | 0.2 | All | 0.0% |
| | 30 | 2000 | 750 | 600 | **203250** | 11.2 | MB-I, MB-II | **203250** | 0.2 | All | 0.0% |
| | 30 | 2000 | 1000 | 500 | **263116** | 19.6 | MB-II | 263834 | 0.5 | DB-KM | 0.3% |
| | 30 | 2000 | 1000 | 600 | **268774** | 11.4 | MB-I, MB-II | 269148 | 0 | DB-KM | 0.1% |
| | 50 | 1000 | 750 | 500 | **200429** | 13.7 | MB-I, MB-II | 200784 | 0.8 | DB-KM | 0.2% |
| | 50 | 1000 | 750 | 600 | **203250** | 10 | MB-I, MB-II | **203250** | 0.2 | All | 0.0% |
| | 50 | 1000 | 1000 | 500 | **233363** | 10.7 | MB-II | 234213 | 0.2 | Agg. | 0.4% |
| | 50 | 1000 | 1000 | 600 | **250654** | 14.5 | MB-II | 252097 | 0.2 | Agg. | 0.6% |
| | 50 | 2000 | 750 | 500 | **203250** | 12.7 | MB-I, MB-II | **203250** | 0.2 | All | 0.0% |
| | 50 | 2000 | 750 | 600 | **203250** | 9.3 | MB-I, MB-II | **203250** | 0.2 | All | 0.0% |
| | 50 | 2000 | 1000 | 500 | **257480** | 17.6 | MB-II | 260466 | 0 | DB-Agg. | 1.2% |
| | 50 | 2000 | 1000 | 600 | **265720** | 12.4 | MB-I, MB-II | 267551 | 0.8 | DB-KM | 0.7% |
| | 100 | 1000 | 750 | 500 | **200373** | 28.3 | MB-I, MB-II | 201909 | 3.4 | DB-KM | 0.8% |
| | 100 | 1000 | 750 | 600 | **203250** | 12 | MB-I, MB-II | **203250** | 0.2 | All | 0.0% |
| | 100 | 1000 | 1000 | 500 | **226787** | 15.1 | MB-I, MB-II | 227486 | 0 | DB-Agg. | 0.3% |
| | 100 | 1000 | 1000 | 600 | **247984** | 23.1 | MB-I, MB-II | 248716 | 0.1 | DB-Agg. | 0.3% |
| | 100 | 2000 | 750 | 500 | **203250** | 25.1 | MB-I, MB-II | **203250** | 0.3 | All | 0.0% |
| | 100 | 2000 | 750 | 600 | **203250** | 8.5 | MB-I, MB-II | **203250** | 0.1 | All | 0.0% |
| | 100 | 2000 | 1000 | 500 | **251524** | 35.3 | MB-I, MB-II | 253395 | 2.9 | DB-KM | 0.7% |
| | 100 | 2000 | 1000 | 600 | **264146** | 35.6 | MB-I, MB-II | 264764 | 2 | DB-KM | 0.2% |
| | 200 | 1000 | 750 | 500 | **200339** | 51.2 | MB-II | 203250 | 0.4 | All | 1.5% |
| | 200 | 1000 | 750 | 600 | **203250** | 15 | MB-I, MB-II | **203250** | 0.4 | All | 0.0% |
| | 200 | 1000 | 1000 | 500 | **226481** | 26.4 | MB-I, MB-II | 227788 | 0.4 | Agg. | 0.6% |
| | 200 | 1000 | 1000 | 600 | **247967** | 39.3 | MB-I, MB-II | 249172 | 0.3 | Agg. | 0.5% |
| | 200 | 2000 | 750 | 500 | **203250** | 78.8 | MB-I, MB-II | **203250** | 0.3 | All | 0.0% |
| | 200 | 2000 | 750 | 600 | **203250** | 9.8 | MB-I, MB-II | **203250** | 0.3 | All | 0.0% |
| | 200 | 2000 | 1000 | 500 | **250939** | 191.9 | MB-I, MB-II | 252829 | 0.4 | Agg. | 0.8% |
| | 200 | 2000 | 1000 | 600 | **264121** | 153 | MB-I, MB-II | 268864 | 4.6 | DB-KM | 1.8% |

| | | | | | Best Model-based Heuristic | | | Best Clustering-based Heuristic | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | F3 | Cost | Time | Method | Cost | Time | Method | Diff. |
| RUHIIRA - 4 | 30 | 1000 | 750 | 500 | **181500** | 9.1 | MB-I, MB-II | **181500** | 0.3 | All | 0.0% |
| | 30 | 1000 | 750 | 600 | **181500** | 10.3 | MB-I, MB-II | **181500** | 0.3 | All | 0.0% |
| | 30 | 1000 | 1000 | 500 | **231227** | 6.3 | MB-I, MB-II | 232069 | 0 | Agg. | 0.4% |
| | 30 | 1000 | 1000 | 600 | **239191** | 7.3 | MB-I, MB-II | 239877 | 0 | DB-KM, DB-Agg. | 0.3% |
| | 30 | 2000 | 750 | 500 | **181500** | 8.3 | MB-I, MB-II | **181500** | 0.1 | All | 0.0% |
| | 30 | 2000 | 750 | 600 | **181500** | 7.5 | MB-I, MB-II | **181500** | 0.2 | All | 0.0% |
| | 30 | 2000 | 1000 | 500 | **241546** | 8.4 | MB-I, MB-II | 242000 | 0.1 | All | 0.2% |
| | 30 | 2000 | 1000 | 600 | **242000** | 7.6 | MB-I, MB-II | **242000** | 0.2 | All | 0.0% |
| | 50 | 1000 | 750 | 500 | **181424** | 6.7 | MB-I, MB-II | **181424** | 0 | DB-KM | 0.0% |
| | 50 | 1000 | 750 | 600 | **181500** | 6.5 | MB-I, MB-II | **181500** | 0.1 | All | 0.0% |
| | 50 | 1000 | 1000 | 500 | **225093** | 7.1 | MB-II | 226600 | 0.2 | Agg. | 0.7% |
| | 50 | 1000 | 1000 | 600 | **236955** | 9.8 | MB-II | 237502 | 0 | DB-KM | 0.2% |
| | 50 | 2000 | 750 | 500 | **181500** | 8 | MB-I, MB-II | **181500** | 0.2 | All | 0.0% |
| | 50 | 2000 | 750 | 600 | **181500** | 7.8 | MB-I, MB-II | **181500** | 0.1 | All | 0.0% |
| | 50 | 2000 | 1000 | 500 | **240924** | 7.5 | MB-I, MB-II | **240924** | 0 | DB-KM, DB-Agg. | 0.0% |
| | 50 | 2000 | 1000 | 600 | **241724** | 8.1 | MB-I, MB-II | **241724** | 0 | DB-KM | 0.0% |
| | 100 | 1000 | 750 | 500 | **181414** | 7.6 | MB-I, MB-II | **181500** | 0.3 | All | 0.0% |
| | 100 | 1000 | 750 | 600 | **181500** | 5.5 | MB-I, MB-II | **181500** | 0.2 | All | 0.0% |
| | 100 | 1000 | 1000 | 500 | **220059** | 8.2 | MB-I, MB-II | 221008 | 0.1 | DB-Agg. | 0.4% |
| | 100 | 1000 | 1000 | 600 | **235002** | 10 | MB-I, MB-II | 235793 | 0.1 | DB-Agg. | 0.3% |
| | 100 | 2000 | 750 | 500 | **181500** | 7.7 | MB-I, MB-II | **181500** | 0.2 | All | 0.0% |
| | 100 | 2000 | 750 | 600 | **181500** | 8.2 | MB-I, MB-II | **181500** | 0.1 | All | 0.0% |
| | 100 | 2000 | 1000 | 500 | **238909** | 14.3 | MB-II | 240258 | 0.1 | DB-Agg. | 0.6% |
| | 100 | 2000 | 1000 | 600 | **241528** | 11 | MB-I, MB-II | 241896 | 2.5 | DB-KM | 0.2% |
| | 200 | 1000 | 750 | 500 | **181414** | 15.8 | MB-I, MB-II | **181500** | 0.3 | All | 0.0% |
| | 200 | 1000 | 750 | 600 | **181500** | 5.2 | MB-I, MB-II | **181500** | 0.3 | All | 0.0% |
| | 200 | 1000 | 1000 | 500 | **219629** | 11.3 | MB-I, MB-II | 220990 | 0.2 | Agg., DB-Agg. | 0.6% |
| | 200 | 1000 | 1000 | 600 | **235002** | 6.9 | MB-I, MB-II | 239307 | 0.7 | DB-Agg. | 1.8% |
| | 200 | 2000 | 750 | 500 | **181500** | 6.7 | MB-I, MB-II | **181500** | 0.3 | All | 0.0% |
| | 200 | 2000 | 750 | 600 | **181500** | 4.7 | MB-I, MB-II | **181500** | 0.3 | All | 0.0% |
| | 200 | 2000 | 1000 | 500 | **238437** | 27.8 | MB-I, MB-II | 241537 | 6.4 | DB-KM | 1.3% |
| | 200 | 2000 | 1000 | 600 | **241528** | 19.6 | MB-I, MB-II | 242000 | 0.3 | All | 0.2% |

# Chapter 6

# Conclusion

In this thesis, we studied a planar facility location-allocation problem in the context of rural electrification. As access to electricity is still a major impediment to the economic growth of developing countries, the rural electrification problem needs urgent attention to meet SDGs. Here, we consider two different decentralized systems for the electrification of rural households. In the nano-grid option, each household is electrified individually by the stand-alone systems. The houses with solar panels on the rooftop would be an example of nano-grid systems. In the micro-grid systems, on the other hand, multiple households are electrified by a single generation point, where each household is connected via low voltage cables. However, these low voltage connections can not exceed a specific distance limit due to the voltage drop and power loss concerns.

As the total investment cost may include varying cost components based on the renewable generation technology considered, we provide different formulations incorporating the different combinations of the fixed facility opening cost and the variable charges paid per household. In addition to the facility costs, we also consider the cost of the low voltage connections between the households and the serving facilities.

In this study, we aim to evaluate the trade-off between nano-grid and micro-grid systems, determine the optimal number of each facility type, and identify the cost-efficient facility location-allocations. For this purpose, we proposed a MIQCP formulation and developed six heuristic approaches to tackle the rural energy planning problem. The heuristic methods are classified as model-based heuristics or clustering-based approaches depending on the major characteristics of the solution methodology.

In the model-based multi-stage heuristics, we propose to solve the discrete counterpart of the MIQCP formulations, introducing promising candidate locations for facilities. We then use the solution of the discrete problem as a starting solution for the Cooper's iterative algorithm. Since the distance limit constraint is enforced on the micro-grid clusters, Cooper's heuristic and Weiszfeld's algorithm are modified to guarantee that the proposed location is within the feasible region.

In addition to the model-based heuristics, we also developed new solution methods that incorporate well-known clustering techniques such as the agglomerative clustering, DBSCAN, and k-means algorithm. For the agglomeration process, we proposed a new dissimilarity measure called GeomDiff and compared the new measure with the other six existing dissimilarity measures. At the end of computational analysis on the experimental data, we identified three prominent measures to be used in the experiments on real-life instances.

The numerical analysis indicates that while the model-based methods generally outperform the clustering-based approaches regardless of the cost structure, the clustering-based algorithms allow rapid assessments with only minor deviations from the model-based heuristics. These faster algorithms also provide a flexibility for the computational environment as they do no require commercial solvers for optimization. In fact, computational experiments have shown that clustering algorithms works at least 100 times faster than the model-based heuristics in dispersed areas for the fixed cost problem, whereas it can work 350 times faster for the instances solved within the CPU time limit in densely populated samples. For the variable cost formulation, on the other hand, clustering-based approaches are observed to perform 40 times faster in average.

As a future research direction, the low voltage network can be designed in different topologies. Besides, developing better heuristics for the defined problems can always be in our future agenda. Another extension can be made by incorporating the mini-grid systems, which are larger networks compared to micro-grid structures and can connect more points by expanding to larger distances. In this extension, we could consider a two-level network design to distribute the electricity between mini-grid compatible clusters.

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# Appendix A

# Comparison of the Existing Dissimilarity Measures and the Proposed Measure on the Synthetic Data

In this section, we present a comparative analysis of the seven existing measures and the new measure we proposed, called GeomDiff. As alternative dissimilarity measures could identify different pairs of 'similar' clusters in the iterations, the merging strategy and the final configuration may change significantly depending on the choice of the dissimilarity measure. In Tables A.1 - A.6, we present the comparative results of the alternative measures for the synthetic data sets S654 and S1060. In the tables, the first set of columns show the details of the problem instances in terms of the distance threshold and facility costs, and the remaining columns present the total cost and the CPU time for each dissimilarity measure that we have discussed in Section 4.2.1.

Tables A.1 - A.2 demonstrate that GeomDiff outperforms the existing measures on both S654 and S1060 for the fixed cost formulation. GeomDiff returns the best result in 21 and 25 instances out of 45 solutions for S654 and S1060. Complete measure follows GeomDiff as the second-best performing measure providing the least-cost solution in 19 out of 45 instances for S1060. The results of the variable cost formulation are also provided in Tables A.3 - A.4. According to Tables A.3 - A.4, GeomDiff is the superior measure in 37 instances for S654, while Ward's method outperforms the other alternatives in 38 instances of S1060. Finally, the fixed and variable cost problem results show similarities to the solutions of the fixed cost formulation. Tables A.2, A.4 - A.6 indicate that GeomDiff outperforms the existing measures in 25 and 20 instances out of 30 solutions on S654 and S1060, respectively. Complete measure is the second-best performing measure for S1060 as it provides the least-cost solution in 14 instances among 30 solutions. Additionally, it can be observed that the running time is less than 10 seconds for almost all instances. We also note that the increase in the distance threshold leads to longer solution times for all problem types having fixed, variable, and fixed and variable cost components.

Table A.1: Agglomerative Clustering Results with Existing Dissimilarity Measures on 654 (Fixed Cost)

| | | | GeomDiff | | Average | | Centroid | | Complete | | Hausdorff | | Ward | | Single | | Minimax | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| DLim | F1 | F2 | Cost | Time | Cost | Time | Cost | Time | Cost | Time | Cost | Time | Cost | Time | Cost | Time | Cost | Time |
| 200 | 1K | 500 | 77864 | 3.4 | 79324 | 4.6 | 79397 | 2.2 | 78120 | 2.0 | 79788 | 1.8 | **75343** | 2.7 | 96745 | 2.6 | 75745 | 2.7 |
| 200 | 1K | 750 | 80474 | 3.8 | 84350 | 4.0 | 84973 | 2.1 | 80780 | 2.8 | 84605 | 2.7 | **78002** | 2.7 | 126746 | 3.0 | 78697 | 2.7 |
| 200 | 1K | 1K | 82474 | 3.4 | 88100 | 3.2 | 88973 | 2.5 | 83030 | 1.9 | 88105 | 2.6 | **80252** | 2.3 | 141996 | 2.3 | 81197 | 2.9 |
| 200 | 2K | 500 | 114872 | 2.7 | 103735 | 2.6 | 103808 | 2.1 | 102395 | 2.8 | 100547 | 2.1 | 105884 | 1.6 | 123939 | 1.6 | **99853** | 2.3 |
| 200 | 2K | 750 | 121781 | 2.6 | 116271 | 2.4 | 116354 | 2.3 | 108787 | 2.5 | 116288 | 2.7 | 112276 | 2.1 | 130245 | 2.7 | **106245** | 1.9 |
| 200 | 2K | 1K | 126864 | 2.6 | 121604 | 2.0 | 122354 | 2.0 | 113620 | 2.0 | 123788 | 2.2 | 117109 | 2.1 | 142745 | 2.3 | **111745** | 2.7 |
| 200 | 5K | 500 | 190808 | 2.4 | 158262 | 3.2 | **157638** | 2.1 | 162611 | 2.4 | 161934 | 2.5 | 165405 | 1.6 | 165335 | 2.1 | 161175 | 2.0 |
| 200 | 5K | 750 | 222246 | 2.9 | **169574** | 2.3 | 169658 | 1.9 | 175768 | 1.9 | 176130 | 2.0 | 190519 | 2.2 | 194835 | 1.8 | 172488 | 2.1 |
| 200 | 5K | 1K | 236236 | 2.9 | **179324** | 2.2 | 179408 | 2.0 | 185935 | 1.8 | 188880 | 1.9 | 200269 | 1.9 | 224335 | 2.2 | 182238 | 1.6 |
| 400 | 1K | 500 | **73147** | 4.4 | 78656 | 2.4 | 78728 | 2.5 | 77440 | 2.2 | 78567 | 2.1 | 74884 | 2.1 | 100939 | 2.6 | 75330 | 2.2 |
| 400 | 1K | 750 | **75042** | 5.0 | 84350 | 2.5 | 84973 | 2.3 | 79958 | 2.3 | 84605 | 2.6 | 77401 | 2.9 | 110441 | 2.8 | 78574 | 2.8 |
| 400 | 1K | 1K | **75889** | 5.4 | 88100 | 2.7 | 88973 | 2.8 | 81958 | 3.0 | 88105 | 2.3 | 78165 | 2.7 | 116691 | 3.2 | 81074 | 3.1 |
| 400 | 2K | 500 | **99127** | 3.9 | 107339 | 2.6 | 107171 | 2.2 | 100843 | 1.7 | 110877 | 2.0 | 101047 | 2.6 | 112828 | 2.2 | 99523 | 1.8 |
| 400 | 2K | 750 | **103430** | 4.7 | 113143 | 2.1 | 112976 | 2.2 | 106648 | 1.9 | 116227 | 1.9 | 105816 | 2.3 | 121689 | 2.4 | 105330 | 2.5 |
| 400 | 2K | 1K | **105951** | 4.5 | 117436 | 2.3 | 117268 | 2.4 | 110940 | 2.2 | 119393 | 2.3 | 108337 | 3.5 | 129439 | 2.6 | 110330 | 2.4 |
| 400 | 5K | 500 | 149531 | 4.5 | 145737 | 1.9 | 146192 | 2.6 | 144243 | 1.7 | 144155 | 2.4 | 155634 | 2.3 | **143379** | 1.9 | 144133 | 2.4 |
| 400 | 5K | 750 | 157742 | 4.2 | 155109 | 1.8 | 154942 | 2.6 | 154170 | 2.3 | **153655** | 2.1 | 172710 | 2.2 | 154129 | 2.2 | 155686 | 1.7 |
| 400 | 5K | 1K | 163242 | 4.2 | 163859 | 2.2 | 163692 | 2.5 | **159670** | 1.8 | 163155 | 2.2 | 177460 | 2.9 | 164828 | 2.1 | 164436 | 2.0 |
| 600 | 1K | 500 | **73960** | 6.6 | 78577 | 2.6 | 78650 | 2.3 | 77249 | 2.2 | 78567 | 2.8 | 74692 | 2.3 | 100826 | 2.6 | 75236 | 2.2 |
| 600 | 1K | 750 | **75132** | 6.8 | 84350 | 2.6 | 84973 | 2.7 | 79958 | 2.4 | 84605 | 2.5 | 76956 | 2.7 | 110436 | 2.6 | 78574 | 2.1 |
| 600 | 1K | 1K | **75479** | 6.9 | 88100 | 4.0 | 88973 | 2.7 | 81958 | 2.8 | 88105 | 2.6 | 78044 | 2.7 | 116686 | 2.4 | 81074 | 2.7 |
| 600 | 2K | 500 | 100537 | 6.0 | 107339 | 2.2 | 107171 | 2.2 | 100843 | 1.9 | 110816 | 2.1 | 101606 | 2.6 | 112715 | 2.5 | **99523** | 1.8 |
| 600 | 2K | 750 | **103590** | 6.1 | 112438 | 2.5 | 112271 | 2.5 | 105771 | 2.3 | 115834 | 2.4 | 104659 | 2.3 | 119906 | 2.1 | 104444 | 2.1 |
| 600 | 2K | 1K | **104639** | 6.5 | 114883 | 2.3 | 114716 | 2.9 | 108388 | 1.8 | 118379 | 2.4 | 105708 | 2.2 | 125656 | 2.3 | 108444 | 2.6 |
| 600 | 5K | 500 | 153323 | 6.2 | 144435 | 2.3 | 144613 | 2.0 | 142975 | 1.8 | 142820 | 2.0 | 152326 | 2.0 | 143177 | 2.0 | **142797** | 1.9 |
| 600 | 5K | 750 | 160753 | 6.0 | 152831 | 2.4 | 152641 | 2.1 | **151003** | 2.5 | 151228 | 2.2 | 161984 | 2.5 | 151779 | 2.6 | 151123 | 2.2 |
| 600 | 5K | 1K | 165503 | 6.4 | 158261 | 2.6 | 157891 | 2.2 | **156253** | 2.2 | 159478 | 2.3 | 166734 | 2.0 | 162364 | 2.2 | 156623 | 2.3 |

| | | | GeomDiff | | Average | | Centroid | | Complete | | Hausdorff | | Ward | | Single | | Minimax | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| DLim | F1 | F2 | Cost | Time | Cost | Time | Cost | Time | Cost | Time | Cost | Time | Cost | Time | Cost | Time | Cost | Time |
| 800 | 1K | 500 | **73593** | 8.1 | 78577 | 2.3 | 78650 | 2.7 | 77249 | 2.3 | 78567 | 2.0 | 74692 | 2.0 | 100826 | 2.1 | 75236 | 2.7 |
| 800 | 1K | 750 | **74495** | 7.8 | 84350 | 2.1 | 84973 | 2.8 | 79958 | 2.3 | 84605 | 2.9 | 76529 | 3.2 | 110436 | 3.4 | 78574 | 2.9 |
| 800 | 1K | 1K | **74591** | 7.6 | 88100 | 2.7 | 88973 | 2.4 | 81958 | 2.7 | 88105 | 2.5 | 78044 | 2.8 | 116686 | 2.5 | 81074 | 2.6 |
| 800 | 2K | 500 | 99648 | 7.9 | 107339 | 2.5 | 107171 | 2.7 | 100843 | 2.1 | 110816 | 2.9 | 101145 | 2.7 | 112715 | 1.7 | **99523** | 2.2 |
| 800 | 2K | 750 | **102688** | 7.5 | 111980 | 2.1 | 111811 | 2.6 | 105395 | 2.2 | 115777 | 2.5 | 104187 | 2.6 | 119562 | 2.4 | 103976 | 2.1 |
| 800 | 2K | 1K | **103729** | 8.0 | 112729 | 2.3 | 112562 | 2.4 | 106179 | 2.4 | 116915 | 2.6 | 105226 | 3.0 | 122719 | 2.3 | 105076 | 2.3 |
| 800 | 5K | 500 | 145926 | 7.3 | 144435 | 2.6 | 144595 | 2.4 | 145183 | 2.1 | 142820 | 1.9 | 149897 | 2.9 | 143177 | 2.6 | **142797** | 2.6 |
| 800 | 5K | 750 | 152350 | 7.3 | 152581 | 2.0 | 152516 | 2.6 | 152356 | 2.3 | 150979 | 2.1 | 159942 | 2.6 | 151542 | 2.3 | **150875** | 2.4 |
| 800 | 5K | 1K | 156074 | 7.2 | 155942 | 2.1 | 155947 | 2.4 | 155461 | 2.3 | 157136 | 2.0 | 163088 | 2.7 | 160033 | 2.6 | **154281** | 2.4 |
| 1000 | 1K | 500 | **73593** | 9.7 | 78577 | 2.7 | 78650 | 2.7 | 77249 | 2.2 | 78567 | 2.4 | 74692 | 2.6 | 100826 | 2.6 | 75236 | 2.6 |
| 1000 | 1K | 750 | **74495** | 9.5 | 84350 | 2.4 | 84973 | 3.0 | 79958 | 2.4 | 84605 | 3.0 | 76529 | 3.2 | 110436 | 2.7 | 78574 | 3.1 |
| 1000 | 1K | 1K | **74591** | 9.6 | 88100 | 2.8 | 88973 | 2.8 | 81958 | 2.6 | 88105 | 2.9 | 78044 | 3.1 | 116686 | 2.4 | 81074 | 2.6 |
| 1000 | 2K | 500 | 101769 | 8.9 | 107339 | 2.3 | 107171 | 2.6 | 100843 | 2.1 | 110816 | 2.7 | 101145 | 2.7 | 112715 | 2.6 | **99523** | 2.5 |
| 1000 | 2K | 750 | **103564** | 9.4 | 111980 | 2.3 | 111811 | 2.6 | 105395 | 2.5 | 115777 | 2.3 | 104187 | 2.6 | 119562 | 2.6 | 103976 | 2.5 |
| 1000 | 2K | 1K | **103805** | 9.6 | 112532 | 2.4 | 112366 | 3.0 | 105970 | 2.1 | 116907 | 2.6 | 105213 | 2.6 | 122511 | 2.4 | 104900 | 2.5 |
| 1000 | 5K | 500 | 145186 | 8.8 | 144435 | 2.4 | 144595 | 2.4 | 143968 | 2.0 | 142820 | 2.3 | 146964 | 2.3 | 143177 | 2.6 | **142797** | 2.7 |
| 1000 | 5K | 750 | 153164 | 9.0 | 152581 | 2.3 | 152516 | 2.7 | 151141 | 2.2 | 150979 | 2.5 | 154720 | 2.7 | 151542 | 2.0 | **150875** | 2.4 |
| 1000 | 5K | 1K | 156188 | 9.5 | 155542 | 2.2 | 155556 | 2.6 | 154030 | 1.9 | 156736 | 2.2 | 157727 | 2.6 | 159637 | 2.4 | **153882** | 2.3 |

Table A.2: Agglomerative Clustering Results with Existing Dissimilarity Measures on 1060 (Fixed Cost)

| | | | GeomDiff | | Average | | Centroid | | Complete | | Hausdorff | | Ward | | Single | | Minimax | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| DLim | F1 | F2 | Cost | Time | Cost | Time | Cost | Time | Cost | Time | Cost | Time | Cost | Time | Cost | Time | Cost | Time |
| 200 | 1K | 500 | 435224 | 11.3 | 419427 | 10.8 | 448830 | 9.4 | **414687** | 8.0 | 443349 | 9.8 | 423978 | 8.9 | 491491 | 2.8 | 429961 | 10.6 |
| 200 | 1K | 750 | 502395 | 5.1 | 473399 | 7.0 | 552763 | 4.1 | **449138** | 6.0 | 528538 | 4.9 | 463971 | 5.9 | 719050 | 1.7 | 500881 | 4.8 |
| 200 | 1K | 1K | 550895 | 4.8 | 507149 | 5.2 | 633513 | 3.6 | **459888** | 6.0 | 584788 | 5.2 | 479971 | 4.8 | 930300 | 1.9 | 555381 | 5.3 |
| 200 | 2K | 500 | **530000** | 4.0 | **530000** | 4.7 | **530000** | 2.7 | **530000** | 3.5 | **530000** | 3.1 | **530000** | 4.4 | **530000** | 1.3 | **530000** | 3.4 |
| 200 | 2K | 750 | 710368 | 10.5 | 673724 | 9.6 | 795000 | 3.4 | **665723** | 8.4 | 795000 | 3.5 | 687492 | 9.5 | 741741 | 2.3 | 695994 | 10.3 |
| 200 | 2K | 1K | 812224 | 11.3 | 770427 | 9.0 | 859330 | 9.8 | **740232** | 8.5 | 841849 | 9.4 | 774478 | 9.2 | 968991 | 2.4 | 800961 | 10.7 |
| 200 | 5K | 500 | **530000** | 3.6 | **530000** | 4.1 | **530000** | 3.0 | **530000** | 5.2 | **530000** | 4.2 | **530000** | 4.0 | **530000** | 1.4 | **530000** | 4.0 |
| 200 | 5K | 750 | **795000** | 3.5 | **795000** | 4.3 | **795000** | 3.2 | **795000** | 4.4 | **795000** | 3.5 | **795000** | 4.1 | **795000** | 1.3 | **795000** | 3.9 |
| 200 | 5K | 1K | **1060K** | 3.7 | **1060K** | 4.4 | **1060K** | 3.6 | **1060K** | 4.1 | **1060K** | 3.3 | **1060K** | 4.1 | **1060K** | 1.5 | **1060K** | 3.5 |
| 400 | 1K | 500 | 369434 | 4.7 | **367958** | 5.6 | 368904 | 5.1 | 371543 | 5.5 | 370132 | 5.0 | 369418 | 4.9 | 393092 | 8.6 | 369380 | 5.8 |
| 400 | 1K | 750 | **375484** | 6.8 | 379128 | 6.6 | 382128 | 5.7 | 377048 | 6.2 | 389525 | 6.3 | 378388 | 7.1 | 519255 | 4.7 | 377827 | 6.6 |
| 400 | 1K | 1K | **377984** | 6.2 | 383878 | 6.5 | 388378 | 6.5 | 378720 | 6.9 | 395025 | 5.9 | 380138 | 6.6 | 597755 | 5.1 | 381577 | 6.7 |
| 400 | 2K | 500 | **530000** | 4.7 | **530000** | 4.8 | **530000** | 5.1 | **530000** | 5.2 | **530000** | 4.4 | **530000** | 5.5 | **530000** | 4.1 | **530000** | 5.3 |
| 400 | 2K | 750 | 556829 | 5.4 | 535991 | 5.0 | 540784 | 5.6 | **524287** | 5.9 | 536588 | 5.3 | 555195 | 5.8 | 585087 | 7.7 | 528644 | 4.9 |
| 400 | 2K | 1K | 580670 | 6.4 | 557255 | 6.3 | 564734 | 5.1 | **536333** | 4.8 | 561191 | 5.0 | 580705 | 5.3 | 659592 | 8.8 | 549129 | 6.7 |
| 400 | 5K | 500 | **530000** | 5.9 | **530000** | 4.0 | **530000** | 4.0 | **530000** | 5.3 | **530000** | 4.6 | **530000** | 4.7 | **530000** | 4.0 | **530000** | 4.6 |
| 400 | 5K | 750 | **795000** | 4.6 | **795000** | 4.9 | **795000** | 5.0 | **795000** | 4.7 | **795000** | 4.5 | **795000** | 4.9 | **795000** | 3.5 | **795000** | 4.6 |
| 400 | 5K | 1K | 1060K | 4.4 | 1060K | 4.9 | 1060K | 4.7 | **859585** | 5.5 | 1060K | 4.7 | 1060K | 4.9 | 1060K | 3.5 | 1060K | 5.6 |
| 600 | 1K | 500 | **364106** | 5.2 | 366496 | 5.6 | 366138 | 6.2 | 368666 | 4.5 | 369670 | 4.6 | 365432 | 5.6 | 386835 | 8.2 | 370430 | 5.4 |
| 600 | 1K | 750 | **366380** | 8.3 | 375442 | 6.6 | 376188 | 6.0 | 374295 | 6.3 | 376627 | 6.7 | 369893 | 7.5 | 516072 | 5.6 | 374566 | 6.6 |
| 600 | 1K | 1K | **367380** | 7.5 | 378442 | 6.8 | 380188 | 6.3 | 375795 | 6.5 | 382140 | 6.5 | 370890 | 7.2 | 593572 | 5.0 | 376816 | 6.7 |
| 600 | 2K | 500 | 464874 | 6.3 | **462167** | 5.1 | 462312 | 5.8 | 467895 | 5.9 | 463241 | 5.0 | 465143 | 5.8 | 530000 | 4.7 | 468903 | 5.8 |
| 600 | 2K | 750 | 496608 | 6.1 | 494042 | 6.1 | **493425** | 5.7 | 502456 | 4.7 | 501170 | 5.3 | 494448 | 5.1 | 537249 | 7.8 | 494585 | 5.1 |
| 600 | 2K | 1K | 498961 | 5.5 | 504679 | 5.7 | 501812 | 5.4 | 506136 | 5.9 | 517147 | 5.1 | **495767** | 5.8 | 573603 | 8.4 | 497013 | 5.9 |
| 600 | 5K | 500 | **530000** | 4.7 | **530000** | 5.1 | **530000** | 5.1 | **530000** | 5.7 | **530000** | 4.5 | **530000** | 5.0 | **530000** | 3.6 | **530000** | 5.3 |
| 600 | 5K | 750 | **795000** | 5.7 | **795000** | 5.5 | **795000** | 5.7 | **795000** | 5.5 | **795000** | 5.3 | **795000** | 4.9 | **795000** | 4.3 | **795000** | 4.9 |
| 600 | 5K | 1K | 789698 | 5.5 | 769819 | 6.4 | **763454** | 4.8 | 769609 | 5.0 | 784874 | 5.3 | 777069 | 5.1 | 1060K | 3.6 | 769420 | 5.3 |

| | | | GeomDiff | | Average | | Centroid | | Complete | | Hausdorff | | Ward | | Single | | Minimax | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| DLim | F1 | F2 | Cost | Time | Cost | Time | Cost | Time | Cost | Time | Cost | Time | Cost | Time | Cost | Time | Cost | Time |
| 800 | 1K | 500 | **364831** | 7.2 | 366496 | 5.4 | 366138 | 5.4 | 368654 | 5.0 | 369648 | 5.6 | 365434 | 6.1 | 387756 | 8.2 | 370382 | 5.3 |
| 800 | 1K | 750 | **365838** | 8.4 | 375253 | 6.3 | 376188 | 6.5 | 374284 | 6.0 | 376371 | 6.3 | 369544 | 5.8 | 519931 | 5.3 | 374499 | 7.7 |
| 800 | 1K | 1K | **366588** | 7.6 | 378253 | 6.2 | 380188 | 7.1 | 375784 | 7.0 | 382119 | 6.2 | 370294 | 6.8 | 598431 | 5.3 | 376749 | 7.3 |
| 800 | 2K | 500 | 467636 | 6.9 | 465094 | 6.2 | **463256** | 6.0 | 472204 | 6.1 | 468557 | 5.5 | 466317 | 6.1 | 530000 | 4.5 | 467627 | 5.6 |
| 800 | 2K | 750 | **487124** | 6.6 | 489290 | 5.3 | 489058 | 5.7 | 501524 | 5.3 | 496899 | 5.6 | 487373 | 5.7 | 533794 | 7.6 | 490309 | 5.4 |
| 800 | 2K | 1K | **487874** | 6.3 | 491529 | 5.1 | 492093 | 6.3 | 503275 | 6.1 | 501096 | 5.0 | 488678 | 5.3 | 551004 | 8.6 | 492455 | 6.5 |
| 800 | 5K | 500 | **530000** | 6.3 | **530000** | 5.2 | **530000** | 4.4 | **530000** | 5.7 | **530000** | 5.1 | **530000** | 5.0 | **530000** | 3.6 | **530000** | 5.2 |
| 800 | 5K | 750 | 693024 | 5.8 | **689349** | 5.1 | 697708 | 5.5 | 701093 | 5.5 | 700070 | 5.1 | 693115 | 5.0 | 795000 | 4.4 | 701702 | 5.8 |
| 800 | 5K | 1K | 722278 | 6.2 | **718595** | 6.1 | 723729 | 5.7 | 735883 | 5.3 | 730605 | 5.2 | 723696 | 4.8 | 1060K | 4.2 | 729547 | 5.7 |
| 1000 | 1K | 500 | **364822** | 8.9 | 366496 | 5.3 | 366138 | 6.3 | 368654 | 5.7 | 369648 | 5.5 | 365434 | 5.9 | 387756 | 8.8 | 370382 | 7.1 |
| 1000 | 1K | 750 | **365829** | 8.6 | 375253 | 6.6 | 376188 | 6.8 | 374284 | 7.4 | 376371 | 7.4 | 369544 | 7.2 | 519931 | 6.2 | 374499 | 6.6 |
| 1000 | 1K | 1K | **366579** | 8.5 | 378253 | 7.3 | 380188 | 7.7 | 375784 | 6.9 | 382119 | 6.1 | 370294 | 7.6 | 598431 | 5.6 | 376749 | 6.6 |
| 1000 | 2K | 500 | 467318 | 8.1 | 465094 | 5.8 | **463256** | 5.3 | 472142 | 5.7 | 468275 | 5.5 | 466306 | 5.8 | 530000 | 4.2 | 467597 | 6.0 |
| 1000 | 2K | 750 | 487430 | 7.1 | 489290 | 6.3 | 489058 | 5.3 | 501462 | 5.0 | 496618 | 4.7 | **487158** | 5.9 | 533794 | 8.2 | 490279 | 5.8 |
| 1000 | 2K | 1K | **488400** | 8.1 | 491345 | 6.0 | 491909 | 6.7 | 503213 | 6.0 | 500815 | 6.0 | 488463 | 6.7 | 546459 | 8.9 | 492277 | 5.6 |
| 1000 | 5K | 500 | **530000** | 7.3 | **530000** | 5.2 | **530000** | 6.3 | **530000** | 5.1 | **530000** | 5.0 | **530000** | 6.7 | **530000** | 3.7 | **530000** | 4.8 |
| 1000 | 5K | 750 | 694598 | 7.5 | **692191** | 5.8 | 700592 | 5.5 | 711250 | 5.3 | 701338 | 4.5 | 694215 | 6.0 | 795000 | 3.9 | 704023 | 5.3 |
| 1000 | 5K | 1K | 710869 | 7.7 | **708533** | 5.2 | 715515 | 5.1 | 737298 | 4.9 | 723264 | 4.7 | 710665 | 5.5 | 1060K | 4.2 | 725672 | 5.7 |

Table A.3: Agglomerative Clustering Results with Existing Dissimilarity Measures on 654 (Variable Cost)

| | | | GeomDiff | | Average | | Centroid | | Complete | | Hausdorff | | Ward | | Single | | Minimax | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| DLim | F1 | F2 | Cost | Time | Cost | Time | Cost | Time | Cost | Time | Cost | Time | Cost | Time | Cost | Time | Cost | Time |
| 200 | 1K | 500 | **351120** | 5.9 | 361397 | 5.4 | 362091 | 3.0 | 356010 | 4.0 | 360735 | 4.4 | 352092 | 4.1 | 404496 | 3.5 | 361116 | 4.0 |
| 200 | 1K | 750 | **361478** | 3.5 | 383397 | 4.0 | 385091 | 2.3 | 371843 | 2.3 | 383679 | 2.4 | 364640 | 2.3 | 465496 | 2.7 | 381329 | 2.5 |
| 200 | 1K | 1K | **386162** | 3.3 | 424715 | 2.8 | 426252 | 2.5 | 407843 | 2.2 | 425679 | 2.5 | 398196 | 2.5 | 648496 | 2.3 | 412197 | 2.5 |
| 200 | 2K | 500 | 510364 | 3.0 | 517654 | 2.7 | 518953 | 2.1 | 512820 | 2.5 | 516878 | 2.3 | **510259** | 2.6 | 552746 | 2.2 | 516135 | 2.1 |
| 200 | 2K | 750 | **522478** | 3.2 | 541397 | 3.1 | 542841 | 2.4 | 532343 | 2.6 | 542985 | 1.9 | 525140 | 2.4 | 613746 | 2.2 | 541079 | 2.1 |
| 200 | 2K | 1K | **547662** | 3.2 | 585965 | 2.8 | 587252 | 2.2 | 568343 | 2.4 | 585679 | 1.8 | 559446 | 2.4 | 796746 | 2.3 | 573197 | 2.1 |
| 200 | 5K | 500 | **654K** | 2.9 | **654K** | 2.8 | **654K** | 1.9 | **654K** | 2.2 | **654K** | 2.1 | **654K** | 1.9 | **654K** | 1.6 | **654K** | 2.1 |
| 200 | 5K | 750 | **683478** | 3.0 | 699397 | 2.8 | 700591 | 2.5 | 692493 | 2.3 | 700235 | 2.3 | 685640 | 2.4 | 761996 | 2.3 | 700829 | 2.4 |
| 200 | 5K | 1K | **709162** | 3.2 | 747215 | 2.3 | 748252 | 2.6 | 728843 | 1.9 | 745679 | 1.8 | 720696 | 2.1 | 944996 | 2.1 | 734197 | 2.9 |
| 400 | 1K | 500 | **351120** | 4.9 | 361397 | 2.4 | 362091 | 2.1 | 356010 | 2.7 | 360735 | 2.0 | 352092 | 2.4 | 404496 | 2.3 | 361116 | 2.5 |
| 400 | 1K | 750 | **360918** | 4.6 | 383397 | 2.5 | 385091 | 2.6 | 371843 | 2.2 | 383679 | 2.4 | 364640 | 2.7 | 432690 | 2.4 | 381329 | 2.6 |
| 400 | 1K | 1K | 377249 | 4.9 | 422266 | 2.6 | 422940 | 2.4 | 406177 | 2.4 | 424563 | 2.2 | **374665** | 2.8 | 508552 | 2.7 | 412074 | 2.8 |
| 400 | 2K | 500 | 510364 | 5.2 | 517654 | 2.3 | 518953 | 2.8 | 512820 | 2.2 | 516878 | 2.4 | **510259** | 2.3 | 552746 | 2.5 | 516135 | 2.4 |
| 400 | 2K | 750 | **522168** | 4.6 | 541397 | 2.5 | 542841 | 2.5 | 532343 | 2.4 | 542985 | 2.4 | 525140 | 2.6 | 589690 | 2.7 | 541079 | 2.3 |
| 400 | 2K | 1K | 539950 | 4.9 | 583766 | 2.4 | 584440 | 2.9 | 567677 | 1.9 | 585679 | 2.1 | **537415** | 2.5 | 665802 | 2.4 | 573074 | 2.3 |
| 400 | 5K | 500 | **654K** | 4.4 | **654K** | 2.6 | **654K** | 2.1 | **654K** | 1.9 | **654K** | 2.0 | **654K** | 2.6 | **654K** | 2.1 | **654K** | 2.1 |
| 400 | 5K | 750 | **683418** | 4.8 | 699397 | 2.5 | 700591 | 2.3 | 692493 | 2.1 | 700235 | 2.8 | 685640 | 2.5 | 746690 | 2.4 | 700829 | 2.6 |
| 400 | 5K | 1K | 702450 | 5.0 | 745266 | 2.4 | 745940 | 2.5 | 728843 | 2.2 | 745679 | 2.3 | **700165** | 2.1 | 823052 | 2.5 | 734074 | 2.8 |
| 600 | 1K | 500 | **351120** | 7.1 | 361397 | 2.7 | 362091 | 2.8 | 356010 | 2.2 | 360735 | 2.2 | 352092 | 2.3 | 404496 | 2.2 | 361116 | 2.3 |
| 600 | 1K | 750 | **360918** | 7.0 | 383397 | 2.8 | 385091 | 3.0 | 371843 | 1.9 | 383679 | 2.6 | 364640 | 2.4 | 432690 | 2.9 | 381329 | 2.2 |
| 600 | 1K | 1K | **369516** | 7.5 | 422266 | 2.7 | 422940 | 2.6 | 406177 | 2.3 | 424410 | 2.6 | 374544 | 2.6 | 508547 | 2.8 | 412074 | 2.9 |
| 600 | 2K | 500 | 510364 | 6.3 | 517654 | 2.3 | 518953 | 2.7 | 512820 | 2.3 | 516878 | 2.6 | **510259** | 2.4 | 552746 | 2.2 | 516135 | 2.3 |
| 600 | 2K | 750 | **522168** | 7.1 | 541397 | 2.8 | 542841 | 2.7 | 532343 | 2.4 | 542985 | 2.7 | 525140 | 2.7 | 589690 | 2.7 | 541079 | 2.8 |
| 600 | 2K | 1K | **532766** | 6.9 | 583766 | 2.8 | 584440 | 2.3 | 567677 | 2.6 | 585679 | 2.6 | 537294 | 2.8 | 665797 | 2.7 | 573074 | 2.3 |
| 600 | 5K | 500 | **654K** | 6.8 | **654K** | 2.0 | **654K** | 2.3 | **654K** | 1.8 | **654K** | 2.1 | **654K** | 2.4 | **654K** | 2.2 | **654K** | 2.1 |
| 600 | 5K | 750 | **683418** | 6.8 | 699397 | 2.4 | 700591 | 2.9 | 692493 | 2.6 | 700235 | 2.0 | 685640 | 2.6 | 746690 | 2.8 | 700829 | 2.5 |
| 600 | 5K | 1K | **696016** | 6.4 | 745266 | 2.1 | 745940 | 3.0 | 728843 | 2.2 | 745679 | 2.1 | 700044 | 2.6 | 823047 | 2.9 | 734074 | 2.1 |

| | | | GeomDiff | | Average | | Centroid | | Complete | | Hausdorff | | Ward | | Single | | Minimax | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| DLim | F1 | F2 | Cost | Time | Cost | Time | Cost | Time | Cost | Time | Cost | Time | Cost | Time | Cost | Time | Cost | Time |
| 800 | 1K | 500 | **351120** | 7.7 | 361397 | 2.2 | 362091 | 2.8 | 356010 | 2.4 | 360735 | 2.6 | 352092 | 2.4 | 404496 | 2.6 | 361116 | 2.3 |
| 800 | 1K | 750 | **360918** | 8.1 | 383397 | 2.2 | 385091 | 2.5 | 371843 | 2.0 | 383679 | 2.4 | 364640 | 2.4 | 432690 | 3.0 | 381329 | 2.6 |
| 800 | 1K | 1K | **366261** | 7.9 | 422266 | 2.1 | 422940 | 2.8 | 406177 | 2.3 | 424410 | 2.4 | 374544 | 2.5 | 505087 | 2.4 | 412074 | 2.7 |
| 800 | 2K | 500 | 510364 | 7.5 | 517654 | 2.3 | 518953 | 2.4 | 512820 | 2.3 | 516878 | 2.4 | **510259** | 2.4 | 552746 | 2.7 | 516135 | 2.4 |
| 800 | 2K | 750 | **522168** | 7.8 | 541397 | 2.8 | 542841 | 2.3 | 532343 | 2.4 | 542985 | 2.6 | 525140 | 2.7 | 589690 | 3.1 | 541079 | 2.5 |
| 800 | 2K | 1K | **529761** | 7.3 | 583766 | 2.4 | 584440 | 2.8 | 567677 | 2.5 | 585679 | 2.4 | 537294 | 3.0 | 665797 | 2.7 | 573074 | 2.5 |
| 800 | 5K | 500 | **654K** | 7.2 | **654K** | 2.3 | **654K** | 2.4 | **654K** | 2.0 | **654K** | 2.1 | **654K** | 2.0 | **654K** | 2.7 | **654K** | 2.5 |
| 800 | 5K | 750 | **683418** | 7.8 | 699397 | 1.8 | 700591 | 2.8 | 692493 | 2.8 | 700235 | 2.4 | 685640 | 2.6 | 746690 | 2.9 | 700829 | 2.9 |
| 800 | 5K | 1K | **693261** | 7.5 | 745266 | 2.1 | 745940 | 2.9 | 728843 | 2.7 | 745679 | 2.3 | 700044 | 2.5 | 823047 | 2.5 | 734074 | 2.5 |
| 1000 | 1K | 500 | **351120** | 9.5 | 361397 | 2.3 | 362091 | 2.8 | 356010 | 2.5 | 360735 | 2.6 | 352092 | 2.4 | 404496 | 3.1 | 361116 | 2.9 |
| 1000 | 1K | 750 | **360918** | 9.9 | 383397 | 2.0 | 385091 | 2.9 | 371843 | 2.6 | 383679 | 3.0 | 364640 | 2.3 | 432690 | 2.6 | 381329 | 2.4 |
| 1000 | 1K | 1K | **366261** | 10.6 | 422266 | 2.5 | 422940 | 2.8 | 406177 | 2.3 | 424410 | 2.7 | 374544 | 2.7 | 505087 | 2.3 | 412074 | 2.9 |
| 1000 | 2K | 500 | 510364 | 10.0 | 517654 | 2.4 | 518953 | 2.6 | 512820 | 2.8 | 516878 | 2.4 | **510259** | 3.2 | 552746 | 2.1 | 516135 | 2.6 |
| 1000 | 2K | 750 | **522168** | 9.1 | 541397 | 2.8 | 542841 | 3.3 | 532343 | 2.6 | 542985 | 3.0 | 525140 | 2.5 | 589690 | 2.7 | 541079 | 2.8 |
| 1000 | 2K | 1K | **529761** | 9.3 | 583766 | 2.4 | 584440 | 3.0 | 567677 | 2.6 | 585679 | 2.2 | 537294 | 2.8 | 665797 | 2.5 | 573074 | 3.2 |
| 1000 | 5K | 500 | **654K** | 9.8 | **654K** | 2.2 | **654K** | 2.5 | **654K** | 2.2 | **654K** | 2.5 | **654K** | 2.8 | **654K** | 3.1 | **654K** | 2.1 |
| 1000 | 5K | 750 | **683418** | 9.8 | 699397 | 2.2 | 700591 | 2.6 | 692493 | 2.6 | 700235 | 2.5 | 685640 | 3.2 | 746690 | 2.7 | 700829 | 3.0 |
| 1000 | 5K | 1K | **693261** | 9.3 | 745266 | 2.5 | 745940 | 3.0 | 728843 | 2.6 | 745679 | 2.3 | 700044 | 2.6 | 823047 | 2.1 | 734074 | 2.8 |

Table A.4: Agglomerative Clustering Results with Existing Dissimilarity Measures on 1060 (Variable Cost)

| | | | GeomDiff | | Average | | Centroid | | Complete | | Hausdorff | | Ward | | Single | | Minimax | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| DLim | F1 | F2 | Cost | Time | Cost | Time | Cost | Time | Cost | Time | Cost | Time | Cost | Time | Cost | Time | Cost | Time |
| 200 | 1K | 500 | 696895 | 5.0 | 685073 | 8.1 | 743013 | 4.2 | 662675 | 5.6 | 707478 | 4.8 | **658971** | 4.7 | 963800 | 2.0 | 709381 | 4.5 |
| 200 | 1K | 750 | 890895 | 5.2 | 820649 | 6.2 | 1066013 | 4.2 | **706732** | 5.1 | 932478 | 4.3 | 722971 | 4.9 | 1808800 | 2.0 | 927381 | 4.8 |
| 200 | 1K | 1K | 1472895 | 4.7 | 1225649 | 5.1 | 2035013 | 5.0 | **835732** | 4.8 | 1607478 | 4.7 | 914971 | 5.3 | 4343800 | 1.7 | 1581381 | 4.2 |
| 200 | 2K | 500 | 913395 | 4.5 | 914502 | 4.8 | 926876 | 3.9 | 903307 | 5.6 | 915948 | 4.5 | **901399** | 5.6 | 1017550 | 1.7 | 919881 | 4.8 |
| 200 | 2K | 750 | 1107395 | 4.8 | 1051899 | 4.8 | 1250263 | 3.8 | **960982** | 4.9 | 1141228 | 4.7 | 971971 | 4.9 | 1862550 | 1.6 | 1137881 | 5.0 |
| 200 | 2K | 1K | 1689395 | 5.1 | 1456899 | 4.9 | 2219263 | 4.8 | **1089982** | 4.9 | 1816228 | 4.4 | 1163971 | 5.1 | 4397550 | 1.8 | 1791881 | 3.9 |
| 200 | 5K | 500 | **1060K** | 3.8 | **1060K** | 4.0 | **1060K** | 2.8 | **1060K** | 4.0 | **1060K** | 3.4 | **1060K** | 4.2 | **1060K** | 1.2 | **1060K** | 3.8 |
| 200 | 5K | 750 | 1323895 | 4.6 | 1283149 | 4.7 | 1434513 | 4.4 | **1215175** | 5.1 | 1349978 | 4.3 | 1220971 | 4.6 | 1916300 | 1.6 | 1348381 | 5.3 |
| 200 | 5K | 1K | 1905895 | 5.2 | 1688149 | 5.6 | 2403513 | 3.9 | **1344232** | 5.5 | 2024978 | 4.7 | 1412971 | 5.3 | 4451300 | 1.4 | 2002381 | 4.1 |
| 400 | 1K | 500 | 663167 | 6.2 | 680258 | 6.1 | 686362 | 5.9 | 660840 | 6.8 | 681548 | 6.0 | **654016** | 6.8 | 765755 | 4.9 | 687327 | 6.6 |
| 400 | 1K | 750 | 690288 | 5.8 | 733869 | 6.9 | 739128 | 5.5 | 685808 | 5.3 | 730583 | 5.1 | **675898** | 5.4 | 1079755 | 5.3 | 735416 | 5.8 |
| 400 | 1K | 1K | 733049 | 6.4 | 792769 | 5.9 | 818878 | 6.5 | 728652 | 6.0 | 803367 | 6.4 | **717790** | 5.9 | 2021755 | 4.3 | 789212 | 6.3 |
| 400 | 2K | 500 | 909325 | 6.4 | 914472 | 5.8 | 919977 | 6.7 | 903211 | 5.9 | 914942 | 5.8 | **901296** | 6.3 | 949640 | 9.8 | 919252 | 5.6 |
| 400 | 2K | 750 | 951038 | 6.1 | 988158 | 6.6 | 995128 | 5.8 | 946558 | 5.5 | 988583 | 6.0 | **936898** | 5.6 | 1266255 | 6.1 | 989916 | 6.6 |
| 400 | 2K | 1K | 995549 | 6.3 | 1053019 | 5.8 | 1077628 | 5.4 | 990902 | 6.4 | 1062625 | 6.5 | **980370** | 5.7 | 2208255 | 5.6 | 1050092 | 5.4 |
| 400 | 5K | 500 | **1060K** | 4.6 | **1060K** | 4.8 | **1060K** | 4.9 | **1060K** | 4.7 | **1060K** | 4.4 | **1060K** | 4.9 | **1060K** | 4.9 | **1060K** | 4.7 |
| 400 | 5K | 750 | 1209763 | 6.3 | 1241908 | 5.7 | 1251128 | 6.1 | 1206196 | 6.4 | 1246230 | 5.6 | **1197825** | 5.7 | 1452755 | 4.6 | 1242777 | 6.1 |
| 400 | 5K | 1K | 1257674 | 6.0 | 1313269 | 5.7 | 1336378 | 5.8 | 1253152 | 5.9 | 1321625 | 5.7 | **1242370** | 5.5 | 2394755 | 5.2 | 1310592 | 5.4 |
| 600 | 1K | 500 | 663167 | 7.2 | 680258 | 5.4 | 686362 | 6.1 | 660840 | 6.5 | 681548 | 5.4 | **654016** | 6.0 | 766396 | 4.9 | 687327 | 6.0 |
| 600 | 1K | 750 | 689192 | 6.4 | 733790 | 5.7 | 739091 | 6.3 | 685806 | 6.3 | 730502 | 6.2 | **675898** | 6.8 | 1077017 | 4.5 | 734932 | 5.9 |
| 600 | 1K | 1K | 720277 | 7.0 | 787162 | 6.4 | 804188 | 5.9 | 728617 | 5.9 | 802880 | 6.1 | **717731** | 6.3 | 2007017 | 4.5 | 783254 | 5.7 |
| 600 | 2K | 500 | 909325 | 7.4 | 914472 | 5.7 | 919977 | 5.6 | 903211 | 6.1 | 914942 | 6.3 | **901296** | 6.8 | 950267 | 10.1 | 919252 | 5.8 |
| 600 | 2K | 750 | 950192 | 7.0 | 988158 | 5.0 | 995091 | 6.0 | 946556 | 6.7 | 988502 | 6.6 | **936898** | 6.0 | 1264517 | 4.8 | 989910 | 6.0 |
| 600 | 2K | 1K | 984027 | 7.1 | 1048162 | 5.6 | 1065188 | 5.9 | 990867 | 5.6 | 1062382 | 5.9 | **980369** | 6.5 | 2194517 | 5.4 | 1045004 | 6.0 |
| 600 | 5K | 500 | **1060K** | 4.9 | **1060K** | 4.5 | **1060K** | 5.0 | **1060K** | 4.1 | **1060K** | 4.8 | **1060K** | 5.0 | **1060K** | 4.4 | **1060K** | 4.4 |
| 600 | 5K | 750 | 1209763 | 7.2 | 1241908 | 6.5 | 1251091 | 5.9 | 1206196 | 5.7 | 1246155 | 5.7 | **1197825** | 6.7 | 1451896 | 5.2 | 1242777 | 5.8 |
| 600 | 5K | 1K | 1247777 | 6.6 | 1309162 | 5.9 | 1326188 | 6.4 | 1253117 | 5.9 | 1321382 | 6.6 | **1242369** | 5.9 | 2382017 | 4.9 | 1306754 | 5.6 |

| | | | GeomDiff | | Average | | Centroid | | Complete | | Hausdorff | | Ward | | Single | | Minimax | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| DLim | F1 | F2 | Cost | Time | Cost | Time | Cost | Time | Cost | Time | Cost | Time | Cost | Time | Cost | Time | Cost | Time |
| 800 | 1K | 500 | 663167 | 7.6 | 680258 | 6.3 | 686362 | 5.6 | 660840 | 6.1 | 681548 | 6.6 | **654016** | 6.9 | 767156 | 5.0 | 687327 | 6.3 |
| 800 | 1K | 750 | 689192 | 7.9 | 733790 | 5.2 | 739091 | 6.5 | 685806 | 5.9 | 730502 | 6.6 | **675898** | 7.3 | 1081431 | 5.3 | 734932 | 6.9 |
| 800 | 1K | 1K | 718245 | 7.0 | 787162 | 6.1 | 804188 | 6.5 | 728617 | 6.6 | 802880 | 6.3 | **717731** | 7.3 | 2023431 | 4.9 | 783254 | 7.5 |
| 800 | 2K | 500 | 909325 | 6.8 | 914472 | 5.8 | 919977 | 6.4 | 903211 | 5.4 | 914942 | 5.9 | **901296** | 6.6 | 950267 | 10.9 | 919252 | 6.4 |
| 800 | 2K | 750 | 950192 | 7.6 | 988158 | 6.6 | 995091 | 7.1 | 946556 | 5.7 | 988502 | 6.9 | **936898** | 6.5 | 1267931 | 5.6 | 989910 | 5.6 |
| 800 | 2K | 1K | 981995 | 7.2 | 1048162 | 5.5 | 1065188 | 6.1 | 990867 | 6.6 | 1062382 | 6.0 | **980369** | 6.7 | 2209931 | 5.8 | 1045004 | 6.4 |
| 800 | 5K | 500 | **1060K** | 6.9 | **1060K** | 4.4 | **1060K** | 5.0 | **1060K** | 5.6 | **1060K** | 5.0 | **1060K** | 4.1 | **1060K** | 3.9 | **1060K** | 5.4 |
| 800 | 5K | 750 | 1209763 | 6.8 | 1241908 | 6.3 | 1251091 | 7.1 | 1206196 | 6.9 | 1246155 | 5.9 | **1197825** | 7.4 | 1454431 | 5.1 | 1242777 | 6.7 |
| 800 | 5K | 1K | 1245745 | 7.9 | 1309162 | 5.9 | 1326188 | 6.9 | 1253117 | 6.1 | 1321382 | 6.2 | **1242369** | 6.2 | 2396431 | 5.0 | 1306754 | 6.7 |
| 1000 | 1K | 500 | 663167 | 8.1 | 680258 | 6.6 | 686362 | 6.7 | 660840 | 7.4 | 681548 | 6.5 | **654016** | 6.9 | 767156 | 5.3 | 687327 | 6.4 |
| 1000 | 1K | 750 | 689192 | 8.1 | 733790 | 6.5 | 739091 | 7.1 | 685806 | 6.5 | 730502 | 6.6 | **675898** | 6.2 | 1081431 | 4.9 | 734932 | 7.4 |
| 1000 | 1K | 1K | 718245 | 8.4 | 787162 | 5.6 | 804188 | 6.9 | 728617 | 5.9 | 802880 | 6.3 | **717731** | 6.9 | 2023431 | 5.1 | 783254 | 7.0 |
| 1000 | 2K | 500 | 909325 | 8.2 | 914472 | 6.0 | 919977 | 6.5 | 903211 | 6.2 | 914942 | 6.3 | **901296** | 6.1 | 950267 | 11.6 | 919252 | 6.4 |
| 1000 | 2K | 750 | 950192 | 8.5 | 988158 | 6.9 | 995091 | 6.9 | 946556 | 5.7 | 988502 | 7.2 | **936898** | 6.7 | 1267931 | 5.4 | 989910 | 6.9 |
| 1000 | 2K | 1K | 981995 | 9.0 | 1048162 | 6.9 | 1065188 | 6.8 | 990867 | 5.9 | 1062382 | 6.1 | **980369** | 7.3 | 2209931 | 5.1 | 1045004 | 6.6 |
| 1000 | 5K | 500 | **1060K** | 7.1 | **1060K** | 4.7 | **1060K** | 5.1 | **1060K** | 5.5 | **1060K** | 4.7 | **1060K** | 5.7 | **1060K** | 4.0 | **1060K** | 5.0 |
| 1000 | 5K | 750 | 1209763 | 9.6 | 1241908 | 6.5 | 1251091 | 7.1 | 1206196 | 6.1 | 1246155 | 6.8 | **1197825** | 7.4 | 1454431 | 4.8 | 1242777 | 6.7 |
| 1000 | 5K | 1K | 1245745 | 8.8 | 1309162 | 6.1 | 1326188 | 6.5 | 1253117 | 6.5 | 1321382 | 7.0 | **1242369** | 7.2 | 2396431 | 5.7 | 1306754 | 6.9 |

Table A.5: Agglomerative Clustering Results with Existing Dissimilarity Measures on 654 (Fixed and Variable Cost, $F1 = 1000$)

| | | | GeomDiff | | Average | | Centroid | | Complete | | Hausdorff | | Ward | | Single | | Minimax | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| DLim | F1 | F2 | Cost | Time | Cost | Time | Cost | Time | Cost | Time | Cost | Time | Cost | Time | Cost | Time | Cost | Time |
| 200 | 1K | 500 | 404864 | 6.1 | 406324 | 5.9 | 406397 | 3.5 | 405120 | 3.7 | 406788 | 4.5 | **402343** | 3.4 | 423745 | 3.9 | 402745 | 3.8 |
| 200 | 1K | 750 | 561341 | 3.5 | 560945 | 4.1 | 561068 | 1.8 | 562052 | 2.3 | 559673 | 1.9 | **559252** | 2.2 | 576689 | 2.0 | 559524 | 2.2 |
| 200 | 2K | 500 | 413474 | 4.0 | 422600 | 4.0 | 423973 | 2.7 | 414530 | 2.5 | 422105 | 2.9 | **411752** | 2.3 | 499496 | 2.8 | 413197 | 2.6 |
| 200 | 2K | 750 | 574974 | 3.2 | 582350 | 3.5 | 583473 | 3.2 | 575780 | 2.7 | 582105 | 3.1 | **573002** | 2.7 | 647746 | 2.8 | 574197 | 2.0 |
| 200 | 5K | 500 | **437474** | 4.2 | 452715 | 2.7 | 457007 | 2.8 | 441530 | 1.8 | 462606 | 2.6 | 438752 | 2.9 | 682496 | 2.5 | 443197 | 2.3 |
| 200 | 5K | 750 | **598974** | 3.8 | 613965 | 2.4 | 618007 | 2.7 | 602780 | 2.4 | 623356 | 2.7 | 600002 | 2.7 | 830746 | 2.4 | 604197 | 2.5 |
| 400 | 1K | 500 | **400147** | 4.7 | 405656 | 2.4 | 405728 | 2.4 | 404440 | 2.0 | 405567 | 2.8 | 401884 | 2.5 | 427939 | 2.2 | 402330 | 2.6 |
| 400 | 1K | 750 | **557906** | 4.6 | 560684 | 1.9 | 560770 | 2.7 | 561871 | 2.4 | 559544 | 2.5 | 559149 | 2.1 | 576251 | 2.2 | 559483 | 2.3 |
| 400 | 2K | 500 | **404389** | 5.5 | 422600 | 3.2 | 423973 | 2.5 | 412958 | 2.7 | 422105 | 2.8 | 406665 | 2.6 | 456191 | 3.9 | 413074 | 2.9 |
| 400 | 2K | 750 | **567139** | 5.8 | 582350 | 2.6 | 583473 | 2.4 | 574458 | 2.8 | 582105 | 3.0 | 569415 | 3.0 | 613441 | 2.7 | 574074 | 2.2 |
| 400 | 5K | 500 | **413389** | 4.8 | 448453 | 2.5 | 448286 | 2.8 | 436002 | 2.9 | 444563 | 2.5 | 414875 | 2.4 | 531191 | 2.9 | 443074 | 2.6 |
| 400 | 5K | 750 | **576139** | 5.1 | 609953 | 2.3 | 609786 | 3.5 | 598458 | 2.8 | 606813 | 2.7 | 578125 | 2.5 | 688441 | 2.6 | 604074 | 2.8 |
| 600 | 1K | 500 | **400960** | 7.2 | 405577 | 2.8 | 405650 | 3.0 | 404249 | 2.3 | 405567 | 2.4 | 401692 | 2.3 | 427826 | 2.2 | 402236 | 2.1 |
| 600 | 1K | 750 | 559218 | 6.7 | 560684 | 3.0 | 560770 | 2.3 | 561871 | 2.2 | 559544 | 2.0 | **559149** | 2.8 | 576251 | 2.5 | 559483 | 1.9 |
| 600 | 2K | 500 | **402508** | 7.0 | 422600 | 2.3 | 423973 | 2.7 | 412958 | 2.7 | 422105 | 2.6 | 406168 | 2.9 | 456186 | 2.4 | 413074 | 2.6 |
| 600 | 2K | 750 | **566008** | 6.8 | 582350 | 3.0 | 583473 | 2.6 | 574458 | 2.3 | 582105 | 2.7 | 569294 | 2.9 | 613436 | 2.8 | 574074 | 2.1 |
| 600 | 5K | 500 | **402508** | 6.8 | 448453 | 2.8 | 448286 | 2.4 | 435779 | 3.2 | 444410 | 2.5 | 406168 | 3.6 | 531186 | 3.3 | 443074 | 2.4 |
| 600 | 5K | 750 | **566008** | 6.9 | 609953 | 2.7 | 609786 | 2.6 | 598458 | 2.5 | 606660 | 3.1 | 569668 | 2.7 | 688436 | 2.4 | 604074 | 2.7 |
| 800 | 1K | 500 | **400593** | 7.8 | 405577 | 2.4 | 405650 | 2.8 | 404249 | 2.0 | 405567 | 2.6 | 401692 | 2.8 | 427826 | 2.8 | 402236 | 2.6 |
| 800 | 1K | 750 | **559102** | 7.9 | 560684 | 2.3 | 560770 | 3.2 | 561871 | 2.4 | 559544 | 2.4 | 559149 | 2.3 | 576251 | 2.5 | 559483 | 2.6 |
| 800 | 2K | 500 | **401591** | 8.6 | 422600 | 2.9 | 423973 | 2.6 | 412958 | 2.3 | 422105 | 2.7 | 405686 | 2.7 | 456186 | 3.0 | 413074 | 2.8 |
| 800 | 2K | 750 | **565091** | 8.3 | 582350 | 2.1 | 583473 | 2.9 | 574458 | 3.4 | 582105 | 3.1 | 569186 | 3.2 | 613436 | 2.8 | 574074 | 2.6 |
| 800 | 5K | 500 | **401591** | 8.3 | 448453 | 3.2 | 448286 | 3.0 | 435758 | 2.5 | 444410 | 2.6 | 405686 | 2.7 | 520087 | 2.3 | 443074 | 2.5 |
| 800 | 5K | 750 | **565091** | 8.3 | 609953 | 2.9 | 609786 | 2.9 | 598458 | 2.6 | 606660 | 2.6 | 569186 | 2.8 | 681587 | 2.9 | 604074 | 2.6 |
| 1000 | 1K | 500 | **400593** | 9.3 | 405577 | 2.8 | 405650 | 3.0 | 404249 | 2.6 | 405567 | 2.6 | 401692 | 2.5 | 427826 | 3.2 | 402236 | 2.7 |
| 1000 | 1K | 750 | **559102** | 9.3 | 560684 | 2.4 | 560770 | 2.3 | 561871 | 2.2 | 559544 | 2.8 | 559149 | 3.0 | 576251 | 2.5 | 559483 | 2.5 |
| 1000 | 2K | 500 | **401591** | 9.8 | 422600 | 2.8 | 423973 | 3.0 | 412958 | 2.5 | 422105 | 2.8 | 405686 | 2.4 | 456186 | 2.8 | 413074 | 3.3 |
| 1000 | 2K | 750 | **565091** | 9.4 | 582350 | 3.1 | 583473 | 2.9 | 574458 | 2.6 | 582105 | 2.9 | 569186 | 3.1 | 613436 | 3.1 | 574074 | 3.5 |
| 1000 | 5K | 500 | **401591** | 9.6 | 448453 | 3.1 | 448286 | 2.6 | 435758 | 3.1 | 444410 | 3.4 | 405686 | 3.2 | 520087 | 2.8 | 443074 | 3.1 |
| 1000 | 5K | 750 | **565091** | 9.8 | 609953 | 2.4 | 609786 | 3.2 | 598458 | 2.7 | 606660 | 2.9 | 569186 | 2.7 | 681587 | 2.7 | 604074 | 3.5 |

Table A.6: Agglomerative Clustering Results with Existing Dissimilarity Measures on 1060 (Fixed and Variable Cost, $F1 = 1000$)

| | | | GeomDiff | | Average | | Centroid | | Complete | | Hausdorff | | Ward | | Single | | Minimax | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| DLim | F1 | F2 | Cost | Time | Cost | Time | Cost | Time | Cost | Time | Cost | Time | Cost | Time | Cost | Time | Cost | Time |
| 200 | 1K | 500 | 965224 | 10.4 | 949427 | 10.6 | 978830 | **10.5** | **944687** | 8.2 | 973349 | 10.5 | 953978 | 9.2 | 1021491 | 2.8 | 959961 | 9.3 |
| 200 | 1K | **750** | **1060K** | **3.8** | **1060K** | **4.6** | **1060K** | **2.5** | **1060K** | **4.0** | **1060K** | **3.3** | **1060K** | **4.0** | **1060K** | **1.4** | **1060K** | 3.3 |
| 200 | 2K | 500 | 1177895 | 4.9 | 1104649 | 5.5 | 1325013 | **4.4** | **1011388** | 5.8 | 1227288 | 4.9 | 1041971 | 4.4 | 1882800 | 2.1 | 1194381 | 4.6 |
| 200 | 2K | 750 | 1394395 | 4.5 | 1335899 | 5.6 | 1509263 | **4.6** | **1265638** | 5.9 | 1436038 | 5.1 | 1290971 | 6.0 | 1936550 | 2.3 | 1404881 | 5.3 |
| 200 | 5K | 500 | 1759895 | 5.3 | 1509649 | 6.0 | 2294013 | **4.3** | **1140388** | 5.3 | 1902288 | 4.5 | 1233971 | 5.4 | 4417800 | 2.1 | 1848381 | 5.6 |
| 200 | 5K | 750 | 1976395 | 4.9 | 1740899 | 5.6 | 2478263 | **4.5** | **1394638** | 5.3 | 2111038 | 4.6 | 1482971 | 5.0 | 4471550 | 2.1 | 2058881 | 4.9 |
| 400 | 1K | 500 | 899434 | **5.0** | **897958** | 5.5 | 898904 | 5.3 | 901543 | 5.2 | 900132 | 5.3 | 899418 | 4.9 | 923092 | 8.6 | 899380 | 5.5 |
| 400 | 1K | **750** | **1060K** | **4.4** | **1060K** | **4.9** | **1060K** | **4.3** | **1060K** | **4.9** | **1060K** | **4.3** | **1060K** | **4.9** | **1060K** | **3.6** | **1060K** | 4.8 |
| 400 | 2K | 500 | 912984 | 6.1 | 923378 | 6.0 | 930878 | **6.5** | **911720** | 5.7 | 936025 | 6.2 | 913638 | 6.3 | 1284755 | 5.0 | 919077 | 6.3 |
| 400 | 2K | 750 | 1175484 | 6.6 | 1183628 | 6.2 | 1189628 | **6.8** | **1175220** | 5.8 | 1195525 | 6.4 | 1176888 | 5.8 | 1471255 | 4.6 | 1180327 | 6.7 |
| 400 | 5K | 500 | 942984 | 6.3 | 980378 | 6.1 | 1005878 | **6.7** | **929720** | 5.8 | 1002025 | 6.3 | 934638 | 6.0 | 2226755 | 4.9 | 964077 | 6.5 |
| 400 | 5K | 750 | 1205484 | 5.5 | 1240628 | 5.8 | 1264628 | **5.6** | **1193220** | 6.2 | 1261525 | 5.6 | 1197888 | 6.3 | 2413255 | 5.0 | 1225327 | 6.8 |
| 600 | 1K | **500** | **894106** | 6.1 | 896496 | 6.2 | 896138 | 5.6 | 898666 | 5.5 | 899670 | 5.6 | 895432 | 5.2 | 916835 | 7.5 | 900430 | 5.4 |
| 600 | 1K | **750** | **1060K** | **5.5** | **1060K** | **4.6** | **1060K** | **5.1** | **1060K** | **5.0** | **1060K** | **4.6** | **1060K** | **5.2** | **1060K** | **4.3** | **1060K** | 5.3 |
| 600 | 2K | **500** | **899007** | 6.1 | 914442 | 6.4 | 918188 | 6.2 | 908599 | 6.4 | 919024 | 6.4 | 902390 | 6.6 | 1278572 | 6.1 | 911316 | 5.9 |
| 600 | 2K | **750** | **1163257** | 6.5 | 1176442 | 6.4 | 1179188 | 6.9 | 1172295 | 5.8 | 1180640 | 6.7 | 1166640 | 6.3 | 1466072 | 5.3 | 1174066 | 6.4 |
| 600 | 5K | **500** | **908007** | 7.3 | 950442 | 6.4 | 960218 | 6.4 | 923599 | 7.4 | 958024 | 5.7 | 911390 | 7.1 | 2208572 | 4.1 | 932362 | 6.1 |
| 600 | 5K | **750** | **1172257** | 6.9 | 1212442 | 6.2 | 1221968 | 6.9 | 1187349 | 5.5 | 1219774 | 6.2 | 1175640 | 6.2 | 2396072 | 5.3 | 1195612 | 7.0 |
| 800 | 1K | **500** | **894831** | 6.6 | 896496 | 5.4 | 896138 | 6.1 | 898654 | 5.6 | 899648 | 5.5 | 895434 | 6.2 | 917756 | 8.6 | 900382 | 5.4 |
| 800 | 1K | **750** | **1060K** | **5.7** | **1060K** | **4.4** | **1060K** | **4.8** | **1060K** | **5.3** | **1060K** | **4.9** | **1060K** | **5.2** | **1060K** | **3.8** | **1060K** | 4.3 |
| 800 | 2K | **500** | **898088** | 8.0 | 914253 | 6.9 | 918188 | 7.3 | 908552 | 7.2 | 919002 | 6.5 | 901794 | 6.6 | 1285431 | 5.2 | 910899 | 6.4 |
| 800 | 2K | **750** | **1162338** | 6.7 | 1176253 | 6.4 | 1179188 | 6.9 | 1172284 | 6.3 | 1180619 | 7.2 | 1166044 | 6.8 | 1471931 | 5.0 | 1173999 | 7.3 |
| 800 | 5K | **500** | **907088** | 8.6 | 940861 | 6.4 | 946353 | 6.4 | 923552 | 6.6 | 958002 | 6.3 | 910794 | 7.2 | 2227431 | 4.7 | 930799 | 5.9 |
| 800 | 5K | **750** | **1171338** | 7.6 | 1203861 | 7.1 | 1209353 | 6.0 | 1187302 | 6.8 | 1219752 | 7.0 | 1175044 | 7.0 | 2413931 | 5.8 | 1194549 | 7.6 |
| 1000 | 1K | **500** | **894822** | 8.1 | 896496 | 5.4 | 896138 | 6.4 | 898654 | 6.2 | 899648 | 5.8 | 895434 | 5.2 | 917756 | 8.9 | 900382 | 5.2 |
| 1000 | 1K | **750** | **1060K** | **7.5** | **1060K** | **4.7** | **1060K** | **5.3** | **1060K** | **4.8** | **1060K** | **4.4** | **1060K** | **5.3** | **1060K** | **4.1** | **1060K** | 5.4 |
| 1000 | 2K | **500** | **898079** | 9.2 | 914253 | 6.5 | 918188 | 6.9 | 908552 | 7.0 | 919002 | 7.8 | 901794 | 6.8 | 1285431 | 5.6 | 910899 | 7.1 |
| 1000 | 2K | **750** | **1162329** | 9.1 | 1176253 | 6.8 | 1179188 | 7.2 | 1172284 | 7.1 | 1180619 | 7.8 | 1166044 | 6.6 | 1471931 | 5.1 | 1173999 | 5.9 |
| 1000 | 5K | **500** | **907079** | 8.3 | 940861 | 6.9 | 946353 | 7.0 | 923552 | 5.7 | 958002 | 7.9 | 910794 | 6.7 | 2226575 | 5.5 | 930799 | 6.4 |
| 1000 | 5K | **750** | **1171329** | 8.9 | 1203861 | 6.1 | 1209353 | 7.3 | 1187302 | 6.9 | 1219752 | 6.4 | 1175044 | 7.5 | 2413931 | 5.4 | 1194549 | 7.0 |

# Appendix B

# Effects of the New Augmentation Methodology

Table B.1: The PSCP Solutions for the Synthetic Data Set

| | DLim | $\mathcal{A}$ | SCP | Extended |
|---|---|---|---|---|
| 654 | 200 | 51550 | 36 | 129 |
| | 400 | 75174 | 17 | 156 |
| | 600 | 87623 | 13 | 70 |
| | 800 | 98508 | 9 | 383 |
| | 1000 | 127263 | 7 | 424 |
| 1060 | 200 | 8924 | 301 | 849 |
| | 400 | 23661 | 127 | 441 |
| | 600 | 46125 | 73 | 261 |
| | 800 | 76660 | 50 | 168 |
| | 1000 | 112153 | 35 | 128 |

In this section, we present the benefits of expanding the domain of DFLAP by using the new augmentation method, which is proposed in Section 4.1.2. Tables B.2 - B.4 summarize the results of the discrete counterpart of the planar location-allocation problem, where the candidate sets are formed by the locations obtained from the PSCP (DFLAP) and the augmented set of common intersection points with the PSCP optimal solution (DFLAP Ext.). We also provide the the PSCP results in Table B.1, where the first two columns denote the sample data and the distance threshold, respectively. The third column represents the cardinality of the PSCP domain, which is composed of the demand locations and the circle intersection points. The minimum number of facilities required to cover all demand nodes is given in the fourth column. The fifth column represents the augmented set of optimal PSCP locations and the other common intersection points covering the same demand nodes that have been already covered by the optimal solution. This column corresponds to the cardinality of the candidate sites that we obtained using the new augmentation methodology proposed for the extension of multi-stage heuristic approach.

For the synthetic data sets S654 and S1060, we demonstrate the second stage results of the multi-stage heuristic with different candidate sites, and report the cost improvements to observe the effect of inserting common intersection points to the domain of the problem. These improvements are reported for each problem type having distinct cost structures. The instances exceeding the three hours of CPU time limit are specified with the asterisk symbol (*).

Tables B.2 - B.4 indicate that the new augmentation methodology, which is denoted by DFLAP-Ext., can provide a better solution when the common intersection points are taken into consideration. The maximum improvements for S654 and S1060 are 2.15% and 1.27% , respectively, where both percentages are reported for the fixed cost formulation. For the variable cost and the mixed cost formulations, it is evident that the extended version perform as least as successful as the existing augmentation methodology when it solves to optimality. The improvement is observed to be less than 1% for almost all instances in S654 and S1060. However, there are some exceptional cases that DFLAP performs better than the extended version even with a restricted domain consisting of the optimal locations of the PSCP solution. These exceptional results are observed in the instances where DFLAP-Extended exceeds time limit of three hours. As the extended set of candidate sites include a larger number of potential facility locations, DFLAP-Ext. might fail to find an optimal solution within the time limit and perform poorer than the existing methodology.

Tables B.2 - B.4 demonstrate that the restriction on the micro-grid structures becomes insignificant as the distance limit threshold is increased. In other words, the model evaluates a higher number of possible micro-grid connections as the generation points are allowed to reach the distant households with respect to the lower coverage thresholds. Therefore, model-based heuristics require a longer run time as the computational complexity is worsened with the increasing number of available options for each household. Similarly, the cost parameters escalating the competition between two decentralized options can increase the CPU time dramatically. While the problem becomes more trivial under the cost parameters implying a certain advantage for micro-grid facilities, the significant differences between the costs of two facility types enforce the model to make a trade-off between several alternatives. Hence, this trade-off creates a computational burden and increases the solution time especially for the problems having a fixed cost component.

In general, both DFLAP and DFLAP-Extended exceed the given CPU time limit simultaneously. Only in 5% of the instances exceeding the three hours time limit DFLAP can find the optimal solution for S654 whereas DFLAP-Extended fails to converge to an optimal solution within the specified time limit. However, as the domain of the extended version contains significantly larger number of candidate locations, we expect that DFLAP-Ext. requires a relatively longer runtime to solve the problem. We also note that such cases are observed in densely populated areas more frequently compared to the dispersed settlements such as S1060.

The third-stage costs, relative optimality gaps and the running time of the model based heuristic approaches are given in Appendix C - E for S654 and S1060. Here, MB-I denote the the multi-stage heuristic that we discussed in Section 4.1.1, and MB-II represents the heuristic method that we implement the new augmentation methodology. MB-III, on the other hand, denotes the uni-cost multi-stage heuristic with post process. For S654, the extended version of the multi-stage heuristic (MB-II) outperforms the other model-based heuristic approaches in 21, 24 instances out of 45 solutions in the fixed and the variable cost formulations, respectively. Although there does not exist a specific method dominating the others in these problem types, approximately 77% of the least-cost solutions are provided by MB-II in the fixed and variable cost problem. The reasoning behind the almost equal performances of MB-I and MB-II in the fixed and the variable cost problems is that the solution time tend to exceed the predetermined time limit when densely populated areas are taken into consideration. Hence, in regard to the previous observations, we expect MB-I to perform effectively compared to MB-II on S654 especially for the fixed cost formulation, which is observed to be more compelling compared to the other formulations. We also note that MB-III can perform surprisingly effective when both MB-I and MB-II violate the specified time limit at the same time.

For S1060, the efficiency of the extended multi-stage heuristic ranges between 53% to 65%. While the maximum efficiency is reported in the variable cost formulation, this heuristic approach can provide the least-cost solution around 53% of the instances in the fixed and variable cost problem. Although it has been shown that the use of the extended candidate sites improves the second stage solutions unless the time limit is violated, we observe that the performance of MB-II slightly diminishes at the end of the third-stage of the heuristic method. This result can be associated with the fact that Cooper's iterative algorithm tend to converge to the local optima in a smaller number of iterations when it starts with an initial configuration having a better quality. Therefore, even if the time limit is not violated, MB-I can still work effectively as Cooper's iterative heuristic can make significant improvements on the optimal solution of the DFLAP.

Table B.2: DFLAP Results on the Synthetic Data (Fixed Cost)

| | | | | 654 | | | 1060 | |
|---|---|---|---|---|---|---|---|---|
| DistLim | F1 | F2 | DFLAP | DFLAP Ext. | %Cost Imp. | DFLAP | DFLAP Ext. | %Cost Imp. |
| 200 | 1000 | 500 | 74294 | 74155 | 0.19% | 406245 | 402296 | 0.97% |
| 200 | 1000 | 750 | 77234 | 77074 | 0.21% | 439809 | 434621 | 1.18% |
| 200 | 1000 | 1000 | 79484 | 79324 | 0.20% | 447966 | 442655 | 1.19% |
| 200 | 2000 | 500 | 101895* | 101755* | 0.14% | 497882 | 496513 | 0.27% |
| 200 | 2000 | 750 | 106433* | 106046* | 0.36% | 635474 | 631806 | 0.58% |
| 200 | 2000 | 1000 | 111608 | 111485 | 0.11% | 693314 | 688101 | 0.75% |
| 200 | 5000 | 500 | 157194* | 156739* | 0.29% | 522642 | 522579 | 0.01% |
| 200 | 5000 | 750 | 170803* | 170242* | 0.33% | 770461 | 770066 | 0.05% |
| 200 | 5000 | 1000 | 180075* | 180654* | **-0.32%** | 993382 | 992013 | 0.14% |
| 400 | 1000 | 500 | 72998 | 73826* | **-1.13%** | 361595 | 361413 | 0.05% |
| 400 | 1000 | 750 | 75217 | 75130 | 0.12% | 371164 | 370170 | 0.27% |
| 400 | 1000 | 1000 | 76491 | 76398 | 0.12% | 374008 | 372734 | 0.34% |
| 400 | 2000 | 500 | 99983* | 100447* | -0.46% | 463119 | 462793 | 0.07% |
| 400 | 2000 | 750 | 103482* | 104692* | **-1.17%** | 512316 | 510032 | 0.45% |
| 400 | 2000 | 1000 | 107669* | 105351* | 2.15% | 524906 | 521058 | 0.73% |
| 400 | 5000 | 500 | 146591* | 147475* | **-0.60%** | 517413 | 517413 | 0.00% |
| 400 | 5000 | 750 | 157077* | 156835* | 0.15% | 728314 | 727044 | 0.17% |
| 400 | 5000 | 1000 | 163730* | 163661* | 0.04% | 822320 | 818706 | 0.44% |
| 600 | 1000 | 500 | 72999* | 73540* | **-0.74%** | 359080 | 359087 | 0.00% |
| 600 | 1000 | 750 | 74682 | 74682 | 0.00% | 363265 | 363252 | 0.00% |
| 600 | 1000 | 1000 | 75131 | 75131 | 0.00% | 365056 | 365002 | 0.01% |
| 600 | 2000 | 500 | 100218* | 101068* | **-0.85%** | 458907 | 458854 | 0.01% |
| 600 | 2000 | 750 | 104084* | 103508* | 0.55% | 483052 | 482912 | 0.03% |
| 600 | 2000 | 1000 | 104271* | 105304* | -0.99% | 486249 | 486097 | 0.03% |
| 600 | 5000 | 500 | 147486* | 150657* | **-2.15%** | 517314 | 517314 | 0.00% |
| 600 | 5000 | 750 | 157293* | 155044* | 1.43% | 689553* | 690871* | **-0.19%** |
| 600 | 5000 | 1000 | 164088* | 162794* | 0.79% | 728017* | 738693* | **-1.47%** |
| 800 | 1000 | 500 | 73840* | 74035 * | **-0.26%** | 359079* | 359106* | **-0.01%** |
| 800 | 1000 | 750 | 74312 | 74292 | 0.03% | 362745 | 362745 | 0.00% |
| 800 | 1000 | 1000 | 74408 | 74389 | 0.03% | 363596 | 363596 | 0.00% |
| 800 | 2000 | 500 | 101325* | 101269* | 0.06% | 458907 | 458907 | 0.00% |
| 800 | 2000 | 750 | 103111* | 103935* | **-0.80%** | 480960* | 481055* | **-0.02%** |
| 800 | 2000 | 1000 | 103638* | 104749* | **-1.07%** | 482137 | 482133 | 0.00% |
| 800 | 5000 | 500 | 146857* | 150338* | **-2.37%** | 517314 | 517314 | 0.00% |
| 800 | 5000 | 750 | 154970* | 159332* | **-2.81%** | 695053* | 698208* | **-0.45%** |
| 800 | 5000 | 1000 | 157162* | 157717* | **-0.35%** | 718486* | 712078* | 0.89% |
| 1000 | 1000 | 500 | 72995* | 73834* | **-1.15%** | 359080 | 359077 | 0.00% |
| 1000 | 1000 | 750 | 74312 | 74312 | 0.00% | 362735 | 362753 | **-0.01%** |
| 1000 | 1000 | 1000 | 74408 | 74408 | 0.00% | 363596 | 363592 | 0.00% |
| 1000 | 2000 | 500 | 100890* | 100655* | 0.23% | 458907 | 458907 | 0.00% |
| 1000 | 2000 | 750 | 103320* | 103969* | **-0.63%** | 481239* | 481272* | **-0.01%** |
| 1000 | 2000 | 1000 | 103361* | 104746* | **-1.34%** | 481954 | 481957 | 0.00% |
| 1000 | 5000 | 500 | 147558* | 147125* | 0.29% | 517314* | 517314* | 0.00% |
| 1000 | 5000 | 750 | 157445* | 155917* | 0.97% | 691681* | 691717* | **-0.01%** |
| 1000 | 5000 | 1000 | 159967* | 161736* | **-1.11%** | 708678* | 711628* | **-0.42%** |

Table B.3: DFLAP Results on the Synthetic Data (Variable Cost)

| | | | | 654 | | | 1060 | |
|---|---|---|---|---|---|---|---|---|
| DLim | F3 | F2 | DFLAP | DFLAP Ext. | %Cost Imp. | DFLAP | DFLAP Ext. | %Cost Imp. |
| 200 | 500 | 1000 | 339631 | 339594 | 0.01% | 636251 | 633893 | 0.37% |
| 200 | 500 | 2000 | 347646 | 347610 | 0.01% | 649325 | 646923 | 0.37% |
| 200 | 500 | 5000 | 371646 | 371610 | 0.01% | 688325 | 685923 | 0.35% |
| 200 | 750 | 1000 | 500859 | 500823 | 0.01% | 893725 | 892214 | 0.17% |
| 200 | 750 | 2000 | 509146 | 509110 | 0.01% | 911075 | 908673 | 0.26% |
| 200 | 750 | 5000 | 533146 | 533110 | 0.01% | 950075 | 947673 | 0.25% |
| 200 | 1000 | 1000 | 654000 | 654000 | 0.00% | 1060000 | 1060000 | 0.00% |
| 200 | 1000 | 2000 | 670646 | 670610 | 0.01% | 1172825 | 1170423 | 0.20% |
| 200 | 1000 | 5000 | 694646 | 694610 | 0.01% | 1211825 | 1209423 | 0.20% |
| 400 | 500 | 1000 | 338641 | 338454 | 0.06% | 621298 | 621107 | 0.03% |
| 400 | 500 | 2000 | 338976 | 338602 | 0.11% | 624677 | 624414 | 0.04% |
| 400 | 500 | 5000 | 338976 | 338602 | 0.11% | 633677 | 633414 | 0.04% |
| 400 | 750 | 1000 | 500541 | 500541 | 0.00% | 883253 | 883253 | 0.00% |
| 400 | 750 | 2000 | 502476 | 502102 | 0.07% | 888927 | 888664 | 0.03% |
| 400 | 750 | 5000 | 502476 | 502102 | 0.07% | 897927 | 897664 | 0.03% |
| 400 | 1000 | 1000 | 654000 | 654000 | 0.00% | 1060000 | 1060000 | 0.00% |
| 400 | 1000 | 2000 | 665976 | 665602 | 0.06% | 1153177 | 1152914 | 0.02% |
| 400 | 1000 | 5000 | 665976 | 665602 | 0.06% | 1162177 | 1161914 | 0.02% |
| 600 | 500 | 1000 | 338094 | 338094 | 0.00% | 620549 | 620545 | 0.00% |
| 600 | 500 | 2000 | 338215 | 338215 | 0.00% | 622992 | 622986 | 0.00% |
| 600 | 500 | 5000 | 338215 | 338215 | 0.00% | 628992 | 628986 | 0.00% |
| 600 | 750 | 1000 | 500541 | 500541 | 0.00% | 883253 | 883253 | 0.00% |
| 600 | 750 | 2000 | 501715 | 501715 | 0.00% | 887492 | 887486 | 0.00% |
| 600 | 750 | 5000 | 501715 | 501715 | 0.00% | 893492 | 893486 | 0.00% |
| 600 | 1000 | 1000 | 654000 | 654000 | 0.00% | 1060000 | 1060000 | 0.00% |
| 600 | 1000 | 2000 | 665215 | 665215 | 0.00% | 1151992 | 1151986 | 0.00% |
| 600 | 1000 | 5000 | 665215 | 665215 | 0.00% | 1157992 | 1157986 | 0.00% |
| 800 | 500 | 1000 | 338094 | 338094 | 0.00% | 620524 | 620521 | 0.00% |
| 800 | 500 | 2000 | 338215 | 338215 | 0.00% | 623121 | 623080 | 0.01% |
| 800 | 500 | 5000 | 338215 | 338215 | 0.00% | 629121 | 629080 | 0.01% |
| 800 | 750 | 1000 | 500541 | 500541 | 0.00% | 883253 | 883253 | 0.00% |
| 800 | 750 | 2000 | 501715 | 501715 | 0.00% | 887621 | 887580 | 0.00% |
| 800 | 750 | 5000 | 501715 | 501715 | 0.00% | 893621 | 893580 | 0.00% |
| 800 | 1000 | 1000 | 654000 | 654000 | 0.00% | 1060000 | 1060000 | 0.00% |
| 800 | 1000 | 2000 | 665215 | 665215 | 0.00% | 1152053 | 1152053 | 0.00% |
| 800 | 1000 | 5000 | 665215 | 665215 | 0.00% | 1158121 | 1158080 | 0.00% |
| 1000 | 500 | 1000 | 338024 | 338024 | 0.00% | 620460 | 620460 | 0.00% |
| 1000 | 500 | 2000 | 338082 | 338082 | 0.00% | 622460 | 622460 | 0.00% |
| 1000 | 500 | 5000 | 338082 | 338082 | 0.00% | 622776 | 622747 | 0.00% |
| 1000 | 750 | 1000 | 500541 | 500541 | 0.00% | 883253 | 883253 | 0.00% |
| 1000 | 750 | 2000 | 501582 | 501582 | 0.00% | 886960 | 886960 | 0.00% |
| 1000 | 750 | 5000 | 501582 | 501582 | 0.00% | 887776 | 887747 | 0.00% |
| 1000 | 1000 | 1000 | 654000 | 654000 | 0.00% | 1060000 | 1060000 | 0.00% |
| 1000 | 1000 | 2000 | 665082 | 665082 | 0.00% | 1151460 | 1151460 | 0.00% |
| 1000 | 1000 | 5000 | 665082 | 665082 | 0.00% | 1152776 | 1152747 | 0.00% |

Table B.4: DFLAP Results on the Synthetic Data (Fixed and Variable Cost)

| | | | | | 654 | | | 1060 | |
|---|---|---|---|---|---|---|---|---|---|
| DistLim | F1 | F2 | F3 | DFLAP | DFLAP Ext. | %Cost Imp. | DFLAP | DFLAP Ext. | %Cost Imp. |
| 200 | 1000 | 1000 | 500 | 401294 | 401155 | 0.03% | 936245 | 932296 | 0.42% |
| 200 | 1000 | 1000 | 750 | 557842* | 558690* | **-0.15%** | 1054142 | 1053927 | 0.02% |
| 200 | 1000 | 2000 | 500 | 406484 | 406324 | 0.04% | 977966 | 972655 | 0.54% |
| 200 | 1000 | 2000 | 750 | 569984 | 569824 | 0.03% | 1242966 | 1237655 | 0.43% |
| 200 | 1000 | 5000 | 500 | 406484 | 406324 | 0.04% | 977966 | 972655 | 0.54% |
| 200 | 1000 | 5000 | 750 | 569984 | 569824 | 0.03% | 1242966 | 1237655 | 0.43% |
| 400 | 1000 | 1000 | 500 | 399998 | 400826* | **-0.21%** | 891595 | 891413 | 0.02% |
| 400 | 1000 | 1000 | 750 | 558612* | 558930* | **-0.06%** | 1053937 | 1053937 | 0.00% |
| 400 | 1000 | 2000 | 500 | 403491 | 403398 | 0.02% | 904008 | 902734 | 0.14% |
| 400 | 1000 | 2000 | 750 | 566991 | 566898 | 0.02% | 1169008 | 1167734 | 0.11% |
| 400 | 1000 | 5000 | 500 | 403491 | 403398 | 0.02% | 904008 | 902734 | 0.14% |
| 400 | 1000 | 5000 | 750 | 566991 | 566898 | 0.02% | 1169008 | 1167734 | 0.11% |
| 600 | 1000 | 1000 | 500 | 399999* | 400540* | **-0.14%** | 889080 | 889087 | 0.00% |
| 600 | 1000 | 1000 | 750 | 558902* | 560060* | **-0.21%** | 1053937 | 1053937 | 0.00% |
| 600 | 1000 | 2000 | 500 | 402131 | 402131 | 0.00% | 895056 | 895002 | 0.01% |
| 600 | 1000 | 2000 | 750 | 565631 | 565631 | 0.00% | 1160056 | 1160002 | 0.00% |
| 600 | 1000 | 5000 | 500 | 402131 | 402131 | 0.00% | 895056 | 895002 | 0.01% |
| 600 | 1000 | 5000 | 750 | 565631 | 565631 | 0.00% | 1160056 | 1160002 | 0.00% |
| 800 | 1000 | 1000 | 500 | 400840* | 400773* | 0.02% | 889079 | 889106 | 0.00% |
| 800 | 1000 | 1000 | 750 | 559473* | 559517* | **-0.01%** | 1053937 | 1053937 | 0.00% |
| 800 | 1000 | 2000 | 500 | 401408 | 401389 | 0.00% | 893596 | 893596 | 0.00% |
| 800 | 1000 | 2000 | 750 | 564908 | 564889 | 0.00% | 1158596 | 1158596 | 0.00% |
| 800 | 1000 | 5000 | 500 | 401408 | 401389 | 0.00% | 893596 | 893596 | 0.00% |
| 800 | 1000 | 5000 | 750 | 564908 | 564889 | 0.00% | 1158596 | 1158596 | 0.00% |
| 1000 | 1000 | 1000 | 500 | 399995* | 400834 * | **-0.21%** | 889080 | 889077 | 0.00% |
| 1000 | 1000 | 1000 | 750 | 559623* | 560197* | **-0.10%** | 1053937 | 1053937 | 0.00% |
| 1000 | 1000 | 2000 | 500 | 401408 | 401408 | 0.00% | 893596 | 893592 | 0.00% |
| 1000 | 1000 | 2000 | 750 | 564908 | 564908 | 0.00% | 1158596 | 1158592 | 0.00% |
| 1000 | 1000 | 5000 | 500 | 401408 | 401408 | 0.00% | 893596 | 893592 | 0.00% |
| 1000 | 1000 | 5000 | 750 | 564908 | 564908 | 0.00% | 1158596 | 1158592 | 0.00% |

# Appendix C

# Computational Results of the Fixed Cost Problem on the Synthetic Data

Table C.1: Results of the Model-based Heuristics on S654 (Fixed Cost)

| | | | | MB-I | | | | | MB-II | | | | | Unicost Post Process (MB-III) | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | Cost | Time | Gap | M | N | Cost | Time | Gap | M | N | Cost | Time | M | N | |
| | 200 | 1000 | 500 | 73815 | 6336.0 | 0 | 29 | 23 | **73766** | 5674.4 | 0 | 29 | 23 | 74161 | 87.8 | 35 | 9 | MB-II |
| | 200 | 1000 | 750 | 76411 | 171.6 | 0 | 35 | 9 | **76362** | 2633.8 | 0 | 35 | 9 | 76411 | 85.6 | 35 | 9 | MB-II |
| | 200 | 1000 | 1000 | **78661** | 96.3 | 0 | 35 | 9 | **78612** | 125.3 | 0 | 35 | 9 | 78661 | 84.5 | 35 | 9 | MB-II |
| | 200 | 2000 | 500 | 101032 | 10843.2 | 6.03 | 26 | 32 | 101135 | 10885.5 | 5.61 | 26 | 32 | 106912 | 92.5 | 31 | 9 | MB-I |
| | 200 | 2000 | 750 | 105763 | 10841.6 | 0.97 | 24 | 24 | **105724** | 10884.4 | 0.37 | 24 | 24 | 109162 | 95.3 | 31 | 9 | MB-II |
| | 200 | 2000 | 1000 | **111002** | 7519.6 | 0 | 26 | 19 | **111002** | 5367.8 | 0 | 26 | 19 | 111412 | 95.0 | 31 | 9 | MB-I, MB-II |
| | 200 | 5000 | 500 | **155233** | 10864.1 | 11.29 | 15 | 76 | 155551 | 10899.8 | 11.65 | 15 | 62 | 197068 | 77.8 | 27 | 9 | MB-I |
| | 200 | 5000 | 750 | 169361 | 10841.7 | 8.91 | 20 | 40 | **168694** | 10884.7 | 8.16 | 19 | 40 | 199318 | 79.3 | 27 | 9 | MB-II |
| | 200 | 5000 | 1000 | 178694 | 10842.5 | 6.09 | 19 | 40 | **177653** | 10885.3 | 6.51 | 17 | 41 | 201568 | 79.1 | 27 | 9 | MB-II |
| | 400 | 1000 | 500 | **72621** | 7581.5 | 0 | 29 | 15 | 73419 | 10886.5 | 2.59 | 32 | 15 | 73792 | 36.4 | 33 | 3 | MB-I |
| | 400 | 1000 | 750 | 74552 | 210.0 | 0 | 32 | 6 | 74552 | 340.6 | 0 | 32 | 6 | 74542 | 37.1 | 33 | 3 | MB-III |
| | 400 | 1000 | 1000 | **75292** | 53.8 | 0 | 33 | 3 | **75292** | 115.8 | 0 | 33 | 3 | **75292** | 36.8 | 33 | 3 | All |
| | 400 | 2000 | 500 | **99402** | 10845.9 | 6.24 | 24 | 24 | 99939 | 10884.8 | 7.82 | 25 | 24 | 103835 | 36.4 | 27 | 3 | MB-I |
| | 400 | 2000 | 750 | **101965** | 10845.5 | 1.9 | 23 | 14 | 104137 | 10887.1 | 4.76 | 27 | 14 | 104585 | 36.8 | 27 | 3 | MB-I |
| | 400 | 2000 | 1000 | 106814 | 10845.8 | 3.48 | 29 | 7 | **104627** | 10888.5 | 0.83 | 25 | 7 | 105335 | 36.5 | 27 | 3 | MB-II |
| | 400 | 5000 | 500 | 144721 | 10848.6 | 15.21 | 14 | 41 | **144688** | 10886.2 | 16.52 | 14 | 41 | 171320 | 82.9 | 18 | 3 | MB-II |
| | 400 | 5000 | 750 | **154529** | 10846.5 | 12.59 | 15 | 27 | 154582 | 10887.4 | 13.21 | 15 | 27 | 172070 | 84.7 | 18 | 3 | MB-I |
| | 400 | 5000 | 1000 | 160788 | 10845.6 | 8.1 | 16 | 24 | **160755** | 10884.8 | 9.04 | 16 | 24 | 172820 | 83.6 | 18 | 3 | MB-II |
| | 600 | 1000 | 500 | **72552** | 10852.1 | 0.63 | 29 | 14 | 72649 | 10881.5 | 1.73 | 29 | 15 | 74186 | 49.8 | 32 | 1 | MB-I |
| | 600 | 1000 | 750 | 74260 | 224.2 | 0 | 31 | 6 | **74260** | 219.6 | 0 | 31 | 6 | 74436 | 48.8 | 32 | 1 | MB-I, MB-II |
| | 600 | 1000 | 1000 | 74687 | 68.8 | 0 | 32 | 1 | **74686** | 94.7 | 0 | 32 | 1 | **74686** | 49.7 | 32 | 1 | MB-II, MB-III |
| | 600 | 2000 | 500 | **98756** | 10852.9 | 7.29 | 23 | 27 | 99768 | 10881.0 | 7.9 | 25 | 27 | 103794 | 71.2 | 27 | 0 | MB-I |
| 654 | 600 | 2000 | 750 | 103181 | 10853.0 | 3.92 | 26 | 12 | **102070** | 10879.7 | 4.27 | 24 | 12 | 103794 | 72.1 | 27 | 0 | MB-II |
| | 600 | 2000 | 1000 | **103144** | 10853.0 | 1.27 | 25 | 4 | 104051 | 10880.8 | 3.28 | 27 | 3 | 103794 | 72.6 | 27 | 0 | MB-I |
| | 600 | 5000 | 500 | **144130** | 10853.3 | 18.48 | 13 | 38 | 146997 | 10881.9 | 22.14 | 15 | 39 | 169336 | 104.7 | 19 | 0 | MB-I |
| | 600 | 5000 | 750 | 155360 | 10854.0 | 13.87 | 15 | 33 | **153249** | 10880.8 | 18.01 | 13 | 31 | 169336 | 102.7 | 19 | 0 | MB-II |
| | 600 | 5000 | 1000 | **158026** | 10855.4 | 13.48 | 15 | 21 | 160738 | 10880.5 | 15.56 | 15 | 19 | 169336 | 104.2 | 19 | 0 | MB-I |
| | 800 | 1000 | 500 | 73445 | 10875.6 | 2.34 | 32 | 15 | **73149** | 10917.1 | 2.29 | 31 | 15 | 73968 | 67.2 | 32 | 0 | MB-II |
| | 800 | 1000 | 750 | **73871** | 534.1 | 0 | 31 | 2 | **73871** | 6128.8 | 0 | 31 | 2 | 73968 | 65.6 | 32 | 0 | MB-I, MB-II |
| | 800 | 1000 | 1000 | **73968** | 88.8 | 0 | 32 | 0 | **73968** | 141.9 | 0 | 32 | 0 | **73968** | 65.8 | 32 | 0 | All |
| | 800 | 2000 | 500 | **99872** | 10875.1 | 8.83 | 25 | 27 | 100284 | 10920.0 | 11.97 | 26 | 27 | 102660 | 81.7 | 25 | 0 | MB-I |
| | 800 | 2000 | 750 | 102322 | 10875.4 | 2.75 | 25 | 8 | **102302** | 10918.1 | 8.23 | 25 | 7 | 102660 | 80.6 | 25 | 0 | MB-II |
| | 800 | 2000 | 1000 | 103102 | 10875.1 | 2.05 | 26 | 2 | 104201 | 10918.3 | 6.32 | 28 | 2 | **102660** | 81.6 | 25 | 0 | MB-III |

| | | | | MB-I | | | | | MB-II | | | | | Unicost Post Process (MB-III) | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | Cost | Time | Gap | M | N | Cost | Time | Gap | M | N | Cost | Time | M | N | |
| | 800 | 5000 | 500 | **143849** | 10875.3 | 19.68 | 12 | 40 | 146370 | 10919.6 | 25.55 | 15 | 40 | 161454 | 125.9 | 14 | 0 | MB-I |
| | 800 | 5000 | 750 | **151799** | 10872.7 | 18.7 | 12 | 29 | 153644 | 10918.9 | 22.92 | 14 | 31 | 161454 | 127.4 | 14 | 0 | MB-I |
| | 800 | 5000 | 1000 | **155425** | 10872.0 | 13.98 | 14 | 13 | 155876 | 10917.3 | 16.14 | 12 | 14 | 161454 | 141.9 | 14 | 0 | MB-I |
| | 1000 | 1000 | 500 | **72622** | 10893.9 | 0.63 | 29 | 15 | 72944 | 10943.0 | 1.84 | 30 | 15 | 73968 | 88.4 | 32 | 0 | MB-I |
| | 1000 | 1000 | 750 | **73871** | 366.0 | 0 | 31 | 2 | 73884 | 647.5 | 0 | 31 | 2 | 73968 | 89.1 | 32 | 0 | MB-I |
| | 1000 | 1000 | 1000 | **73981** | 109.9 | 0 | 32 | 0 | 73981 | 167.2 | 0 | 32 | 0 | **73968** | 87.6 | 32 | 0 | MB-III |
| | 1000 | 2000 | 500 | 99245 | 10897.6 | 8.28 | 24 | 27 | **99244** | 10944.0 | 10.88 | 24 | 27 | 102257 | 88.1 | 24 | 0 | MB-II |
| | 1000 | 2000 | 750 | 102306 | 10892.8 | 6.37 | 25 | 6 | 103426 | 10944.6 | 6 | 27 | 7 | **102257** | 88.2 | 24 | 0 | MB-III |
| | 1000 | 2000 | 1000 | 102537 | 10894.5 | 1.92 | 25 | 1 | 104196 | 10941.6 | 3.82 | 28 | 1 | **102257** | 87.5 | 24 | 0 | MB-III |
| | 1000 | 5000 | 500 | **144909** | 10897.3 | 21.77 | 14 | 42 | 145172 | 10943.6 | 28.26 | 14 | 40 | 155456 | 89.8 | 13 | 0 | MB-I |
| | 1000 | 5000 | 750 | 153657 | 10893.8 | 18.83 | 15 | 27 | **153211** | 10945.0 | 21.24 | 15 | 20 | 155456 | 90.3 | 13 | 0 | MB-II |
| | 1000 | 5000 | 1000 | **154698** | 10892.9 | 16.62 | 14 | 2 | 155775 | 10944.4 | 18.85 | 15 | 11 | 155456 | 90.1 | 13 | 0 | MB-I |

Table C.2: Results of the Clustering-based Heuristics on S654 (Fixed Cost)

| | | | | Agglomerative (Agg) | | | | | DBSCAN - KMeans (DB-KM) | | | | DBSCAN - Agglomerative (DB-Agg) | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | Cost | Type | Time | M | N | Cost | Time | M | N | Cost | Type | Time | M | N | |
| | 200 | 1000 | 500 | 75343 | Ward | 2.7 | 34 | 19 | 76698 | 3.9 | 26 | 23 | **74313** | Comp. | 1.9 | 29 | 23 | DB-Agg. |
| | 200 | 1000 | 750 | **78002** | Ward | 2.7 | 39 | 9 | 79982 | 3.0 | 31 | 13 | 78407 | GeomDiff | 3.0 | 35 | 13 | Agg. |
| | 200 | 1000 | 1000 | **80252** | Ward | 2.3 | 39 | 9 | 83295 | 3.4 | 30 | 13 | 81657 | GeomDiff | 2.8 | 35 | 13 | Agg. |
| | 200 | 2000 | 500 | 102395 | Comp. | 2.8 | 23 | 30 | **101416** | 3.5 | 24 | 30 | 102346 | Ward | 1.0 | 27 | 30 | DB-KM |
| | 200 | 2000 | 750 | 108787 | Comp. | 2.5 | 25 | 22 | **107293** | 3.0 | 25 | 23 | 109171 | GeomDiff | 3.1 | 26 | 23 | DB-KM |
| | 200 | 2000 | 1000 | 113620 | Comp. | 2.0 | 26 | 19 | **113043** | 3.8 | 25 | 23 | 114921 | GeomDiff | 2.6 | 26 | 23 | DB-KM |
| | 200 | 5000 | 500 | 162611 | Comp. | 2.4 | 19 | 57 | 160801 | 3.5 | 17 | 83 | **158717** | Ward | 1.4 | 18 | 81 | DB-Agg. |
| | 200 | 5000 | 750 | 175768 | Comp. | 1.9 | 20 | 48 | 172175 | 3.6 | 20 | 45 | **169658** | Ward | 1.6 | 25 | 39 | DB-Agg. |
| | 200 | 5000 | 1000 | 185935 | Comp. | 1.8 | 22 | 35 | 188174 | 3.9 | 23 | 35 | **179408** | Ward | 1.4 | 25 | 39 | DB-Agg. |
| | 400 | 1000 | 500 | **73147** | GeomDiff | 4.4 | 29 | 14 | 96210 | 0.6 | 15 | 14 | 73670 | GeomDiff | 5.7 | 28 | 14 | Agg. |
| | 400 | 1000 | 750 | **75042** | GeomDiff | 5.0 | 32 | 5 | 98983 | 0.7 | 18 | 8 | 75838 | GeomDiff | 5.3 | 31 | 8 | Agg. |
| | 400 | 1000 | 1000 | **75889** | GeomDiff | 5.4 | 33 | 3 | 100694 | 0.8 | 18 | 8 | 77838 | GeomDiff | 5.0 | 31 | 8 | Agg. |
| | 400 | 2000 | 500 | **99127** | GeomDiff | 3.9 | 21 | 24 | 110407 | 0.6 | 13 | 24 | **99127** | GeomDiff | 6.2 | 21 | 24 | Agg., DB-Agg. |
| | 400 | 2000 | 750 | **103430** | GeomDiff | 4.7 | 23 | 14 | 114710 | 0.6 | 15 | 14 | **103430** | GeomDiff | 4.8 | 23 | 14 | Agg., DB-Agg. |
| | 400 | 2000 | 1000 | **105951** | GeomDiff | 4.5 | 25 | 7 | 118527 | 0.8 | 15 | 14 | 106930 | GeomDiff | 4.8 | 23 | 14 | Agg. |
| | 400 | 5000 | 500 | **144243** | Comp. | 1.7 | 10 | 44 | 146696 | 0.6 | 12 | 35 | 144650 | GeomDiff | 5.5 | 11 | 35 | Agg. |
| | 400 | 5000 | 750 | 154170 | Comp. | 2.3 | 12 | 22 | 155405 | 0.7 | 13 | 24 | **153361** | GeomDiff | 4.8 | 12 | 24 | DB-Agg. |
| | 400 | 5000 | 1000 | 159670 | Comp. | 1.8 | 12 | 22 | 161405 | 0.9 | 13 | 24 | **159361** | GeomDiff | 5.2 | 12 | 24 | DB-Agg. |
| | 600 | 1000 | 500 | **73960** | GeomDiff | 6.6 | 29 | 12 | 144559 | 1.1 | 12 | 9 | 100651 | GeomDiff | 7.3 | 25 | 12 | Agg. |
| | 600 | 1000 | 750 | **75132** | GeomDiff | 6.8 | 32 | 3 | 147504 | 1.1 | 14 | 2 | 101824 | GeomDiff | 7.3 | 28 | 3 | Agg. |
| | 600 | 1000 | 1000 | **75479** | GeomDiff | 6.9 | 33 | 1 | 147611 | 1.1 | 15 | 0 | 102170 | GeomDiff | 8.1 | 29 | 1 | Agg. |
| | 600 | 2000 | 500 | **100537** | GeomDiff | 6.0 | 21 | 19 | 156554 | 1.2 | 10 | 22 | 123987 | Ward | 1.8 | 17 | 33 | Agg. |
| 654 | 600 | 2000 | 750 | **103590** | GeomDiff | 6.1 | 23 | 9 | 159573 | 1.4 | 13 | 6 | 127180 | GeomDiff | 8.4 | 20 | 9 | Agg. |
| | 600 | 2000 | 1000 | **104639** | GeomDiff | 6.5 | 25 | 2 | 160051 | 1.4 | 14 | 2 | 128229 | GeomDiff | 7.8 | 22 | 2 | Agg. |
| | 600 | 5000 | 500 | **142975** | Comp. | 1.8 | 10 | 33 | 183427 | 1.3 | 8 | 46 | 161645 | Ward | 1.8 | 12 | 34 | Agg. |
| | 600 | 5000 | 750 | **151003** | Comp. | 2.5 | 11 | 21 | 195086 | 1.1 | 10 | 25 | 169743 | Ward | 1.7 | 13 | 29 | Agg. |
| | 600 | 5000 | 1000 | **156253** | Comp. | 2.2 | 11 | 21 | 195462 | 1.3 | 10 | 19 | 174923 | Ward | 1.2 | 14 | 18 | Agg. |
| | 800 | 1000 | 500 | **73593** | GeomDiff | 8.1 | 29 | 11 | 215221 | 2.6 | 8 | 101 | 147249 | GeomDiff | 7.2 | 21 | 11 | Agg. |
| | 800 | 1000 | 750 | **74495** | GeomDiff | 7.8 | 32 | 2 | 214508 | 2.0 | 10 | 2 | 148150 | GeomDiff | 7.5 | 24 | 2 | Agg. |
| | 800 | 1000 | 1000 | **74591** | GeomDiff | 7.6 | 33 | 0 | 214605 | 2.5 | 11 | 0 | 148247 | GeomDiff | 6.9 | 25 | 0 | Agg. |
| | 800 | 2000 | 500 | **99648** | GeomDiff | 7.9 | 21 | 19 | 217176 | 2.0 | 8 | 96 | 166397 | GeomDiff | 6.9 | 15 | 19 | Agg. |
| | 800 | 2000 | 750 | **102688** | GeomDiff | 7.5 | 23 | 7 | 234207 | 2.9 | 11 | 2 | 169437 | GeomDiff | 6.8 | 17 | 7 | Agg. |
| | 800 | 2000 | 1000 | **103729** | GeomDiff | 8.0 | 25 | 2 | 289839 | 1.9 | 9 | 2 | 170478 | GeomDiff | 7.5 | 19 | 2 | Agg. |

| | | | | Agglomerative (Agg) | | | | | DBSCAN - KMeans (DB-KM) | | | | DBSCAN - Agglomerative (DB-Agg) | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | Cost | Type | Time | M | N | Cost | Time | M | N | Cost | Type | Time | M | N | |
| | 800 | 5000 | 500 | **145183** | Comp. | 2.1 | 10 | 30 | 235735 | 2.6 | 6 | 251 | 198371 | Ward | 1.2 | 7 | 165 | Agg. |
| | 800 | 5000 | 750 | **152350** | GeomDiff | 7.3 | 12 | 14 | 268921 | 2.4 | 7 | 24 | 206406 | Ward | 1.6 | 9 | 14 | Agg. |
| | 800 | 5000 | 1000 | **155461** | Comp. | 2.3 | 11 | 12 | 254991 | 2.5 | 9 | 10 | 209792 | Ward | 1.7 | 10 | 4 | Agg. |
| | 1000 | 1000 | 500 | **73593** | GeomDiff | 9.7 | 29 | 11 | 198045 | 2.4 | 7 | 20 | 93956 | GeomDiff | 14.6 | 25 | 11 | Agg. |
| | 1000 | 1000 | 750 | **74495** | GeomDiff | 9.5 | 32 | 2 | 202080 | 2.6 | 9 | 0 | 94857 | GeomDiff | 12.4 | 28 | 2 | Agg. |
| | 1000 | 1000 | 1000 | **74591** | GeomDiff | 9.6 | 33 | 0 | 202080 | 2.2 | 9 | 0 | 94954 | GeomDiff | 12.3 | 29 | 0 | Agg. |
| | 1000 | 2000 | 500 | **100843** | Comp. | 2.1 | 22 | 28 | 205045 | 2.3 | 7 | 20 | 117710 | Ward | 2.8 | 18 | 19 | Agg. |
| | 1000 | 2000 | 750 | **103564** | GeomDiff | 9.4 | 23 | 3 | 210045 | 2.8 | 7 | 20 | 120752 | Ward | 3.2 | 20 | 7 | Agg. |
| | 1000 | 2000 | 1000 | **103805** | GeomDiff | 9.6 | 24 | 0 | 211080 | 2.2 | 9 | 0 | 121066 | GeomDiff | 12.1 | 21 | 0 | Agg. |
| | 1000 | 5000 | 500 | **143968** | Comp. | 2.0 | 10 | 30 | 225197 | 2.3 | 6 | 34 | 155298 | Ward | 2.8 | 9 | 33 | Agg. |
| | 1000 | 5000 | 750 | **151141** | Comp. | 2.2 | 11 | 17 | 231045 | 2.7 | 7 | 20 | 163220 | Ward | 2.4 | 11 | 12 | Agg. |
| | 1000 | 5000 | 1000 | **154030** | Comp. | 1.9 | 11 | 9 | 235331 | 2.6 | 8 | 2 | 166260 | Ward | 2.4 | 12 | 1 | Agg. |

Table C.3: Results of the Model-based Heuristics on S1060 (Fixed Cost)

| | | | | MB-I | | | | | MB-II | | | | | Unicost Post Process (MB-III) | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | Cost | Time | Gap | M | N | Cost | Time | Gap | M | N | Cost | Time | M | N | |
| | 200 | 1000 | 500 | 400292 | 564.2 | 0 | 165 | 280 | **399356** | 724.7 | 0 | 177 | 240 | 423954 | 328.6 | 281 | 22 | MB-II |
| | 200 | 1000 | 750 | 427827 | 412.1 | 0 | 266 | 42 | **427688** | 623.6 | 0 | 262 | 44 | 429454 | 323.9 | 281 | 22 | MB-II |
| | 200 | 1000 | 1000 | **434954** | 397.8 | 0 | 281 | 22 | 435207 | 600.1 | 0 | 279 | 22 | **434954** | 321.6 | 281 | 22 | MB-I, MB-III |
| | 200 | 2000 | 500 | **496098** | 1415.1 | 0 | 33 | 793 | 496109 | 1343.0 | 0 | 33 | 793 | 704359 | 305.0 | 280 | 21 | MB-I |
| | 200 | 2000 | 750 | 629488 | 499.9 | 0 | 139 | 347 | **629406** | 942.5 | 0 | 138 | 350 | 709609 | 306.2 | 280 | 21 | MB-II |
| | 200 | 2000 | 1000 | 684163 | 446.2 | 0 | 199 | 169 | **683864** | 775.6 | 0 | 199 | 169 | 714859 | 305.1 | 280 | 21 | MB-II |
| | 200 | 5000 | 500 | **522579** | 1466.0 | 0 | 2 | 1013 | **522579** | 1238.6 | 0 | 2 | 1013 | 1544359 | 305.1 | 280 | 21 | MB-I, MB-II |
| | 200 | 5000 | 750 | 769925 | 1373.3 | 0 | 11 | 934 | 769799 | 1770.7 | 0 | 12 | 926 | 1549609 | 306.2 | 280 | 21 | MB-II |
| | 200 | 5000 | 1000 | **991598** | 1506.5 | 0 | 33 | 793 | **991609** | 1456.5 | 0 | 33 | 793 | 1554859 | 305.3 | 280 | 21 | MB-I |
| | 400 | 1000 | 500 | 360215 | 386.7 | 0 | 155 | 72 | **360124** | 560.9 | 0 | 155 | 67 | 366974 | 217.2 | 181 | 7 | MB-II |
| | 400 | 1000 | 750 | 368277 | 318.4 | 0 | 176 | 19 | **367651** | 525.8 | 0 | 173 | 18 | 368724 | 217.8 | 181 | 7 | MB-II |
| | 400 | 1000 | 1000 | 370474 | 285.7 | 0 | 181 | 7 | **369562** | 461.6 | 0 | 177 | 6 | 370474 | 217.4 | 181 | 7 | MB-II |
| | 400 | 2000 | 500 | 462138 | 758.3 | 0 | 61 | 403 | **462040** | 1120.3 | 0 | 61 | 392 | 514148 | 135.7 | 131 | 6 | MB-II |
| | 400 | 2000 | 750 | 508263 | 888.6 | 0 | 120 | 78 | **507511** | 2956.3 | 0 | 121 | 68 | 515648 | 135.7 | 131 | 6 | MB-II |
| | 400 | 2000 | 1000 | 517802 | 648.1 | 0 | 129 | 32 | **517047** | 1633.6 | 0 | 126 | 28 | 517148 | 135.5 | 131 | 6 | MB-II |
| | 400 | 5000 | 500 | **517160** | 1480.6 | 0 | 2 | 990 | **517160** | 1702.8 | 0 | 2 | 990 | 893600 | 127.9 | 124 | 3 | MB-I, MB-II |
| | 400 | 5000 | 750 | 726913 | 836.8 | 0 | 35 | 600 | **726444** | 1238.8 | 0 | 36 | 586 | 894350 | 128.1 | 124 | 3 | MB-II |
| | 400 | 5000 | 1000 | 815882 | 708.7 | 0 | 75 | 244 | **815516** | 2049.2 | 0 | 75 | 243 | 895100 | 127.7 | 124 | 3 | MB-II |
| | 600 | 1000 | 500 | **357808** | 388.1 | 0 | 147 | 40 | 357895 | 600.4 | 0 | 147 | 40 | 360768 | 141.0 | 155 | 5 | MB-I |
| | 600 | 1000 | 750 | **361776** | 274.5 | 0 | 151 | 11 | 361779 | 436.6 | 0 | 151 | 11 | 362018 | 141.0 | 155 | 5 | MB-I |
| | 600 | 1000 | 1000 | 363268 | 201.6 | 0 | 155 | 5 | **363257** | 378.6 | 0 | 155 | 5 | 363268 | 140.9 | 155 | 5 | MB-II |
| | 600 | 2000 | 500 | 457618 | 1347.7 | 0 | 63 | 318 | **457612** | 1674.1 | 0 | 63 | 319 | 484024 | 114.2 | 102 | 3 | MB-II |
| 1060 | 600 | 2000 | 750 | **480951** | 3324.1 | 0 | 94 | 26 | 481067 | 6138.2 | 0 | 95 | 22 | 484774 | 114.7 | 102 | 3 | MB-I |
| | 600 | 2000 | 1000 | **483644** | 672.1 | 0 | 101 | 8 | **483617** | 1884.1 | 0 | 101 | 8 | 485524 | 114.6 | 102 | 3 | MB-II |
| | 600 | 5000 | 500 | **517134** | 1798.6 | 0 | 2 | 988 | **517134** | 1958.4 | 0 | 2 | 988 | 738971 | 114.1 | 78 | 2 | MB-I, MB-II |
| | 600 | 5000 | 750 | **687615** | 11068.8 | 0.25 | 48 | 269 | 688651 | 11248.8 | 0.61 | 48 | 277 | 739471 | 114.2 | 78 | 2 | MB-I |
| | 600 | 5000 | 1000 | **723707** | 11001.8 | 1.24 | 70 | 63 | 732843 | 11165.4 | 3.13 | 75 | 35 | 739971 | 114.1 | 78 | 2 | MB-I |
| | 800 | 1000 | 500 | **357837** | 484.7 | 0 | 147 | 38 | 357891 | 613.2 | 0 | 147 | 41 | 360585 | 235.5 | 150 | 3 | MB-I |
| | 800 | 1000 | 750 | **361271** | 339.7 | 0 | 150 | 6 | 361273 | 530.6 | 0 | 150 | 6 | 361335 | 235.0 | 150 | 3 | MB-I |
| | 800 | 1000 | 1000 | 362127 | 301.5 | 0 | 150 | 3 | **362085** | 496.5 | 0 | 150 | 3 | **362085** | 235.6 | 150 | 3 | MB-IIMB-III |
| | 800 | 2000 | 500 | **457627** | 1878.3 | 0 | 63 | 315 | 457627 | 2497.9 | 0 | 63 | 319 | 478582 | 211.0 | 93 | 3 | MB-I |
| | 800 | 2000 | 750 | 478969 | 11074.3 | 0.04 | 93 | 11 | **478960** | 11261.4 | 0.17 | 93 | 13 | 479332 | 213.2 | 93 | 3 | MB-II |
| | 800 | 2000 | 1000 | 480159 | 2563.0 | 0 | 94 | 4 | 480135 | 3230.5 | 0 | 93 | 4 | **480082** | 210.8 | 93 | 3 | MB-III |

| | DLim | F1 | F2 | MB-I Cost | MB-I Time | MB-I Gap | MB-I M | MB-I N | MB-II Cost | MB-II Time | MB-II Gap | MB-II M | MB-II N | Unicost Post Process (MB-III) Cost | Unicost Post Process (MB-III) Time | Unicost Post Process (MB-III) M | Unicost Post Process (MB-III) N | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 800 | 5000 | 500 | **517134** | 2491.9 | 0 | 2 | 988 | **517134** | 6460.5 | 0 | 2 | 988 | 703111 | 215.6 | 64 | 2 | MB-I, MB-II |
| | 800 | 5000 | 750 | **689213** | 11180.8 | 3.38 | 54 | 175 | 691081 | 11331.7 | 4.07 | 55 | 166 | 703611 | 214.9 | 64 | 2 | MB-I |
| | 800 | 5000 | 1000 | 707348 | 11081.9 | 6.23 | 68 | 15 | **701761** | 11267.8 | 5.47 | 66 | 14 | 704111 | 214.2 | 64 | 2 | MB-II |
| | 1000 | 1000 | 500 | 357881 | 514.1 | 0 | 147 | 42 | **357872** | 572.1 | 0 | 147 | 40 | 360578 | 222.1 | 150 | 3 | MB-II |
| | 1000 | 1000 | 750 | **361231** | 321.3 | 0 | 150 | 6 | 361268 | 537.3 | 0 | 150 | 6 | 361328 | 222.8 | 150 | 3 | MB-I |
| | 1000 | 1000 | 1000 | 362120 | 284.9 | 0 | 150 | 3 | 362108 | 482.6 | 0 | 150 | 3 | **362078** | 223.0 | 150 | 3 | MB-III |
| | 1000 | 2000 | 500 | **457613** | 3500.5 | 0 | 63 | 319 | 457690 | 3778.9 | 0 | 63 | 317 | 478506 | 195.8 | 93 | 3 | MB-I |
| | 1000 | 2000 | 750 | 479406 | 11056.3 | 0.19 | 95 | 11 | **479251** | 11253.8 | 0.26 | 96 | 11 | 479256 | 197.3 | 93 | 3 | MB-II |
| | 1000 | 2000 | 1000 | 480008 | 4878.5 | 0 | 93 | 3 | 480033 | 3928.3 | 0 | 94 | 3 | **480006** | 195.8 | 93 | 3 | MB-III |
| | 1000 | 5000 | 500 | **517134** | 12158.9 | 0.26 | 2 | 988 | 517134 | 12388.8 | 0.17 | 2 | 988 | 696586 | 192.9 | 59 | 2 | MB-I, MB-II |
| | 1000 | 5000 | 750 | **686373** | 11220.8 | 6.36 | 45 | 238 | 687007 | 11349.6 | 7.02 | 51 | 152 | 697086 | 194.8 | 59 | 2 | MB-I |
| | 1000 | 5000 | 1000 | 699770 | 11051.8 | 6.29 | 63 | 11 | 699126 | 11292.6 | 6.7 | 61 | 12 | **697586** | 193.6 | 59 | 2 | MB-III |

Table C.4: Results of the Clustering-based Heuristics on S1060 (Fixed Cost)

| | | | | Agglomerative (Agg) | | | | | DBSCAN - KMeans (DB-KM) | | | | DBSCAN - Agglomerative (DB-Agg) | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | Cost | Type | Time | M | N | Cost | Time | M | N | Cost | Type | Time | M | N | |
| | 200 | 1000 | 500 | **414687** | Complete | 7.1 | 189 | 276 | 415692 | 7.5 | 166 | 352 | 416445 | GeomDiff | 1.8 | 166 | 359 | Agg. |
| | 200 | 1000 | 750 | **449138** | Complete | 5.6 | 304 | 43 | 478444 | 6.3 | 240 | 206 | 479016 | GeomDiff | 0.2 | 241 | 209 | Agg. |
| | 200 | 1000 | 1000 | **459888** | Complete | 5.4 | 304 | 43 | 532146 | 7.1 | 241 | 208 | 531266 | GeomDiff | 0.3 | 241 | 209 | Agg. |
| | 200 | 2000 | 500 | 530000 | GeomDiff | 5.1 | 0 | 1060 | **500836** | 7.4 | 28 | 839 | 508984 | GeomDiff | 0.6 | 23 | 890 | DB-KM |
| | 200 | 2000 | 750 | **665723** | Complete | 5.5 | 131 | 447 | 667503 | 7.0 | 120 | 489 | 669881 | GeomDiff | 1.6 | 122 | 491 | Agg. |
| | 200 | 2000 | 1000 | **740232** | Complete | 6.2 | 192 | 267 | 756061 | 6.5 | 167 | 348 | 761945 | GeomDiff | 1.7 | 166 | 359 | Agg. |
| | 200 | 5000 | 500 | 530000 | GeomDiff | 4.0 | 0 | 1060 | **525373** | 5.8 | 3 | 1009 | 530000 | GeomDiff | 0.3 | 0 | 1060 | DB-KM |
| | 200 | 5000 | 750 | 795000 | GeomDiff | 3.7 | 0 | 1060 | **772836** | 7.1 | 11 | 939 | 787749 | GeomDiff | 0.6 | 5 | 1010 | DB-KM |
| | 200 | 5000 | 1000 | 1060000 | GeomDiff | 4.1 | 0 | 1060 | **1004579** | 6.1 | 24 | 862 | 1017066 | Comp. | 0.6 | 17 | 916 | DB-KM |
| | 400 | 1000 | 500 | 369418 | Ward | 4.8 | 186 | 48 | 377299 | 39.9 | 141 | 56 | **368356** | GeomDiff | 1.6 | 183 | 40 | DB-Agg. |
| | 400 | 1000 | 750 | 375484 | GeomDiff | 6.1 | 206 | 10 | 390171 | 41.5 | 162 | 14 | **374026** | GeomDiff | 2.1 | 195 | 13 | DB-Agg. |
| | 400 | 1000 | 1000 | 377984 | GeomDiff | 6.2 | 206 | 10 | 395143 | 41.7 | 164 | 13 | **377276** | GeomDiff | 1.8 | 195 | 13 | DB-Agg. |
| | 400 | 2000 | 500 | 530000 | GeomDiff | 4.5 | 0 | 1060 | **473487** | 40.9 | 58 | 471 | 491817 | Comp. | 1.7 | 16 | 833 | DB-KM |
| | 400 | 2000 | 750 | 524287 | Complete | 4.3 | 136 | 56 | 531710 | 41.0 | 131 | 80 | **524285** | Comp. | 1.7 | 135 | 61 | DB-Agg. |
| | 400 | 2000 | 1000 | 536333 | Complete | 4.5 | 153 | 14 | 546795 | 40.7 | 148 | 38 | **535973** | Comp. | 1.8 | 152 | 17 | DB-Agg. |
| | 400 | 5000 | 500 | 530000 | GeomDiff | 4.3 | 0 | 1060 | **517373** | 40.5 | 2 | 992 | 530000 | GeomDiff | 2.0 | 0 | 1060 | DB-KM |
| | 400 | 5000 | 750 | 795000 | GeomDiff | 4.1 | 0 | 1060 | **739134** | 41.4 | 18 | 796 | 745752 | Comp. | 2.3 | 10 | 885 | DB-KM |
| | 400 | 5000 | 1000 | **859585** | Complete | 5.1 | 64 | 396 | 877191 | 43.1 | 68 | 392 | 951236 | Comp. | 1.7 | 18 | 813 | Agg. |
| | 600 | 1000 | 500 | **364106** | GeomDiff | 6.2 | 165 | 18 | 403198 | 34.3 | 100 | 44 | **364106** | GeomDiff | 4.6 | 165 | 18 | Agg., DB-Agg. |
| | 600 | 1000 | 750 | **366380** | GeomDiff | 7.1 | 162 | 4 | 408245 | 31.1 | 111 | 4 | **366380** | GeomDiff | 6.1 | 162 | 4 | Agg., DB-Agg. |
| | 600 | 1000 | 1000 | **367380** | GeomDiff | 6.8 | 162 | 4 | 409245 | 35.1 | 111 | 4 | **367380** | GeomDiff | 6.4 | 162 | 4 | Agg., DB-Agg. |
| | 600 | 2000 | 500 | **464874** | GeomDiff | 5.3 | 63 | 340 | 475084 | 31.8 | 52 | 364 | 491847 | Ward | 5.1 | 14 | 833 | Agg. |
| 1060 | 600 | 2000 | 750 | 494448 | Ward | 5.1 | 110 | 9 | 511674 | 33.0 | 103 | 12 | **494025** | Ward | 4.6 | 109 | 10 | DB-Agg. |
| | 600 | 2000 | 1000 | 495767 | Ward | 5.2 | 112 | 3 | 518079 | 32.1 | 108 | 7 | **495594** | Ward | 4.0 | 111 | 4 | DB-Agg. |
| | 600 | 5000 | 500 | 530000 | GeomDiff | 4.4 | 0 | 1060 | 521157 | 33.5 | 2 | 980 | **517161** | GeomDiff | 4.9 | 2 | 989 | DB-Agg. |
| | 600 | 5000 | 750 | 795000 | GeomDiff | 4.9 | 0 | 1060 | 709067 | 33.7 | 30 | 539 | 741521 | Comp. | 5.1 | 13 | 837 | DB-KM |
| | 600 | 5000 | 1000 | 769609 | Complete | 5.1 | 78 | 84 | 764565 | 32.0 | 74 | 111 | 768571 | Comp. | 5.1 | 79 | 84 | DB-KM |
| | 800 | 1000 | 500 | **364831** | GeomDiff | 6.8 | 157 | 11 | 453965 | 27.9 | 59 | 280 | **364831** | GeomDiff | 9.6 | 157 | 11 | Agg., DB-Agg. |
| | 800 | 1000 | 750 | **365838** | GeomDiff | 7.1 | 160 | 3 | 453937 | 25.7 | 79 | 3 | **365838** | GeomDiff | 11.4 | 160 | 3 | Agg., DB-Agg. |
| | 800 | 1000 | 1000 | **366588** | GeomDiff | 7.9 | 160 | 3 | 454687 | 26.8 | 79 | 3 | **366588** | GeomDiff | 12.0 | 160 | 3 | Agg., DB-Agg. |
| | 800 | 2000 | 500 | **466317** | Ward | 5.1 | 55 | 324 | 498063 | 26.4 | 29 | 645 | 467074 | Ward | 7.3 | 55 | 320 | Agg. |
| | 800 | 2000 | 750 | 487124 | GeomDiff | 6.1 | 97 | 3 | 545047 | 26.7 | 76 | 7 | **487034** | Ward | 8.1 | 92 | 4 | DB-Agg. |
| | 800 | 2000 | 1000 | **487874** | GeomDiff | 6.8 | 97 | 3 | 546402 | 27.2 | 78 | 3 | **487874** | GeomDiff | 9.8 | 97 | 3 | Agg., DB-Agg. |

| | | | | Agglomerative (Agg) | | | | | DBSCAN - KMeans (DB-KM) | | | | DBSCAN - Agglomerative (DB-Agg) | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | Cost | Type | Time | M | N | Cost | Time | M | N | Cost | Type | Time | M | N | |
| | 800 | 5000 | 500 | 530000 | GeomDiff | 6.8 | 0 | 1060 | **517692** | 28.5 | 2 | 984 | 523558 | GeomDiff | 10.1 | 1 | 1025 | DB-KM |
| | 800 | 5000 | 750 | **693024** | GeomDiff | 6.2 | 47 | 249 | 704202 | 27.4 | 31 | 406 | **693024** | GeomDiff | 9.6 | 47 | 249 | Agg., DB-Agg. |
| | 800 | 5000 | 1000 | **722278** | GeomDiff | 5.5 | 74 | 20 | 757129 | 26.3 | 67 | 33 | **722278** | GeomDiff | 8.8 | 74 | 20 | Agg., DB-Agg. |
| | 1000 | 1000 | 500 | **364822** | GeomDiff | 8.5 | 157 | 11 | 484497 | 21.7 | 20 | 706 | **364822** | GeomDiff | 13.6 | 157 | 11 | Agg., DB-Agg. |
| | 1000 | 1000 | 750 | **365829** | GeomDiff | 9.6 | 160 | 3 | 543360 | 21.8 | 55 | 4 | **365829** | GeomDiff | 15.1 | 160 | 3 | Agg., DB-Agg. |
| | 1000 | 1000 | 1000 | **366579** | GeomDiff | 8.7 | 160 | 3 | 544299 | 19.8 | 56 | 2 | **366579** | GeomDiff | 14.3 | 160 | 3 | Agg., DB-Agg. |
| | 1000 | 2000 | 500 | **466306** | Ward | 4.7 | 56 | 310 | 501988 | 21.1 | 12 | 817 | **466306** | Ward | 9.1 | 56 | 310 | Agg., DB-Agg. |
| | 1000 | 2000 | 750 | **487158** | Ward | 5.5 | 94 | 4 | 590562 | 20.2 | 55 | 12 | **487158** | Ward | 9.3 | 94 | 4 | Agg., DB-Agg. |
| | 1000 | 2000 | 1000 | **488400** | GeomDiff | 8.2 | 102 | 3 | 599360 | 21.3 | 55 | 4 | **488400** | GeomDiff | 13.5 | 102 | 3 | Agg., DB-Agg. |
| | 1000 | 5000 | 500 | 530000 | GeomDiff | 7.0 | 0 | 1060 | **518042** | 21.6 | 2 | 981 | 523558 | GeomDiff | 11.0 | 1 | 1025 | DB-KM |
| | 1000 | 5000 | 750 | **694215** | Ward | 5.2 | 45 | 230 | 715451 | 22.0 | 28 | 402 | **694215** | Ward | 10.2 | 45 | 230 | Agg., DB-Agg. |
| | 1000 | 5000 | 1000 | **710665** | Ward | 5.1 | 65 | 4 | 763370 | 21.3 | 54 | 6 | **710665** | Ward | 7.5 | 65 | 4 | Agg., DB-Agg. |

# Appendix D

# Computational Results of the Variable Cost Problem on the Synthetic Data

Table D.1: Results of the Model-based Heuristics on S654 (Variable Cost)

| | | | | MB-I | | | | | MB-II | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F3 | F2 | Cost | Time | Gap | M | N | Cost | Time | Gap | M | N | |
| 654 | 200 | 500 | 1000 | **339281** | 113.6 | 0 | 318 | 9 | 339284 | 162.9 | 0 | 318 | 9 | MB-I |
| | 200 | 500 | 2000 | **347072** | 112.8 | 0 | 318 | 8 | 347075 | 165.6 | 0 | 318 | 8 | MB-I |
| | 200 | 500 | 5000 | **371070** | 111.2 | 0 | 318 | 8 | 371075 | 160.8 | 0 | 318 | 8 | MB-I |
| | 200 | 750 | 1000 | **500595** | 112.2 | 0 | 318 | 10 | 500598 | 160.5 | 0 | 318 | 10 | MB-I |
| | 200 | 750 | 2000 | **508572** | 114.6 | 0 | 318 | 8 | 508575 | 161.1 | 0 | 318 | 8 | MB-I |
| | 200 | 750 | 5000 | **532570** | 111.2 | 0 | 318 | 8 | 532575 | 162.2 | 0 | 318 | 8 | MB-I |
| | 200 | 1000 | 1000 | **654000** | 153.0 | 0 | 0 | 654 | **654000** | 200.6 | 0 | 0 | 654 | MB-I, MB-II |
| | 200 | 1000 | 2000 | **670072** | 113.9 | 0 | 318 | 8 | 670075 | 160.4 | 0 | 318 | 8 | MB-I |
| | 200 | 1000 | 5000 | **694070** | 114.7 | 0 | 318 | 8 | 694075 | 159.6 | 0 | 318 | 8 | MB-I |
| | 400 | 500 | 1000 | **338150** | 121.5 | 0 | 320 | 4 | **338150** | 165.6 | 0 | 320 | 4 | MB-I, MB-II |
| | 400 | 500 | 2000 | **338204** | 122.0 | 0 | 320 | 0 | **338204** | 169.1 | 0 | 320 | 0 | MB-I, MB-II |
| | 400 | 500 | 5000 | **338204** | 121.3 | 0 | 320 | 0 | **338204** | 168.8 | 0 | 320 | 0 | MB-I, MB-II |
| | 400 | 750 | 1000 | 500534 | 122.1 | 0 | 318 | 9 | **500529** | 169.9 | 0 | 318 | 9 | MB-II |
| | 400 | 750 | 2000 | **501704** | 121.1 | 0 | 320 | 0 | **501704** | 170.4 | 0 | 320 | 0 | MB-I, MB-II |
| | 400 | 750 | 5000 | **501704** | 122.3 | 0 | 320 | 0 | **501704** | 170.1 | 0 | 320 | 0 | MB-I, MB-II |
| | 400 | 1000 | 1000 | **654000** | 162.7 | 0 | 0 | 654 | **654000** | 206.6 | 0 | 0 | 654 | MB-I, MB-II |
| | 400 | 1000 | 2000 | **665204** | 123.2 | 0 | 320 | 0 | **665204** | 169.7 | 0 | 320 | 0 | MB-I, MB-II |
| | 400 | 1000 | 5000 | **665204** | 119.8 | 0 | 320 | 0 | **665204** | 167.6 | 0 | 320 | 0 | MB-I, MB-II |
| | 600 | 500 | 1000 | **338083** | 129.7 | 0 | 320 | 3 | 338085 | 157.1 | 0 | 320 | 3 | MB-I |
| | 600 | 500 | 2000 | **338204** | 129.2 | 0 | 320 | 0 | 338209 | 159.8 | 0 | 320 | 0 | MB-I |
| | 600 | 500 | 5000 | **338204** | 128.0 | 0 | 320 | 0 | 338209 | 161.7 | 0 | 320 | 0 | MB-I |
| | 600 | 750 | 1000 | 500529 | 131.5 | 0 | 318 | 9 | **500528** | 164.2 | 0 | 318 | 9 | MB-II |
| | 600 | 750 | 2000 | **501704** | 128.9 | 0 | 320 | 0 | 501709 | 160.5 | 0 | 320 | 0 | MB-I |
| | 600 | 750 | 5000 | **501704** | 129.9 | 0 | 320 | 0 | 501709 | 165.9 | 0 | 320 | 0 | MB-I |
| | 600 | 1000 | 1000 | **654000** | 168.8 | 0 | 0 | 654 | **654000** | 202.2 | 0 | 0 | 654 | MB-I, MB-II |
| | 600 | 1000 | 2000 | **665204** | 131.5 | 0 | 320 | 0 | 665209 | 166.1 | 0 | 320 | 0 | MB-I |
| | 600 | 1000 | 5000 | **665204** | 129.3 | 0 | 320 | 0 | 665209 | 160.0 | 0 | 320 | 0 | MB-I |
| | 800 | 500 | 1000 | 338086 | 151.3 | 0 | 320 | 3 | **338081** | 209.8 | 0 | 320 | 3 | MB-II |
| | 800 | 500 | 2000 | **338204** | 152.8 | 0 | 320 | 0 | 338206 | 210.4 | 0 | 320 | 0 | MB-I |
| | 800 | 500 | 5000 | **338204** | 149.8 | 0 | 320 | 0 | 338206 | 206.8 | 0 | 320 | 0 | MB-I |
| | 800 | 750 | 1000 | **500533** | 154.1 | 0 | 318 | 9 | **500533** | 208.3 | 0 | 318 | 9 | MB-I, MB-II |
| | 800 | 750 | 2000 | **501704** | 150.2 | 0 | 320 | 0 | 501706 | 211.1 | 0 | 320 | 0 | MB-I |
| | 800 | 750 | 5000 | **501704** | 151.5 | 0 | 320 | 0 | 501706 | 208.2 | 0 | 320 | 0 | MB-I |

| | | | | MB-I | | | | | MB-II | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F3 | F2 | Cost | Time | Gap | M | N | Cost | Time | Gap | M | N | |
| | 800 | 1000 | 1000 | **654000** | 189.4 | 0 | 0 | 654 | **654000** | 243.5 | 0 | 0 | 654 | MB-I, MB-II |
| | 800 | 1000 | 2000 | **665204** | 152.9 | 0 | 320 | 0 | 665206 | 209.3 | 0 | 320 | 0 | MB-I |
| | 800 | 1000 | 5000 | **665204** | 155.3 | 0 | 320 | 0 | 665206 | 207.0 | 0 | 320 | 0 | MB-I |
| | 1000 | 500 | 1000 | **338015** | 182.6 | 0 | 321 | 2 | **338015** | 234.8 | 0 | 321 | 2 | MB-I, MB-II |
| | 1000 | 500 | 2000 | **338071** | 181.8 | 0 | 321 | 0 | **338071** | 234.5 | 0 | 321 | 0 | MB-I, MB-II |
| | 1000 | 500 | 5000 | **338071** | 184.3 | 0 | 321 | 0 | **338071** | 239.2 | 0 | 321 | 0 | MB-I, MB-II |
| | 1000 | 750 | 1000 | **500533** | 184.3 | 0 | 318 | 9 | **500531** | 242.1 | 0 | 318 | 9 | MB-II |
| | 1000 | 750 | 2000 | **501571** | 179.0 | 0 | 321 | 0 | **501571** | 245.8 | 0 | 321 | 0 | MB-I, MB-II |
| | 1000 | 750 | 5000 | **501571** | 185.5 | 0 | 321 | 0 | **501571** | 244.0 | 0 | 321 | 0 | MB-I, MB-II |
| | 1000 | 1000 | 1000 | **654000** | 216.0 | 0 | 0 | 654 | **654000** | 281.7 | 0 | 0 | 654 | MB-I, MB-II |
| | 1000 | 1000 | 2000 | **665071** | 183.25 | 0 | 321 | 0 | **665071** | 245.25 | 321 | 0 | 245.25 | MB-I, MB-II |
| | 1000 | 1000 | 5000 | **665071** | 179.53 | 0 | 321 | 0 | **665071** | 243.92 | 321 | 0 | 243.92 | MB-I, MB-II |

Table D.2: Results of the Clustering-based Heuristics on S654 (Variable Cost)

| | | | | Agglomerative (Agg) | | | | | DBSCAN - KMeans (DB-KM) | | | | DBSCAN - Agglomerative (DB-Agg) | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F3 | F2 | Cost | Type | Time | M | N | Cost | Time | M | N | Cost | Type | Time | M | N | |
| | 200 | 500 | 1000 | 351120 | GeomDiff | 5.9 | 84 | 15 | 373795 | 4.9 | 30 | 13 | **345574** | Ward | 1.3 | 152 | 13 | DB-Agg. |
| | 200 | 500 | 2000 | 361478 | GeomDiff | 3.5 | 72 | 10 | 386578 | 5.3 | 30 | 13 | **358574** | Ward | 0.7 | 152 | 13 | DB-Agg. |
| | 200 | 500 | 5000 | **386162** | GeomDiff | 3.3 | 60 | 8 | 425795 | 5.3 | 30 | 13 | 397574 | Ward | 0.8 | 152 | 13 | Agg. |
| | 200 | 750 | 1000 | 510259 | Ward | 2.6 | 135 | 36 | 532982 | 4.4 | 31 | 13 | **505824** | Ward | 0.8 | 152 | 13 | DB-Agg. |
| | 200 | 750 | 2000 | 522478 | GeomDiff | 3.2 | 72 | 10 | 546260 | 3.2 | 31 | 13 | **518824** | Ward | 0.8 | 152 | 13 | DB-Agg. |
| | 200 | 750 | 5000 | **547662** | GeomDiff | 3.2 | 60 | 8 | 586045 | 3.3 | 30 | 13 | 557824 | Ward | 0.8 | 152 | 13 | Agg. |
| | 200 | 1000 | 1000 | **654000** | GeomDiff | 2.9 | 0 | 654 | **654000** | 3.8 | 0 | 654 | **654000** | GeomDiff | 4.4 | 0 | 654 | Agg., DB-KM, DB-Agg. |
| | 200 | 1000 | 2000 | 683478 | GeomDiff | 3.0 | 72 | 10 | 707295 | 3.5 | 30 | 13 | **679074** | Ward | 0.8 | 152 | 13 | DB-Agg. |
| | 200 | 1000 | 5000 | **709162** | GeomDiff | 3.2 | 60 | 8 | 746078 | 3.9 | 30 | 13 | 718074 | Ward | 0.9 | 152 | 13 | Agg. |
| | 400 | 500 | 1000 | 351120 | GeomDiff | 4.9 | 84 | 15 | 405985 | 0.6 | 18 | 8 | **348140** | GeomDiff | 6.0 | 134 | 8 | DB-Agg. |
| | 400 | 500 | 2000 | 360918 | GeomDiff | 4.6 | 69 | 9 | 413694 | 0.5 | 18 | 8 | **356140** | GeomDiff | 5.6 | 134 | 8 | DB-Agg. |
| | 400 | 500 | 5000 | **374665** | Ward | 2.8 | 41 | 3 | 437378 | 0.8 | 18 | 8 | 380140 | GeomDiff | 5.2 | 134 | 8 | Agg. |
| | 400 | 750 | 1000 | 510259 | Ward | 2.3 | 135 | 36 | 567022 | 0.9 | 17 | 19 | **508765** | GeomDiff | 5.8 | 138 | 19 | DB-Agg. |
| | 400 | 750 | 2000 | 522168 | GeomDiff | 4.6 | 69 | 9 | 574944 | 0.8 | 18 | 8 | **517640** | GeomDiff | 5.7 | 134 | 8 | DB-Agg. |
| | 400 | 750 | 5000 | **537415** | Ward | 2.5 | 41 | 3 | 599196 | 0.6 | 18 | 8 | 541640 | GeomDiff | 5.6 | 134 | 8 | Agg. |
| | 400 | 1000 | 1000 | **654000** | GeomDiff | 4.4 | 0 | 654 | **654000** | 0.7 | 0 | 654 | **654000** | GeomDiff | 7.1 | 0 | 654 | Agg., DB-KM, DB-Agg. |
| | 400 | 1000 | 2000 | 683418 | GeomDiff | 4.8 | 69 | 9 | 736696 | 0.4 | 18 | 8 | **679140** | GeomDiff | 5.0 | 134 | 8 | DB-Agg. |
| | 400 | 1000 | 5000 | **700165** | Ward | 2.1 | 41 | 3 | 760378 | 0.6 | 18 | 8 | 703140 | GeomDiff | 5.5 | 134 | 8 | Agg. |
| | 600 | 500 | 1000 | **351120** | GeomDiff | 7.1 | 84 | 15 | 459601 | 1.1 | 15 | 0 | 382634 | GeomDiff | 8.0 | 97 | 7 | Agg. |
| | 600 | 500 | 2000 | **360918** | GeomDiff | 7.0 | 69 | 9 | 459794 | 1.5 | 15 | 0 | 385969 | GeomDiff | 7.2 | 85 | 3 | Agg. |
| | 600 | 500 | 5000 | **369516** | GeomDiff | 7.5 | 37 | 1 | 457455 | 1.8 | 15 | 0 | 394862 | GeomDiff | 8.0 | 60 | 2 | Agg. |
| | 600 | 750 | 1000 | **510259** | Ward | 2.4 | 135 | 36 | 614679 | 1.5 | 10 | 198 | 539206 | Ward | 1.3 | 112 | 151 | Agg. |
| 654 | 600 | 750 | 2000 | **522168** | GeomDiff | 7.1 | 69 | 9 | 623101 | 1.4 | 15 | 0 | 548719 | GeomDiff | 7.4 | 85 | 3 | Agg. |
| | 600 | 750 | 5000 | **532766** | GeomDiff | 6.9 | 37 | 1 | 621423 | 1.6 | 15 | 0 | 557719 | GeomDiff | 7.6 | 85 | 3 | Agg. |
| | 600 | 1000 | 1000 | **654000** | GeomDiff | 6.8 | 0 | 654 | **654000** | 1.2 | 0 | 654 | **654000** | GeomDiff | 7.9 | 0 | 654 | Agg., DB-KM, DB-Agg. |
| | 600 | 1000 | 2000 | **683418** | GeomDiff | 6.8 | 69 | 9 | 784648 | 1.6 | 15 | 0 | 711469 | GeomDiff | 7.5 | 85 | 3 | Agg. |
| | 600 | 1000 | 5000 | **696016** | GeomDiff | 6.4 | 37 | 1 | 784455 | 1.3 | 15 | 0 | 720469 | GeomDiff | 7.4 | 85 | 3 | Agg. |
| | 800 | 500 | 1000 | **351120** | GeomDiff | 7.7 | 84 | 15 | 526790 | 2.8 | 10 | 86 | 439009 | GeomDiff | 6.9 | 51 | 7 | Agg. |
| | 800 | 500 | 2000 | **360918** | GeomDiff | 8.1 | 69 | 9 | 549938 | 2.8 | 12 | 0 | 445449 | GeomDiff | 6.7 | 48 | 6 | Agg. |
| | 800 | 500 | 5000 | **366261** | GeomDiff | 7.9 | 36 | 0 | 549938 | 2.1 | 12 | 0 | 448801 | GeomDiff | 6.8 | 27 | 0 | Agg. |
| | 800 | 750 | 1000 | **510259** | Ward | 2.4 | 135 | 36 | 650451 | 2.1 | 2 | 513 | 569709 | Ward | 1.6 | 58 | 150 | Agg. |
| | 800 | 750 | 2000 | **522168** | GeomDiff | 7.8 | 69 | 9 | 693031 | 2.5 | 11 | 0 | 607449 | GeomDiff | 7.2 | 48 | 6 | Agg. |
| | 800 | 750 | 5000 | **529761** | GeomDiff | 7.3 | 36 | 0 | 700867 | 3.2 | 13 | 0 | 612301 | GeomDiff | 7.2 | 27 | 0 | Agg. |

| | | | | Agglomerative (Agg) | | | | | DBSCAN - KMeans (DB-KM) | | | | DBSCAN - Agglomerative (DB-Agg) | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F3 | F2 | Cost | Type | Time | M | N | Cost | Time | M | N | Cost | Type | Time | M | N | |
| | 800 | 1000 | 1000 | **654000** | GeomDiff | 7.2 | 0 | 654 | **654000** | 1.8 | 0 | 654 | **654000** | GeomDiff | 8.8 | 0 | 654 | Agg., DB-KM, DB-Agg. |
| | 800 | 1000 | 2000 | **683418** | GeomDiff | 7.8 | 69 | 9 | 856531 | 2.3 | 11 | 0 | 769449 | GeomDiff | 7.3 | 48 | 6 | Agg. |
| | 800 | 1000 | 5000 | **693261** | GeomDiff | 7.5 | 36 | 0 | 857605 | 2.9 | 11 | 0 | 775801 | GeomDiff | 6.7 | 27 | 0 | Agg. |
| | 1000 | 500 | 1000 | **351120** | GeomDiff | 9.5 | 84 | 15 | 518045 | 2.2 | 7 | 20 | 379042 | GeomDiff | 12.3 | 71 | 15 | Agg. |
| | 1000 | 500 | 2000 | **360918** | GeomDiff | 9.9 | 69 | 9 | 520080 | 2.0 | 9 | 0 | 388542 | GeomDiff | 11.9 | 58 | 9 | Agg. |
| | 1000 | 500 | 5000 | **366261** | GeomDiff | 10.6 | 36 | 0 | 520080 | 2.3 | 9 | 0 | 391508 | GeomDiff | 12.2 | 31 | 0 | Agg. |
| | 1000 | 750 | 1000 | **510259** | Ward | 3.2 | 135 | 36 | 637161 | 2.3 | 3 | 394 | 538746 | GeomDiff | 12.0 | 88 | 26 | Agg. |
| | 1000 | 750 | 2000 | **522168** | GeomDiff | 9.1 | 69 | 9 | 683580 | 3.0 | 9 | 0 | 549792 | GeomDiff | 12.2 | 58 | 9 | Agg. |
| | 1000 | 750 | 5000 | **529761** | GeomDiff | 9.3 | 36 | 0 | 683580 | 2.3 | 9 | 0 | 555008 | GeomDiff | 11.0 | 31 | 0 | Agg. |
| | 1000 | 1000 | 1000 | **654000** | GeomDiff | 9.8 | 0 | 654 | **654000** | 2.3 | 0 | 654 | **654000** | GeomDiff | 11.6 | 0 | 654 | Agg., DB-KM, DB-Agg. |
| | 1000 | 1000 | 2000 | **683418** | GeomDiff | 9.8 | 69 | 9 | 847080 | 2.2 | 9 | 0 | 711042 | GeomDiff | 12.2 | 58 | 9 | Agg. |
| | 1000 | 1000 | 5000 | **693261** | GeomDiff | 9.3 | 36 | 0 | 847080 | 2.5 | 9 | 0 | 718508 | GeomDiff | 12.2 | 31 | 0 | Agg. |

Table D.3: Results of the Model-based Heuristics on S1060 (Variable Cost)

| | | | | MB-I | | | | | MB-II | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F3 | F2 | Cost | Time | Gap | M | N | Cost | Time | Gap | M | N | Best Method |
| | 200 | 500 | 1000 | 627799 | 690 | 0 | 480 | 14 | **626676** | 778.6 | 0 | 481 | 15 | MB-II |
| | 200 | 500 | 2000 | 640683 | 686 | 0 | 480 | 13 | **639552** | 773.3 | 0 | 481 | 13 | MB-II |
| | 200 | 500 | 5000 | 679715 | 683 | 0 | 480 | 13 | **678552** | 773.0 | 0 | 481 | 13 | MB-II |
| | 200 | 750 | 1000 | 888133 | 576 | 0 | 467 | 58 | **887279** | 805.7 | 0 | 474 | 50 | MB-II |
| | 200 | 750 | 2000 | 902433 | 690 | 0 | 480 | 13 | **901302** | 772.3 | 0 | 481 | 13 | MB-II |
| | 200 | 750 | 5000 | 941433 | 686 | 0 | 480 | 13 | **940302** | 773.3 | 0 | 481 | 13 | MB-II |
| | 200 | 1000 | 1000 | **1060000** | 930 | 0 | 0 | 1060 | **1060000** | 1136.8 | 0 | 0 | 1060 | MB-I, MB-II |
| | 200 | 1000 | 2000 | 1164183 | 664 | 0 | 480 | 13 | **1163052** | 774.3 | 0 | 481 | 13 | MB-II |
| | 200 | 1000 | 5000 | 1203183 | 653 | 0 | 480 | 13 | **1202052** | 775.3 | 0 | 481 | 13 | MB-II |
| | 400 | 500 | 1000 | 620948 | 509 | 0 | 497 | 8 | **620652** | 724.1 | 0 | 498 | 7 | MB-II |
| | 400 | 500 | 2000 | 623775 | 495 | 0 | 496 | 3 | **623741** | 712.4 | 0 | 497 | 3 | MB-II |
| | 400 | 500 | 5000 | 632780 | 508 | 0 | 497 | 3 | **632733** | 738.4 | 0 | 498 | 3 | MB-II |
| | 400 | 750 | 1000 | 883062 | 535 | 0 | 492 | 25 | **883060** | 776.8 | 0 | 493 | 24 | MB-II |
| | 400 | 750 | 2000 | 888025 | 494 | 0 | 496 | 3 | **887991** | 710.4 | 0 | 497 | 3 | MB-II |
| | 400 | 750 | 5000 | 897030 | 509 | 0 | 497 | 3 | **896983** | 716.6 | 0 | 498 | 3 | MB-II |
| | 400 | 1000 | 1000 | **1060000** | 843 | 0 | 0 | 1060 | **1060000** | 1049.7 | 0 | 0 | 1060 | MB-I, MB-II |
| | 400 | 1000 | 2000 | 1152278 | 504 | 0 | 496 | 3 | **1152241** | 710.8 | 0 | 497 | 3 | MB-II |
| | 400 | 1000 | 5000 | 1161280 | 508 | 0 | 497 | 3 | **1161233** | 722.8 | 0 | 498 | 3 | MB-II |
| | 600 | 500 | 1000 | 620334 | 499 | 0 | 500 | 5 | **620330** | 717.6 | 0 | 500 | 5 | MB-II |
| | 600 | 500 | 2000 | **622337** | 509 | 0 | 501 | 2 | 622338 | 704.6 | 0 | 501 | 2 | MB-I |
| | 600 | 500 | 5000 | **628341** | 498 | 0 | 501 | 2 | 628343 | 712.7 | 0 | 500 | 2 | MB-I |
| | 600 | 750 | 1000 | 883062 | 534 | 0 | 493 | 24 | **883057** | 721.2 | 0 | 493 | 24 | MB-II |
| 1060 | 600 | 750 | 2000 | 886838 | 516 | 0 | 501 | 2 | **886838** | 704.1 | 0 | 501 | 2 | MB-II |
| | 600 | 750 | 5000 | **892841** | 499 | 0 | 501 | 2 | 892843 | 708.9 | 0 | 500 | 2 | MB-I |
| | 600 | 1000 | 1000 | **1060000** | 840 | 0 | 0 | 1060 | **1060000** | 1029.7 | 0 | 0 | 1060 | MB-I, MB-II |
| | 600 | 1000 | 2000 | 1151343 | 508 | 0 | 500 | 2 | **1151338** | 724.5 | 0 | 500 | 2 | MB-II |
| | 600 | 1000 | 5000 | **1157341** | 499 | 0 | 501 | 2 | 1157343 | 709.8 | 0 | 500 | 2 | MB-I |
| | 800 | 500 | 1000 | **620287** | 586 | 0 | 500 | 4 | 620297 | 979.0 | 0 | 500 | 4 | MB-I |
| | 800 | 500 | 2000 | **622236** | 603 | 0 | 501 | 2 | 622241 | 799.1 | 0 | 501 | 2 | MB-I |
| | 800 | 500 | 5000 | **628230** | 731 | 0 | 501 | 2 | 628236 | 804.0 | 0 | 501 | 2 | MB-I |
| | 800 | 750 | 1000 | 883057 | 620 | 0 | 492 | 24 | **883057** | 818.5 | 0 | 493 | 24 | MB-I, MB-II |
| | 800 | 750 | 2000 | **886735** | 605 | 0 | 501 | 2 | 886741 | 801.6 | 0 | 501 | 2 | MB-I |
| | 800 | 750 | 5000 | **892730** | 732 | 0 | 501 | 2 | 892736 | 810.9 | 0 | 501 | 2 | MB-I |

| | | | | MB-I | | | | | MB-II | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Dlim | F3 | F2 | Cost | Time | Gap | M | N | Cost | Time | Gap | M | N | |
| | 800 | 1000 | 1000 | **1060000** | 938 | 0 | 0 | 1060 | **1060000** | 1137.9 | 0 | 0 | 1060 | MB-I, MB-II |
| | 800 | 1000 | 2000 | 1151829 | 604 | 0 | 500 | 3 | **1151824** | 787.1 | 0 | 500 | 3 | MB-II |
| | 800 | 1000 | 5000 | **1157230** | 731 | 0 | 501 | 2 | 1157236 | 804.9 | 0 | 501 | 2 | MB-I |
| | 1000 | 500 | 1000 | 620236 | 600 | 0 | 501 | 2 | **620230** | 788.1 | 0 | 501 | 2 | MB-II |
| | 1000 | 500 | 2000 | 622241 | 576 | 0 | 501 | 2 | **622232** | 911.2 | 0 | 501 | 2 | MB-II |
| | 1000 | 500 | 5000 | **622349** | 601 | 0 | 502 | 0 | 622354 | 773.1 | 0 | 501 | 0 | MB-I |
| | 1000 | 750 | 1000 | **883078** | 609 | 0 | 493 | 25 | 883082 | 815.9 | 0 | 493 | 25 | MB-I |
| | 1000 | 750 | 2000 | **886739** | 594 | 0 | 501 | 2 | 886739 | 924.2 | 0 | 501 | 2 | MB-I |
| | 1000 | 750 | 5000 | **887349** | 602 | 0 | 502 | 0 | 887354 | 775.5 | 0 | 501 | 0 | MB-I |
| | 1000 | 1000 | 1000 | **1060000** | 924 | 0 | 0 | 1060 | **1060000** | 1126.7 | 0 | 0 | 1060 | MB-I, MB-II |
| | 1000 | 1000 | 2000 | **1151236** | 598 | 0 | 501 | 2 | 1151241 | 783.8 | 0 | 501 | 2 | MB-I |
| | 1000 | 1000 | 5000 | **1152349** | 601 | 0 | 502 | 0 | 1152354 | 772.8 | 0 | 501 | 0 | MB-I |

Table D.4: Results of the Clustering-based Heuristics on S1060 (Variable Cost)

| | | | | Agglomerative (Agg) | | | | | DBSCAN - KMeans (DB-KM) | | | | DBSCAN - Agglomerative (DB-Agg) | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F3 | F2 | Cost | Type | Time | M | N | Cost | Time | M | N | Cost | Type | Time | M | N | |
| | 200 | 500 | 1000 | **658971** | Ward | 4.7 | 319 | 64 | 716532 | 9.9 | 242 | 205 | 702042 | Ward | 0.1 | 298 | 209 | Agg. |
| | 200 | 500 | 2000 | **706732** | Complete | 5.1 | 306 | 43 | 921711 | 8.8 | 243 | 206 | 909361 | Ward | 0.1 | 291 | 207 | Agg. |
| | 200 | 500 | 5000 | **835732** | Complete | 4.8 | 306 | 43 | 1544434 | 9.1 | 244 | 207 | 1530361 | Ward | 0.3 | 291 | 207 | Agg. |
| | 200 | 750 | 1000 | **901399** | Ward | 5.6 | 339 | 98 | 930024 | 6.9 | 241 | 205 | 914327 | Complete | 0.4 | 302 | 215 | Agg. |
| | 200 | 750 | 2000 | **960982** | Complete | 4.9 | 306 | 43 | 1135058 | 5.8 | 242 | 205 | 1122611 | Ward | 0.1 | 291 | 207 | Agg. |
| | 200 | 750 | 5000 | **1089982** | Complete | 4.9 | 306 | 43 | 1745847 | 6.9 | 243 | 204 | 1743611 | Ward | 0.3 | 291 | 207 | Agg. |
| | 200 | 1000 | 1000 | **1060000** | GeomDiff | 3.8 | 0 | 1060 | **1060000** | 6.9 | 0 | 1060 | **1060000** | GeomDiff | 0.8 | 0 | 1060 | Agg., DB-KM, DB-Agg. |
| | 200 | 1000 | 2000 | **1215175** | Complete | 5.1 | 309 | 45 | 1348925 | 6.4 | 241 | 205 | 1335861 | Ward | 0.2 | 291 | 207 | Agg. |
| | 200 | 1000 | 5000 | **1344232** | Complete | 5.5 | 306 | 43 | 1967754 | 6.8 | 241 | 206 | 1956861 | Ward | 0.3 | 291 | 207 | Agg. |
| | 400 | 500 | 1000 | 654016 | Ward | 6.8 | 310 | 32 | 753883 | 40.8 | 163 | 13 | **653781** | Ward | 1.8 | 329 | 34 | DB-Agg. |
| | 400 | 500 | 2000 | 675898 | Ward | 5.4 | 288 | 16 | 765390 | 40.1 | 164 | 13 | **674534** | Ward | 1.7 | 311 | 18 | DB-Agg. |
| | 400 | 500 | 5000 | **717790** | Ward | 5.9 | 236 | 9 | 806699 | 44.4 | 163 | 13 | 720467 | Ward | 2.0 | 281 | 13 | Agg. |
| | 400 | 750 | 1000 | **901296** | Ward | 6.3 | 339 | 98 | 1008667 | 41.9 | 143 | 175 | 904789 | Ward | 2.0 | 348 | 94 | Agg. |
| | 400 | 750 | 2000 | 936898 | Ward | 5.6 | 288 | 16 | 1028887 | 40.3 | 164 | 13 | **935034** | Ward | 1.2 | 311 | 18 | DB-Agg. |
| | 400 | 750 | 5000 | **980370** | Ward | 5.7 | 260 | 12 | 1071210 | 42.1 | 165 | 14 | 982217 | Ward | 1.2 | 281 | 13 | Agg. |
| | 400 | 1000 | 1000 | **1060000** | GeomDiff | 4.6 | 0 | 1060 | **1060000** | 39.9 | 0 | 1060 | **1060000** | GeomDiff | 2.5 | 0 | 1060 | Agg., DB-KM, DB-Agg. |
| | 400 | 1000 | 2000 | 1197825 | Ward | 5.7 | 305 | 26 | 1289616 | 41.2 | 164 | 13 | **1195225** | Ward | 1.7 | 320 | 22 | DB-Agg. |
| | 400 | 1000 | 5000 | **1242370** | Ward | 5.5 | 260 | 12 | 1330149 | 40.2 | 164 | 13 | 1243967 | Ward | 1.7 | 281 | 13 | Agg. |
| | 600 | 500 | 1000 | 654016 | Ward | 6.0 | 310 | 32 | 826245 | 31.3 | 111 | 4 | **647783** | Ward | 5.9 | 339 | 33 | DB-Agg. |
| | 600 | 500 | 2000 | 675898 | Ward | 6.8 | 288 | 16 | 830906 | 32.5 | 110 | 4 | **665789** | Ward | 5.7 | 324 | 16 | DB-Agg. |
| | 600 | 500 | 5000 | 717731 | Ward | 6.3 | 236 | 9 | 842906 | 33.0 | 110 | 4 | **705645** | Ward | 5.7 | 276 | 9 | DB-Agg. |
| | 600 | 750 | 1000 | 901296 | Ward | 6.8 | 339 | 98 | 1045929 | 33.2 | 41 | 768 | **898725** | Ward | 5.9 | 360 | 105 | DB-Agg. |
| 1060 | 600 | 750 | 2000 | 936898 | Ward | 6.0 | 288 | 16 | 1094245 | 31.7 | 111 | 4 | **926789** | Ward | 7.0 | 324 | 16 | DB-Agg. |
| | 600 | 750 | 5000 | 980369 | Ward | 6.5 | 260 | 12 | 1106906 | 33.0 | 110 | 4 | **968395** | Ward | 6.1 | 276 | 9 | DB-Agg. |
| | 600 | 1000 | 1000 | **1060000** | GeomDiff | 4.9 | 0 | 1060 | **1060000** | 31.3 | 0 | 1060 | **1060000** | GeomDiff | 6.1 | 0 | 1060 | Agg., DB-KM, DB-Agg. |
| | 600 | 1000 | 2000 | 1197825 | Ward | 6.7 | 305 | 26 | 1358245 | 32.2 | 111 | 4 | **1187789** | Ward | 6.1 | 324 | 16 | DB-Agg. |
| | 600 | 1000 | 5000 | 1242369 | Ward | 5.9 | 260 | 12 | 1370906 | 31.6 | 110 | 4 | **1231145** | Ward | 5.5 | 276 | 9 | DB-Agg. |
| | 800 | 500 | 1000 | 654016 | Ward | 6.9 | 310 | 32 | 900660 | 26.3 | 76 | 44 | **650830** | Ward | 9.6 | 326 | 33 | DB-Agg. |
| | 800 | 500 | 2000 | 675898 | Ward | 7.3 | 288 | 16 | 907187 | 26.5 | 79 | 3 | **670940** | Ward | 8.4 | 306 | 16 | DB-Agg. |
| | 800 | 500 | 5000 | 717731 | Ward | 7.3 | 236 | 9 | 916187 | 26.3 | 79 | 3 | **710901** | GeomDiff | 9.8 | 226 | 5 | DB-Agg. |
| | 800 | 750 | 1000 | 901296 | Ward | 6.6 | 339 | 98 | 1053243 | 27.9 | 17 | 883 | **900131** | Ward | 8.5 | 348 | 101 | DB-Agg. |
| | 800 | 750 | 2000 | 936898 | Ward | 6.5 | 288 | 16 | 1186506 | 26.7 | 78 | 3 | **931940** | Ward | 8.5 | 306 | 16 | DB-Agg. |
| | 800 | 750 | 5000 | 980369 | Ward | 6.7 | 260 | 12 | 1180437 | 26.3 | 79 | 3 | **973986** | Ward | 8.0 | 257 | 9 | DB-Agg. |

| | | | | | Agglomerative (Agg) | | | | DBSCAN - KMeans (DB-KM) | | | | DBSCAN - Agglomerative (DB-Agg) | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F3 | F2 | Cost | Type | Time | M | N | Cost | Time | M | N | Cost | Type | Time | M | N | |
| | 800 | 1000 | 1000 | **1060000** | GeomDiff | 6.9 | 0 | 1060 | **1060000** | 25.3 | 0 | 1060 | **1060000** | GeomDiff | 10.0 | 0 | 1060 | Agg., DB-KM, DB-Agg. |
| | 800 | 1000 | 2000 | 1197825 | Ward | 7.4 | 305 | 26 | 1450756 | 27.2 | 78 | 3 | **1192940** | Ward | 8.3 | 306 | 16 | DB-Agg. |
| | 800 | 1000 | 5000 | 1242369 | Ward | 6.2 | 260 | 12 | 1444687 | 27.2 | 79 | 3 | **1236736** | Ward | 8.1 | 257 | 9 | DB-Agg. |
| | 1000 | 500 | 1000 | 654016 | Ward | 6.9 | 310 | 32 | 985806 | 20.4 | 37 | 404 | **652668** | Ward | 10.7 | 318 | 33 | DB-Agg. |
| | 1000 | 500 | 2000 | 675898 | Ward | 6.2 | 288 | 16 | 1029220 | 21.4 | 55 | 2 | **674010** | Ward | 10.5 | 295 | 16 | DB-Agg. |
| | 1000 | 500 | 5000 | 717731 | Ward | 6.9 | 236 | 9 | 1024524 | 20.5 | 56 | 2 | **713971** | GeomDiff | 14.4 | 215 | 5 | DB-Agg. |
| | 1000 | 750 | 1000 | 901296 | Ward | 6.1 | 339 | 98 | 1056037 | 21.9 | 6 | 945 | **900778** | Ward | 11.1 | 344 | 101 | DB-Agg. |
| | 1000 | 750 | 2000 | 936898 | Ward | 6.7 | 288 | 16 | 1283799 | 19.5 | 56 | 2 | **935010** | Ward | 10.5 | 295 | 16 | DB-Agg. |
| | 1000 | 750 | 5000 | 980369 | Ward | 7.3 | 260 | 12 | 1289024 | 21.4 | 56 | 2 | **977056** | Ward | 10.7 | 246 | 9 | DB-Agg. |
| | 1000 | 1000 | 1000 | **1060000** | GeomDiff | 7.1 | 0 | 1060 | **1060000** | 22.2 | 0 | 1060 | **1060000** | GeomDiff | 12.5 | 0 | 1060 | Agg., DB-KM, DB-Agg. |
| | 1000 | 1000 | 2000 | 1197825 | Ward | 7.4 | 305 | 26 | 1548299 | 21.2 | 56 | 2 | **1196010** | Ward | 11.8 | 295 | 16 | DB-Agg. |
| | 1000 | 1000 | 5000 | 1242369 | Ward | 7.2 | 260 | 12 | 1554299 | 20.7 | 56 | 2 | **1239806** | Ward | 10.9 | 246 | 9 | DB-Agg. |

# Appendix E

# Computational Results of the Fixed and Variable Cost Problem on the Synthetic Data

Table E.1: Results of the Model-based Heuristics on S654 (Fixed and Variable Cost, F1 = 1000)

| | | | | MB-I | | | | | MB-II | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F2 | F3 | Cost | Time | Gap | M | N | Cost | Time | Gap | M | N | |
| 654 | 200 | 1000 | 500 | 400815 | 6403.4 | 0 | 29 | 23 | **400766** | 5642.7 | 0 | 29 | 23 | MB-II |
| | 200 | 1000 | 750 | **557291** | 10852.6 | 3.39 | 25 | 40 | 557614 | 10891.6 | 4.19 | 26 | 40 | MB-I |
| | 200 | 2000 | 500 | 410197 | 100.2 | 0 | 35 | 9 | **410123** | 125.3 | 0 | 35 | 9 | MB-II |
| | 200 | 2000 | 750 | 571447 | 100.9 | 0 | 35 | 9 | **571373** | 136.7 | 0 | 35 | 9 | MB-II |
| | 200 | 5000 | 500 | 437197 | 101.1 | 0 | 35 | 9 | **437123** | 127.6 | 0 | 35 | 9 | MB-II |
| | 200 | 5000 | 750 | 598447 | 100.7 | 0 | 35 | 9 | **598373** | 138.6 | 0 | 35 | 9 | MB-II |
| | 400 | 1000 | 500 | **399621** | 7671.7 | 0 | 29 | 15 | 400419 | 10889.3 | 2.59 | 32 | 15 | MB-I |
| | 400 | 1000 | 750 | **558212** | 10852.0 | 4.54 | 28 | 39 | 558544 | 10891.1 | 5.4 | 29 | 39 | MB-I |
| | 400 | 2000 | 500 | **403828** | 57.8 | 0 | 33 | 3 | **403828** | 117.0 | 0 | 33 | 3 | MB-I, MB-II |
| | 400 | 2000 | 750 | **566542** | 58.4 | 0 | 33 | 3 | **566542** | 120.4 | 0 | 33 | 3 | MB-I, MB-II |
| | 400 | 5000 | 500 | **412828** | 57.6 | 0 | 33 | 3 | **412828** | 116.4 | 0 | 33 | 3 | MB-I, MB-II |
| | 400 | 5000 | 750 | **575578** | 57.0 | 0 | 33 | 3 | **575578** | 118.8 | 0 | 33 | 3 | MB-I, MB-II |
| | 600 | 1000 | 500 | **399564** | 10856.4 | 0.63 | 29 | 14 | 399649 | 10884.3 | 1.73 | 29 | 15 | MB-I |
| | 600 | 1000 | 750 | **558465** | 10883.6 | 4.53 | 28 | 39 | 559696 | 10884.9 | 5.93 | 31 | 39 | MB-I |
| | 600 | 2000 | 500 | **402213** | 73.7 | 0 | 32 | 1 | **402213** | 96.7 | 0 | 32 | 1 | MB-II |
| | 600 | 2000 | 750 | 565437 | 73.0 | 0 | 32 | 1 | **565436** | 98.3 | 0 | 32 | 1 | MB-II |
| | 600 | 5000 | 500 | 405213 | 71.6 | 0 | 32 | 1 | **405213** | 96.9 | 0 | 32 | 1 | MB-II |
| | 600 | 5000 | 750 | 568463 | 71.5 | 0 | 32 | 1 | **568463** | 96.9 | 0 | 32 | 1 | MB-II |
| | 800 | 1000 | 500 | 400445 | 10875.2 | 2.32 | 32 | 15 | **400149** | 10920.9 | 1.95 | 31 | 15 | MB-II |
| | 800 | 1000 | 750 | **558372** | 10877.6 | 5.78 | 28 | 40 | 558517 | 10926.0 | 9.27 | 29 | 38 | MB-I |
| | 800 | 2000 | 500 | **400968** | 89.2 | 0 | 32 | 0 | **400968** | 145.7 | 0 | 32 | 0 | MB-I, MB-II |
| | 800 | 2000 | 750 | **564468** | 89.6 | 0 | 32 | 0 | **564468** | 144.9 | 0 | 32 | 0 | MB-I, MB-II |
| | 800 | 5000 | 500 | **400968** | 89.4 | 0 | 32 | 0 | **400968** | 145.4 | 0 | 32 | 0 | MB-I, MB-II |
| | 800 | 5000 | 750 | **564468** | 89.5 | 0 | 32 | 0 | **564468** | 146.1 | 0 | 32 | 0 | MB-I, MB-II |
| | 1000 | 1000 | 500 | **399622** | 10896.3 | 0.63 | 29 | 15 | 399944 | 10946.9 | 1.84 | 30 | 15 | MB-I |
| | 1000 | 1000 | 750 | 558772 | 10904.0 | 5.17 | 28 | 41 | **558078** | 10950.5 | 7.79 | 27 | 41 | MB-II |
| | 1000 | 2000 | 500 | **400981** | 111.2 | 0 | 32 | 0 | **400981** | 171.8 | 0 | 32 | 0 | MB-I, MB-II |
| | 1000 | 2000 | 750 | **564481** | 112.1 | 0 | 32 | 0 | **564481** | 170.6 | 0 | 32 | 0 | MB-I, MB-II |
| | 1000 | 5000 | 500 | **400981** | 111.7 | 0 | 32 | 0 | **400981** | 170.9 | 0 | 32 | 0 | MB-I, MB-II |
| | 1000 | 5000 | 750 | **564481** | 111.5 | 0 | 32 | 0 | **564481** | 171.6 | 0 | 32 | 0 | MB-I, MB-II |

Table E.2: Results of the Clustering-based Heuristics on S654 (Fixed and Variable Cost, F1 = 1000)

| | | | | Agglomerative (Agg) | | | | DBSCAN - KMeans (DB-KM) | | | | DBSCAN - Agglomerative (DB-Agg) | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F2 | F3 | Cost | Type | Time | M | N | Cost | Time | M | N | Cost | Type | Time | M | N | |
| 654 | 200 | 1000 | 500 | 402343 | Ward | 3.4 | 34 | 19 | 403480 | 4.9 | 26 | 23 | **401313** | Comp. | 0.4 | 29 | 23 | DB-Agg. |
| | 200 | 1000 | 750 | 559252 | Ward | 2.2 | 29 | 39 | 560021 | 5.0 | 21 | 38 | **557906** | Comp. | 0.3 | 25 | 40 | DB-Agg. |
| | 200 | 2000 | 500 | **411752** | Ward | 2.3 | 39 | 9 | 416732 | 3.4 | 31 | 13 | 414565 | Comp. | 0.5 | 34 | 13 | Agg. |
| | 200 | 2000 | 750 | **573002** | Ward | 2.7 | 39 | 9 | 576828 | 3.3 | 30 | 13 | 574815 | Comp. | 0.4 | 34 | 13 | Agg. |
| | 200 | 5000 | 500 | **437474** | GeomDiff | 4.2 | 45 | 8 | 455950 | 3.4 | 31 | 13 | 453565 | Comp. | 0.4 | 34 | 13 | Agg. |
| | 200 | 5000 | 750 | **598974** | GeomDiff | 3.8 | 45 | 8 | 615982 | 4.0 | 31 | 13 | 613815 | Comp. | 0.5 | 34 | 13 | Agg. |
| | 400 | 1000 | 500 | **400147** | GeomDiff | 4.7 | 29 | 14 | 423816 | 0.7 | 15 | 14 | 400670 | GeomDiff | 2.7 | 28 | 14 | Agg. |
| | 400 | 1000 | 750 | **557906** | GeomDiff | 4.6 | 25 | 35 | 580450 | 0.8 | 11 | 64 | **557906** | GeomDiff | 2.8 | 25 | 35 | Agg., DB-Agg. |
| | 400 | 2000 | 500 | **404389** | GeomDiff | 5.5 | 33 | 3 | 431985 | 0.9 | 18 | 8 | 408838 | GeomDiff | 2.7 | 31 | 8 | Agg. |
| | 400 | 2000 | 750 | **567139** | GeomDiff | 5.8 | 33 | 3 | 593196 | 1.0 | 18 | 8 | 570338 | GeomDiff | 3.0 | 31 | 8 | Agg. |
| | 400 | 5000 | 500 | **413389** | GeomDiff | 4.8 | 33 | 3 | 455694 | 0.8 | 18 | 8 | 432838 | GeomDiff | 2.7 | 31 | 8 | Agg. |
| | 400 | 5000 | 750 | **576139** | GeomDiff | 5.1 | 33 | 3 | 617483 | 0.5 | 18 | 8 | 594338 | GeomDiff | 3.2 | 31 | 8 | Agg. |
| | 600 | 1000 | 500 | **400960** | GeomDiff | 7.2 | 29 | 12 | 471556 | 0.8 | 12 | 12 | 427651 | GeomDiff | 3.9 | 25 | 12 | Agg. |
| | 600 | 1000 | 750 | **559149** | Ward | 2.8 | 29 | 38 | 621089 | 1.1 | 6 | 265 | 581473 | GeomDiff | 3.9 | 21 | 171 | Agg. |
| | 600 | 2000 | 500 | **402508** | GeomDiff | 7.0 | 32 | 0 | 472455 | 1.3 | 15 | 0 | 429193 | GeomDiff | 4.3 | 29 | 0 | Agg. |
| | 600 | 2000 | 750 | **566008** | GeomDiff | 6.8 | 32 | 0 | 638294 | 1.2 | 15 | 0 | 592693 | GeomDiff | 4.1 | 29 | 0 | Agg. |
| | 600 | 5000 | 500 | **402508** | GeomDiff | 6.8 | 32 | 0 | 474886 | 1.1 | 15 | 0 | 429193 | GeomDiff | 4.4 | 29 | 0 | Agg. |
| | 600 | 5000 | 750 | **566008** | GeomDiff | 6.9 | 32 | 0 | 635955 | 1.5 | 15 | 0 | 592693 | GeomDiff | 4.1 | 29 | 0 | Agg. |
| | 800 | 1000 | 500 | **400593** | GeomDiff | 7.8 | 29 | 11 | 536176 | 1.6 | 8 | 96 | 474249 | GeomDiff | 4.2 | 21 | 11 | Agg. |
| | 800 | 1000 | 750 | **559102** | GeomDiff | 7.9 | 25 | 32 | 651881 | 1.6 | 1 | 517 | 601857 | Ward | 1.2 | 18 | 175 | Agg. |
| | 800 | 2000 | 500 | **401591** | GeomDiff | 8.6 | 33 | 0 | 607435 | 1.6 | 10 | 0 | 475247 | GeomDiff | 4.4 | 25 | 0 | Agg. |
| | 800 | 2000 | 750 | **565091** | GeomDiff | 8.3 | 33 | 0 | 705105 | 2.1 | 11 | 0 | 638747 | GeomDiff | 4.6 | 25 | 0 | Agg. |
| | 800 | 5000 | 500 | **401591** | GeomDiff | 8.3 | 33 | 0 | 550367 | 2.7 | 13 | 0 | 475247 | GeomDiff | 4.3 | 25 | 0 | Agg. |
| | 800 | 5000 | 750 | **565091** | GeomDiff | 8.3 | 33 | 0 | 705105 | 2.2 | 11 | 0 | 638747 | GeomDiff | 4.4 | 25 | 0 | Agg. |
| | 1000 | 1000 | 500 | **400593** | GeomDiff | 9.3 | 29 | 11 | 525045 | 2.1 | 7 | 20 | 420956 | GeomDiff | 7.5 | 25 | 11 | Agg. |
| | 1000 | 1000 | 750 | **559102** | GeomDiff | 9.3 | 25 | 32 | 639813 | 2.4 | 2 | 408 | 579443 | Ward | 2.0 | 24 | 38 | Agg. |
| | 1000 | 2000 | 500 | **401591** | GeomDiff | 9.8 | 33 | 0 | 529080 | 2.1 | 9 | 0 | 421954 | GeomDiff | 7.8 | 29 | 0 | Agg. |
| | 1000 | 2000 | 750 | **565091** | GeomDiff | 9.4 | 33 | 0 | 692580 | 2.1 | 9 | 0 | 585454 | GeomDiff | 7.5 | 29 | 0 | Agg. |
| | 1000 | 5000 | 500 | **401591** | GeomDiff | 9.6 | 33 | 0 | 529080 | 2.7 | 9 | 0 | 421954 | GeomDiff | 7.4 | 29 | 0 | Agg. |
| | 1000 | 5000 | 750 | **565091** | GeomDiff | 9.8 | 33 | 0 | 692580 | 2.3 | 9 | 0 | 585454 | GeomDiff | 7.4 | 29 | 0 | Agg. |

Table E.3: Results of the Model-based Heuristics on S1060 (Fixed and Variable Cost, F1 = 1000)}

| | | | | MB-I | | | | | MB-II | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F2 | F3 | Cost | Time | Gap | M | N | Cost | Time | Gap | M | N | |
| 1060 | 200 | 1000 | 500 | 930292 | 572.5 | 0 | 165 | 280 | **929356** | 728.3 | 0 | 177 | 240 | MB-II |
| | 200 | 1000 | 750 | 1053977 | 1271.1 | 0 | 12 | 933 | **1053886** | 1577.8 | 0 | 12 | 929 | MB-II |
| | 200 | 2000 | 500 | **975954** | 402.3 | 0 | 281 | 22 | 976457 | 443.2 | 0 | 278 | 23 | MB-I |
| | 200 | 2000 | 750 | **1235454** | 401.7 | 0 | 281 | 22 | 1235707 | 605.1 | 0 | 279 | 22 | MB-I |
| | 200 | 5000 | 500 | **1042095** | 238.4 | 0 | 281 | 22 | 1042457 | 443.1 | 0 | 278 | 23 | MB-I |
| | 200 | 5000 | 750 | **1301595** | 237.8 | 0 | 281 | 22 | 1301957 | 443.9 | 0 | 278 | 23 | MB-I |
| | 400 | 1000 | 500 | 890215 | 391.2 | 0 | 155 | 72 | **890124** | 564.1 | 0 | 155 | 67 | MB-II |
| | 400 | 1000 | 750 | **1053770** | 1931.1 | 0 | 12 | 921 | **1053770** | 1676.9 | 0 | 12 | 921 | MB-I, MB-II |
| | 400 | 2000 | 500 | 904562 | 180.9 | 0 | 181 | 7 | **903082** | 363.2 | 0 | 177 | 6 | MB-II |
| | 400 | 2000 | 750 | 1167224 | 296.4 | 0 | 181 | 7 | **1166062** | 472.8 | 0 | 177 | 6 | MB-II |
| | 400 | 5000 | 500 | 925562 | 181.3 | 0 | 181 | 7 | **921082** | 360.6 | 0 | 177 | 6 | MB-II |
| | 400 | 5000 | 750 | 1188812 | 182.3 | 0 | 181 | 7 | **1184582** | 363.7 | 0 | 177 | 6 | MB-II |
| | 600 | 1000 | 500 | **887808** | 398.2 | 0 | 147 | 40 | 887895 | 608.5 | 0 | 147 | 40 | MB-I |
| | 600 | 1000 | 750 | **1053789** | 2049.7 | 0 | 12 | 923 | 1053796 | 2374.1 | 0 | 12 | 922 | MB-I |
| | 600 | 2000 | 500 | **895855** | 174.1 | 0 | 155 | 5 | 895869 | 350.7 | 0 | 155 | 5 | MB-I |
| | 600 | 2000 | 750 | 1159518 | 208.1 | 0 | 155 | 5 | **1159507** | 386.5 | 0 | 155 | 5 | MB-II |
| | 600 | 5000 | 500 | **910855** | 175.2 | 0 | 155 | 5 | 910869 | 351.3 | 0 | 155 | 5 | MB-I |
| | 600 | 5000 | 750 | **1174605** | 174.1 | 0 | 155 | 5 | 1174619 | 351.3 | 0 | 155 | 5 | MB-I |
| | 800 | 1000 | 500 | **887837** | 488.1 | 0 | 147 | 38 | 887891 | 616.2 | 0 | 147 | 41 | MB-I |
| | 800 | 1000 | 750 | 1053810 | 1729.5 | 0 | 12 | 920 | **1053789** | 2480.1 | 0 | 12 | 923 | MB-II |
| | 800 | 2000 | 500 | **893710** | 270.9 | 0 | 150 | 3 | 893713 | 466.0 | 0 | 150 | 3 | MB-I |
| | 800 | 2000 | 750 | 1157877 | 302.2 | 0 | 150 | 3 | **1157835** | 497.0 | 0 | 150 | 3 | MB-II |
| | 800 | 5000 | 500 | **902710** | 271.7 | 0 | 150 | 3 | 902713 | 465.2 | 0 | 150 | 3 | MB-I |
| | 800 | 5000 | 750 | **1166960** | 274.7 | 0 | 150 | 3 | 1166963 | 466.0 | 0 | 150 | 3 | MB-I |
| | 1000 | 1000 | 500 | 887881 | 516.3 | 0 | 147 | 42 | **887872** | 576.5 | 0 | 147 | 40 | MB-II |
| | 1000 | 1000 | 750 | **1053789** | 1847.2 | 0 | 12 | 923 | **1053789** | 2659.3 | 0 | 12 | 923 | MB-I, MB-II |
| | 1000 | 2000 | 500 | 893752 | 257.3 | 0 | 150 | 3 | **893701** | 455.8 | 0 | 150 | 3 | MB-II |
| | 1000 | 2000 | 750 | **1157828** | 288.8 | 0 | 150 | 3 | 1157858 | 487.8 | 0 | 150 | 3 | MB-I |
| | 1000 | 5000 | 500 | 902752 | 255.8 | 0 | 150 | 3 | **902701** | 460.0 | 0 | 150 | 3 | MB-II |
| | 1000 | 5000 | 750 | 1167002 | 257.2 | 0 | 150 | 3 | **1166951** | 454.3 | 0 | 150 | 3 | MB-II |

Table E.4: Results of the Clustering-based Heuristics on S1060 (Fixed and Variable Cost, F1 = 1000)

| | | | | Agglomerative (Agg) | | | | | DBSCAN - KMeans (DB-KM) | | | | DBSCAN - Agglomerative (DB-Agg) | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F2 | F3 | Cost | Type | Time | M | N | Cost | Time | M | N | Cost | Type | Time | M | N | |
| 1060 | 200 | 1000 | 500 | **944687** | Comp. | 8.2 | 189 | 276 | 946473 | 7.1 | 167 | 351 | 946445 | GeomDiff | 4.5 | 166 | 359 | Agg. |
| | 200 | 1000 | 750 | 1060000 | GeomDiff | 3.8 | 0 | 1060 | **1054001** | 5.3 | 12 | 932 | 1057749 | GeomDiff | 0.1 | 5 | 1010 | DB-KM |
| | 200 | 2000 | 500 | **1011388** | Comp. | 5.8 | 304 | 43 | 1165591 | 8.6 | 243 | 206 | 1165766 | GeomDiff | 0.1 | 241 | 209 | Agg. |
| | 200 | 2000 | 750 | **1265638** | Comp. | 5.9 | 304 | 43 | 1377877 | 6.9 | 241 | 206 | 1378516 | GeomDiff | 0.2 | 241 | 209 | Agg. |
| | 200 | 5000 | 500 | **1140388** | Comp. | 5.3 | 304 | 43 | 1781967 | 6.8 | 240 | 206 | 1787119 | Comp. | 0.1 | 243 | 207 | Agg. |
| | 200 | 5000 | 750 | **1394638** | Comp. | 5.3 | 304 | 43 | 1984780 | 7.1 | 243 | 203 | 2000369 | Comp. | 0.1 | 243 | 207 | Agg. |
| | 400 | 1000 | 500 | 899418 | Ward | 4.9 | 186 | 48 | 910809 | 40.9 | 142 | 55 | **898356** | GeomDiff | 2.2 | 183 | 40 | DB-Agg. |
| | 400 | 1000 | 750 | 1060000 | GeomDiff | 4.4 | 0 | 1060 | 1056032 | 41.3 | 2 | 995 | **1055562** | GeomDiff | 2.2 | 4 | 993 | DB-Agg. |
| | 400 | 2000 | 500 | **911720** | Comp. | 5.7 | 160 | 6 | 931105 | 43.2 | 164 | 13 | 913776 | GeomDiff | 1.9 | 195 | 13 | Agg. |
| | 400 | 2000 | 750 | **1175220** | Comp. | 5.8 | 160 | 6 | 1192836 | 42.2 | 164 | 13 | 1175526 | GeomDiff | 2.1 | 195 | 13 | Agg. |
| | 400 | 5000 | 500 | **929720** | Comp. | 5.8 | 160 | 6 | 968240 | 39.4 | 164 | 13 | 947614 | Comp. | 1.8 | 169 | 11 | Agg. |
| | 400 | 5000 | 750 | **1193220** | Comp. | 6.2 | 160 | 6 | 1229986 | 42.3 | 163 | 13 | 1209864 | Comp. | 1.8 | 169 | 11 | Agg. |
| | 600 | 1000 | 500 | **894106** | GeomDiff | 6.1 | 165 | 18 | 933198 | 33.5 | 100 | 44 | **894106** | GeomDiff | 3.6 | 165 | 18 | Agg., DB-Agg. |
| | 600 | 1000 | 750 | 1060000 | GeomDiff | 5.5 | 0 | 1060 | 1060000 | 30.2 | 0 | 1060 | **1055562** | GeomDiff | 3.7 | 4 | 993 | DB-Agg. |
| | 600 | 2000 | 500 | **899007** | GeomDiff | 6.1 | 156 | 3 | 941245 | 32.9 | 111 | 4 | 899380 | GeomDiff | 3.9 | 162 | 4 | Agg. |
| | 600 | 2000 | 750 | **1163257** | GeomDiff | 6.5 | 156 | 3 | 1204906 | 34.1 | 110 | 4 | 1163380 | GeomDiff | 4.2 | 162 | 4 | Agg. |
| | 600 | 5000 | 500 | **908007** | GeomDiff | 7.3 | 156 | 3 | 952906 | 32.8 | 110 | 4 | 911380 | GeomDiff | 4.1 | 162 | 4 | Agg. |
| | 600 | 5000 | 750 | **1172257** | GeomDiff | 6.9 | 156 | 3 | 1216906 | 33.0 | 110 | 4 | 1175380 | GeomDiff | 4.1 | 162 | 4 | Agg. |
| | 800 | 1000 | 500 | **894831** | GeomDiff | 6.6 | 157 | 11 | 971224 | 26.3 | 62 | 229 | **894831** | GeomDiff | 5.8 | 157 | 11 | Agg., DB-Agg. |
| | 800 | 1000 | 750 | 1060000 | GeomDiff | 5.7 | 0 | 1060 | 1058587 | 24.7 | 1 | 1024 | **1057623** | Comp. | 3.9 | 2 | 1027 | DB-Agg. |
| | 800 | 2000 | 500 | **898088** | GeomDiff | 8.0 | 160 | 3 | 986187 | 26.7 | 79 | 3 | **898088** | GeomDiff | 6.0 | 160 | 3 | Agg., DB-Agg. |
| | 800 | 2000 | 750 | **1162338** | GeomDiff | 6.7 | 160 | 3 | 1264506 | 26.6 | 78 | 3 | **1162338** | GeomDiff | 6.6 | 160 | 3 | Agg., DB-Agg. |
| | 800 | 5000 | 500 | **907088** | GeomDiff | 8.6 | 160 | 3 | 995187 | 25.7 | 79 | 3 | **907088** | GeomDiff | 7.9 | 160 | 3 | Agg., DB-Agg. |
| | 800 | 5000 | 750 | **1171338** | GeomDiff | 7.6 | 160 | 3 | 1273506 | 27.4 | 78 | 3 | **1171338** | GeomDiff | 7.9 | 160 | 3 | Agg., DB-Agg. |
| | 1000 | 1000 | 500 | **894822** | GeomDiff | 8.1 | 157 | 11 | 1014292 | 21.4 | 20 | 707 | **894822** | GeomDiff | 7.4 | 157 | 11 | Agg., DB-Agg. |
| | 1000 | 1000 | 750 | 1060000 | GeomDiff | 7.5 | 0 | 1060 | 1059686 | 21.3 | 1 | 1021 | **1057623** | Comp. | 4.5 | 2 | 1027 | DB-Agg. |
| | 1000 | 2000 | 500 | **898079** | GeomDiff | 9.2 | 160 | 3 | 1068053 | 21.6 | 57 | 2 | **898079** | GeomDiff | 9.5 | 160 | 3 | Agg., DB-Agg. |
| | 1000 | 2000 | 750 | **1162329** | GeomDiff | 9.1 | 160 | 3 | 1339799 | 20.8 | 56 | 2 | **1162329** | GeomDiff | 8.4 | 160 | 3 | Agg., DB-Agg. |
| | 1000 | 5000 | 500 | **907079** | GeomDiff | 8.3 | 160 | 3 | 1073278 | 21.6 | 57 | 2 | **907079** | GeomDiff | 7.3 | 160 | 3 | Agg., DB-Agg. |
| | 1000 | 5000 | 750 | **1171329** | GeomDiff | 8.9 | 160 | 3 | 1343989 | 21.1 | 56 | 2 | **1171329** | GeomDiff | 8.8 | 160 | 3 | Agg., DB-Agg. |

# Appendix F

# Computational Results of the Fixed Cost Problem on Real Instances

Table F.1: Results of the Model based Heuristics on Tiby (Fixed Cost)

| | | | | MB-I | | | | | MB-II | | | | | MB-III | | | | BestMethod |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | Cost | Time | Gap | M | N | Cost | Time | Gap | M | N | Cost | Time | M | N | |
| TIBY - 1 | 30 | 3000 | 750 | 237718 | 84.2 | 0.0 | 48 | 86 | **236917** | 196.1 | 0.0 | 48 | 85 | 264129 | 12.2 | 75 | 5 | MB-II |
| | 30 | 3000 | 1000 | 252561 | 31.8 | 0.0 | 58 | 46 | **251151** | 67.0 | 0.0 | 59 | 41 | 265379 | 10.4 | 75 | 5 | MB-II |
| | 30 | 4000 | 750 | 279509 | 89.0 | 0.0 | 31 | 179 | **279449** | 316.8 | 0.0 | 33 | 167 | 339129 | 10.7 | 75 | 5 | MB-II |
| | 30 | 4000 | 1000 | 307185 | 61.8 | 0.0 | 48 | 86 | **306364** | 134.8 | 0.0 | 48 | 85 | 340379 | 11.0 | 75 | 5 | MB-II |
| | 50 | 3000 | 750 | 165945 | 10821.1 | 1.0 | 33 | 17 | **165901** | 10827.7 | 1.9 | 33 | 17 | 171183 | 13.8 | 38 | 3 | MB-II |
| | 50 | 3000 | 1000 | **169034** | 1871.8 | 0.0 | 35 | 9 | 169044 | 10829.1 | 0.8 | 35 | 9 | 171933 | 15.4 | 38 | 3 | MB-I |
| | 50 | 4000 | 750 | **197557** | 10824.0 | 1.5 | 29 | 39 | **197557** | 10829.1 | 2.1 | 29 | 39 | 209183 | 15.3 | 38 | 3 | MB-I, MB-II |
| | 50 | 4000 | 1000 | 203201 | 10819.9 | 1.0 | 33 | 17 | **203195** | 10835.1 | 1.8 | 33 | 17 | 209933 | 14.2 | 38 | 3 | MB-II |
| | 100 | 3000 | 750 | 141406 | 10821.9 | 12.4 | 20 | 7 | **140231** | 10829.0 | 11.4 | 21 | 7 | 140489 | 15.3 | 18 | 1 | MB-II |
| | 100 | 3000 | 1000 | 144419 | 10821.6 | 10.3 | 25 | 3 | **140696** | 10829.4 | 10.2 | 21 | 4 | 140739 | 15.3 | 18 | 1 | MB-II |
| | 100 | 4000 | 750 | 158253 | 10822.2 | 15.7 | 19 | 8 | **156298** | 10828.8 | 12.7 | 16 | 12 | 158084 | 17.3 | 17 | 1 | MB-II |
| | 100 | 4000 | 1000 | 164680 | 10821.5 | 15.3 | 22 | 5 | 161054 | 10829.8 | 15.3 | 20 | 7 | **158334** | 18.6 | 17 | 1 | MB-III |
| | 200 | 3000 | 750 | 142616 | 10904.7 | 16.7 | 24 | 2 | 142261 | 10919.5 | 19.8 | 22 | 3 | **136219** | 132.8 | 15 | 1 | MB-III |
| | 200 | 3000 | 1000 | 144362 | 10909.6 | 13.7 | 22 | 3 | 144255 | 10921.0 | 22.2 | 24 | 1 | **136469** | 133.9 | 15 | 1 | MB-III |
| | 200 | 4000 | 750 | **150193** | 10904.8 | 22.2 | 14 | 4 | 151147 | 10920.7 | 22.3 | 13 | 7 | 150612 | 130.0 | 14 | 1 | MB-I |
| | 200 | 4000 | 1000 | 152187 | 10904.2 | 23.8 | 15 | 1 | 159009 | 10920.0 | 29.7 | 19 | 2 | **150862** | 132.9 | 14 | 1 | MB-III |
| TIBY - 2 | 30 | 3000 | 750 | 206070 | 379.9 | 0.0 | 41 | 75 | **205585** | 3581.6 | 0.0 | 42 | 70 | 228159 | 13.0 | 65 | 1 | MB-II |
| | 30 | 3000 | 1000 | 218558 | 270.1 | 0.0 | 52 | 32 | **216927** | 456.3 | 0.0 | 52 | 30 | 228409 | 12.3 | 65 | 1 | MB-II |
| | 30 | 4000 | 750 | 241678 | 406.0 | 0.0 | 28 | 145 | **241538** | 5741.1 | 0.0 | 27 | 150 | 293159 | 12.4 | 65 | 1 | MB-II |
| | 30 | 4000 | 1000 | 265820 | 597.0 | 0.0 | 41 | 75 | **265085** | 4593.7 | 0.0 | 42 | 70 | 293409 | 11.4 | 65 | 1 | MB-II |
| | 50 | 3000 | 750 | 141740 | 10815.8 | 2.8 | 28 | 12 | **141503** | 10820.8 | 3.4 | 28 | 10 | 146257 | 12.7 | 32 | 0 | MB-II |
| | 50 | 3000 | 1000 | 143749 | 10815.2 | 1.9 | 29 | 7 | **143724** | 10820.3 | 2.2 | 29 | 7 | 146257 | 13.1 | 32 | 0 | MB-II |
| | 50 | 4000 | 750 | **169584** | 10818.6 | 3.9 | 28 | 12 | 170380 | 10819.8 | 5.4 | 28 | 12 | 178257 | 13.0 | 32 | 0 | MB-I |
| | 50 | 4000 | 1000 | 172006 | 10815.3 | 2.8 | 28 | 10 | **171219** | 10821.1 | 3.7 | 28 | 9 | 178257 | 12.6 | 32 | 0 | MB-II |
| | 100 | 3000 | 750 | 119700 | 10818.8 | 9.7 | 17 | 4 | 121468 | 10821.3 | 14.4 | 20 | 1 | **118253** | 22.6 | 16 | 0 | MB-III |
| | 100 | 3000 | 1000 | 119554 | 10818.4 | 11.0 | 18 | 1 | 121105 | 10822.5 | 11.0 | 19 | 1 | **118253** | 21.7 | 16 | 0 | MB-III |
| | 100 | 4000 | 750 | 135926 | 10817.5 | 13.3 | 15 | 11 | 133310 | 10822.0 | 12.1 | 14 | 8 | **132372** | 30.5 | 13 | 0 | MB-III |
| | 100 | 4000 | 1000 | 134069 | 10817.3 | 10.2 | 15 | 1 | 135353 | 10821.9 | 11.0 | 15 | 6 | **132372** | 30.1 | 13 | 0 | MB-III |
| | 200 | 3000 | 750 | 119750 | 10886.1 | 16.7 | 18 | 1 | 122049 | 10943.5 | 24.9 | 20 | 0 | **116798** | 95.2 | 14 | 0 | MB-III |
| | 200 | 3000 | 1000 | 120667 | 10886.1 | 22.0 | 19 | 0 | 125320 | 10952.3 | 22.9 | 22 | 0 | **116798** | 94.4 | 14 | 0 | MB-III |
| | 200 | 4000 | 750 | 132522 | 10886.9 | 21.8 | 14 | 1 | 134461 | 10943.1 | 28.1 | 16 | 0 | **129167** | 88.9 | 12 | 0 | MB-III |
| | 200 | 4000 | 1000 | 134968 | 10886.8 | 25.7 | 15 | 0 | 138275 | 10943.1 | 26.5 | 18 | 0 | **129167** | 89.2 | 12 | 0 | MB-III |

| | DLim | F1 | F2 | MB-I Cost | MB-I Time | MB-I Gap | MB-I M | MB-I N | MB-II Cost | MB-II Time | MB-II Gap | MB-II M | MB-II N | Unicost Post Process (MB-III) Cost | Unicost Post Process (MB-III) Time | Unicost Post Process (MB-III) M | Unicost Post Process (MB-III) N | BestMethod |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| TIBY - 3 | 30 | 3000 | 750 | 249329 | 46.0 | 0.0 | 44 | 124 | **249306** | 67.5 | 0.0 | 44 | 124 | 288283 | 11.9 | 83 | 8 | MB-II |
| | 30 | 3000 | 1000 | **272153** | 25.3 | 0.0 | 56 | 76 | 272165 | 52.5 | 0.0 | 56 | 76 | 290283 | 10.7 | 83 | 8 | MB-I |
| | 30 | 4000 | 750 | **280774** | 57.4 | 0.0 | 18 | 262 | 280775 | 83.9 | 0.0 | 19 | 256 | 371283 | 10.5 | 83 | 8 | MB-I |
| | 30 | 4000 | 1000 | **324294** | 47.9 | 0.0 | 44 | 124 | 324306 | 118.4 | 0.0 | 44 | 124 | 373283 | 9.7 | 83 | 8 | MB-I |
| | 50 | 3000 | 750 | **183257** | 10816.6 | 0.5 | 37 | 29 | 183286 | 10831.3 | 1.0 | 36 | 34 | 193246 | 10.0 | 46 | 1 | MB-I |
| | 50 | 3000 | 1000 | **188688** | 494.3 | 0.0 | 40 | 16 | 188693 | 6077.6 | 0.0 | 40 | 16 | 193496 | 9.9 | 46 | 1 | MB-I |
| | 50 | 4000 | 750 | 214852 | 10830.3 | 0.7 | 29 | 72 | **214852** | 10834.9 | 1.6 | 29 | 72 | 239246 | 8.5 | 46 | 1 | MB-II |
| | 50 | 4000 | 1000 | 227397 | 5745.7 | 0.0 | 38 | 24 | **227383** | 10822.6 | 1.1 | 38 | 24 | 239496 | 8.8 | 46 | 1 | MB-II |
| | 100 | 3000 | 750 | 148609 | 10815.1 | 5.2 | 24 | 5 | 150338 | 10820.4 | 7.7 | 26 | 1 | **147483** | 15.0 | 23 | 0 | MB-III |
| | 100 | 3000 | 1000 | 147687 | 10816.0 | 1.8 | 23 | 1 | 149042 | 10821.2 | 3.9 | 25 | 1 | **147483** | 14.4 | 23 | 0 | MB-III |
| | 100 | 4000 | 750 | **166741** | 10816.4 | 7.0 | 18 | 26 | 170529 | 10821.5 | 10.3 | 20 | 30 | 169426 | 17.9 | 22 | 0 | MB-I |
| | 100 | 4000 | 1000 | 172774 | 10815.5 | 6.7 | 22 | 8 | 173313 | 10819.8 | 7.1 | 23 | 5 | **169426** | 17.7 | 22 | 0 | MB-III |
| | 200 | 3000 | 750 | 145337 | 10835.3 | 12.7 | 21 | 1 | 146574 | 10842.0 | 14.1 | 22 | 2 | **142641** | 37.0 | 18 | 0 | MB-III |
| | 200 | 3000 | 1000 | 146169 | 10836.0 | 10.6 | 22 | 2 | 144993 | 10841.2 | 6.6 | 21 | 0 | **142641** | 37.2 | 18 | 0 | MB-III |
| | 200 | 4000 | 750 | 162273 | 10836.6 | 19.1 | 17 | 11 | 159542 | 10842.1 | 15.5 | 17 | 1 | **158524** | 47.9 | 15 | 0 | MB-III |
| | 200 | 4000 | 1000 | 160765 | 10836.1 | 18.5 | 17 | 1 | 163559 | 10843.1 | 17.0 | 19 | 1 | **158524** | 49.6 | 15 | 0 | MB-III |
| TIBY - 4 | 30 | 3000 | 750 | 122193 | 48.2 | 0.0 | 22 | 56 | **122129** | 248.4 | 0.0 | 22 | 56 | 134547 | 4.3 | 38 | 3 | MB-II |
| | 30 | 3000 | 1000 | 131117 | 34.1 | 0.0 | 29 | 28 | **131038** | 198.1 | 0.0 | 29 | 28 | 135297 | 2.8 | 38 | 3 | MB-II |
| | 30 | 4000 | 750 | 141871 | 23.0 | 0.0 | 13 | 107 | **141847** | 59.8 | 0.0 | 13 | 107 | 172547 | 3.0 | 38 | 3 | MB-II |
| | 30 | 4000 | 1000 | 158193 | 48.9 | 0.0 | 22 | 56 | **158109** | 203.4 | 0.0 | 22 | 56 | 173297 | 2.8 | 38 | 3 | MB-II |
| | 50 | 3000 | 750 | 85343 | 10804.3 | 0.8 | 16 | 14 | **84799** | 10805.0 | 1.5 | 16 | 13 | 90412 | 4.4 | 21 | 1 | MB-II |
| | 50 | 3000 | 1000 | 88233 | 2373.7 | 0.0 | 17 | 10 | **87610** | 10804.7 | 1.0 | 17 | 9 | 90662 | 5.4 | 21 | 1 | MB-II |
| | 50 | 4000 | 750 | 100537 | 10804.0 | 0.8 | 15 | 18 | **100534** | 10804.3 | 2.5 | 15 | 18 | 111412 | 3.6 | 21 | 1 | MB-II |
| | 50 | 4000 | 1000 | 104681 | 10803.3 | 0.5 | 16 | 14 | **103873** | 10817.7 | 2.5 | 16 | 13 | 111662 | 3.8 | 21 | 1 | MB-II |
| | 100 | 3000 | 750 | **70953** | 10806.2 | 3.7 | 9 | 8 | 71039 | 10807.4 | 5.1 | 10 | 8 | 73712 | 5.3 | 10 | 1 | MB-I |
| | 100 | 3000 | 1000 | **72370** | 5162.0 | 0.0 | 9 | 6 | **72370** | 9778.1 | 0.0 | 9 | 6 | 73962 | 5.1 | 10 | 1 | MB-I, MB-II |
| | 100 | 4000 | 750 | **79458** | 10806.5 | 5.2 | 8 | 8 | 81021 | 10807.4 | 8.7 | 10 | 8 | 86303 | 5.2 | 10 | 0 | MB-I |
| | 100 | 4000 | 1000 | 82809 | 10806.6 | 6.4 | 10 | 7 | **81693** | 10807.4 | 5.5 | 9 | 7 | 86303 | 5.1 | 10 | 0 | MB-II |
| | 200 | 3000 | 750 | 71568 | 10818.7 | 14.8 | 10 | 6 | 71150 | 10819.6 | 9.7 | 10 | 3 | **71145** | 28.1 | 10 | 0 | MB-III |
| | 200 | 3000 | 1000 | **70791** | 10818.8 | 4.5 | 9 | 3 | 72374 | 10818.7 | 8.0 | 10 | 3 | 71145 | 26.5 | 10 | 0 | MB-I |
| | 200 | 4000 | 750 | **78276** | 10818.7 | 10.9 | 8 | 3 | 79776 | 10819.1 | 13.9 | 9 | 3 | 79659 | 30.6 | 7 | 0 | MB-I |
| | 200 | 4000 | 1000 | **78962** | 10819.3 | 11.6 | 8 | 3 | 80706 | 10819.2 | 13.5 | 9 | 4 | 79659 | 31.3 | 7 | 0 | MB-I |

Table F.2: Results of the Clustering based Heuristics on Tiby (Fixed Cost)

| | | | | Agglomerative (Agg) | | | | | DBSCAN - KMeans (DB-KM) | | | | DBSCAN - Agglomerative (DB-Agg) | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | Cost | Type | Time | M | N | Cost | Time | M | N | Cost | Type | Time | M | N | |
| TIBY - 1 | 30 | 3000 | 750 | 318750 | GeomDiff | 1.3 | 40 | 172 | 269790 | 30.6 | 35 | 197 | **267273** | Comp | 0.6 | 40 | 172 | DB-Agg. |
| | 30 | 3000 | 1000 | **301130** | Comp | 0.9 | 58 | 107 | 305244 | 21.1 | 60 | 104 | 302594 | Comp | 0.3 | 58 | 107 | Agg. |
| | 30 | 4000 | 750 | 318750 | GeomDiff | 0.9 | 0 | 425 | **295892** | 19.8 | 23 | 255 | 318750 | GeomDiff | 1.0 | 0 | 425 | DB-KM |
| | 30 | 4000 | 1000 | 353258 | Comp | 1.0 | 40 | 172 | 359685 | 20.4 | 35 | 204 | **350273** | Comp | 0.4 | 40 | 172 | DB-Agg. |
| | 50 | 3000 | 750 | **189309** | Comp | 0.7 | 42 | 26 | 201207 | 19.1 | 44 | 35 | **189309** | Comp | 1.2 | 42 | 26 | Agg., DB-Agg. |
| | 50 | 3000 | 1000 | **197992** | Comp | 0.7 | 46 | 15 | 210721 | 19.3 | 50 | 17 | **197992** | Comp | 1.2 | 46 | 15 | Agg., DB-Agg. |
| | 50 | 4000 | 750 | **224806** | Comp | 0.5 | 33 | 70 | 235195 | 18.3 | 36 | 68 | **224806** | Comp | 0.7 | 33 | 70 | Agg., DB-Agg. |
| | 50 | 4000 | 1000 | **237809** | Comp | 0.6 | 42 | 26 | 249530 | 19.2 | 43 | 34 | **237809** | Comp | 0.6 | 42 | 26 | Agg., DB-Agg. |
| | 100 | 3000 | 750 | 146462 | Comp | 1.2 | 21 | 6 | 146740 | 8.1 | 19 | 3 | **142957** | Ward | 1.1 | 21 | 6 | DB-Agg. |
| | 100 | 3000 | 1000 | 147212 | Comp | 1.2 | 21 | 6 | 151141 | 9.9 | 22 | 5 | **144457** | Ward | 1.1 | 21 | 6 | DB-Agg. |
| | 100 | 4000 | 750 | 165819 | Comp | 1.0 | 20 | 12 | 165509 | 9.6 | 19 | 5 | **163665** | Ward | 1.1 | 20 | 12 | DB-Agg. |
| | 100 | 4000 | 1000 | 167212 | Comp | 0.9 | 21 | 6 | 166490 | 8.4 | 19 | 3 | **165457** | Ward | 0.8 | 21 | 6 | DB-Agg. |
| | 200 | 3000 | 750 | **139323** | Ward | 2.1 | 17 | 1 | 179719 | 3.0 | 6 | 1 | **139323** | Ward | 1.7 | 17 | 1 | Agg., DB-Agg. |
| | 200 | 3000 | 1000 | **139573** | Ward | 1.8 | 17 | 1 | 179969 | 2.9 | 6 | 1 | **139573** | Ward | 2.3 | 17 | 1 | Agg., DB-Agg. |
| | 200 | 4000 | 750 | **155608** | Ward | 1.7 | 16 | 1 | 186082 | 2.8 | 6 | 1 | **155608** | Ward | 2.1 | 16 | 1 | Agg., DB-Agg. |
| | 200 | 4000 | 1000 | **155858** | Ward | 1.7 | 16 | 1 | 185969 | 3.4 | 6 | 1 | **155858** | Ward | 1.9 | 16 | 1 | Agg., DB-Agg. |
| TIBY - 2 | 30 | 3000 | 750 | 241215 | Comp | 0.8 | 43 | 125 | **235208** | 23.4 | 35 | 150 | 235550 | Comp | 0.9 | 38 | 137 | DB-KM |
| | 30 | 3000 | 1000 | 269484 | Comp | 0.8 | 57 | 78 | 263643 | 18.2 | 49 | 96 | **260529** | Comp | 0.6 | 51 | 86 | DB-Agg. |
| | 30 | 4000 | 750 | 297750 | GeomDiff | 1.2 | 0 | 397 | **262455** | 17.8 | 21 | 221 | 297684 | GeomDiff | 0.8 | 1 | 391 | DB-KM |
| | 30 | 4000 | 1000 | 315465 | Comp | 1.0 | 43 | 125 | **307694** | 17.0 | 35 | 150 | 307800 | Comp | 0.6 | 38 | 137 | DB-KM |
| | 50 | 3000 | 750 | **164205** | Comp | 0.7 | 37 | 16 | 174056 | 14.2 | 42 | 12 | **164205** | Comp | 0.8 | 37 | 16 | Agg., DB-Agg. |
| | 50 | 3000 | 1000 | **167945** | Comp | 0.7 | 40 | 6 | 176366 | 15.4 | 43 | 8 | 168495 | Comp | 0.6 | 39 | 10 | Agg. |
| | 50 | 4000 | 750 | **197610** | Comp | 0.5 | 28 | 65 | 205230 | 14.5 | 35 | 36 | **197610** | Comp | 0.6 | 28 | 65 | Agg., DB-Agg. |
| | 50 | 4000 | 1000 | **205205** | Comp | 0.7 | 37 | 16 | 219056 | 14.3 | 42 | 12 | **205205** | Comp | 0.7 | 37 | 16 | Agg., DB-Agg. |
| | 100 | 3000 | 750 | **123130** | Comp | 0.8 | 15 | 4 | 125873 | 7.2 | 18 | 0 | **123130** | Comp | 1.0 | 15 | 4 | Agg., DB-Agg. |
| | 100 | 3000 | 1000 | **124040** | Ward | 0.9 | 19 | 0 | 125375 | 7.3 | 18 | 0 | **124040** | Ward | 0.9 | 19 | 0 | Agg., DB-Agg. |
| | 100 | 4000 | 750 | **137646** | Comp | 1.1 | 14 | 4 | 143873 | 7.3 | 18 | 0 | **137646** | Comp | 0.7 | 14 | 4 | Agg., DB-Agg. |
| | 100 | 4000 | 1000 | **138646** | Comp | 0.5 | 14 | 4 | 143873 | 7.6 | 18 | 0 | **138646** | Comp | 0.9 | 14 | 4 | Agg., DB-Agg. |
| | 200 | 3000 | 750 | **119889** | Ward | 1.3 | 13 | 0 | 154987 | 1.7 | 5 | 0 | **119889** | Ward | 1.3 | 13 | 0 | Agg., DB-Agg. |
| | 200 | 3000 | 1000 | **119889** | Ward | 1.8 | 13 | 0 | 153801 | 1.9 | 5 | 0 | **119889** | Ward | 1.6 | 13 | 0 | Agg., DB-Agg. |
| | 200 | 4000 | 750 | **132488** | GeomDiff | 4.3 | 12 | 0 | 158801 | 1.7 | 5 | 0 | **132488** | GeomDiff | 3.8 | 12 | 0 | Agg., DB-Agg. |
| | 200 | 4000 | 1000 | **132488** | GeomDiff | 4.4 | 12 | 0 | 158801 | 1.8 | 5 | 0 | **132488** | GeomDiff | 4.1 | 12 | 0 | Agg., DB-Agg. |

| | | | | Agglomerative (Agg) | | | | | DBSCAN - KMeans (DB-KM) | | | | DBSCAN - Agglomerative (DB-Agg) | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | Cost | Type | Time | M | N | Cost | Time | M | N | Cost | Type | Time | M | N | |
| TIBY - 3 | 30 | 3000 | 750 | 306750 | GeomDiff | 1.6 | 0 | 409 | 273251 | 18.8 | 29 | 232 | **271895** | Comp | 0.3 | 26 | 243 | DB-Agg. |
| | 30 | 3000 | 1000 | 310050 | Comp | 1.1 | 53 | 132 | 312966 | 13.7 | 50 | 145 | **309715** | Comp | 0.4 | 53 | 132 | DB-Agg. |
| | 30 | 4000 | 750 | 306750 | GeomDiff | 1.3 | 0 | 409 | **294474** | 13.8 | 13 | 314 | 304564 | Ward | 0.2 | 6 | 370 | DB-KM |
| | 30 | 4000 | 1000 | 409000 | GeomDiff | 1.1 | 0 | 409 | 358781 | 13.1 | 30 | 226 | **358645** | Comp | 0.3 | 26 | 243 | DB-Agg. |
| | 50 | 3000 | 750 | 213827 | Comp | 0.7 | 45 | 58 | **210107** | 15.5 | 42 | 63 | 213827 | Comp | 1.0 | 45 | 58 | DB-KM |
| | 50 | 3000 | 1000 | 227104 | Comp | 0.5 | 53 | 31 | **225981** | 16.1 | 49 | 41 | 227433 | Comp | 0.9 | 51 | 38 | DB-KM |
| | 50 | 4000 | 750 | 244361 | Comp | 0.7 | 30 | 127 | **238401** | 15.8 | 27 | 133 | 244361 | Comp | 0.5 | 30 | 127 | DB-KM |
| | 50 | 4000 | 1000 | **273327** | Comp | 0.9 | 45 | 58 | 277694 | 17.4 | 46 | 58 | **273327** | Comp | 0.3 | 45 | 58 | Agg., DB-Agg. |
| | 100 | 3000 | 750 | **152232** | Comp | 0.8 | 23 | 7 | 154180 | 8.6 | 24 | 7 | **152232** | Comp | 0.8 | 23 | 7 | Agg., DB-Agg. |
| | 100 | 3000 | 1000 | **153324** | Comp | 0.8 | 24 | 3 | 158665 | 9.0 | 26 | 4 | **153324** | Comp | 0.8 | 24 | 3 | Agg., DB-Agg. |
| | 100 | 4000 | 750 | **174507** | Comp | 0.5 | 22 | 13 | 174785 | 9.1 | 20 | 26 | **174507** | Comp | 0.8 | 22 | 13 | Agg., DB-Agg. |
| | 100 | 4000 | 1000 | **176982** | Comp | 0.5 | 23 | 7 | 181262 | 8.8 | 25 | 4 | **176982** | Comp | 0.9 | 23 | 7 | Agg., DB-Agg. |
| | 200 | 3000 | 750 | **146273** | GeomDiff | 2.9 | 17 | 0 | 163855 | 4.0 | 10 | 0 | **146273** | GeomDiff | 3.7 | 17 | 0 | Agg., DB-Agg. |
| | 200 | 3000 | 1000 | **146273** | GeomDiff | 3.1 | 17 | 0 | 163842 | 3.5 | 10 | 0 | **146273** | GeomDiff | 3.2 | 17 | 0 | Agg., DB-Agg. |
| | 200 | 4000 | 750 | **160745** | GeomDiff | 2.8 | 13 | 6 | 173529 | 3.2 | 9 | 7 | **160745** | GeomDiff | 3.3 | 13 | 6 | Agg., DB-Agg. |
| | 200 | 4000 | 1000 | **161470** | GeomDiff | 2.6 | 14 | 0 | 173842 | 3.6 | 10 | 0 | **161470** | GeomDiff | 3.1 | 14 | 0 | Agg., DB-Agg. |
| TIBY - 4 | 30 | 3000 | 750 | **134269** | Complete | 0.3 | 23 | 72 | 135278 | 14.8 | 23 | 74 | 135423 | Complete | 0.2 | 19 | 92 | Agg. |
| | 30 | 3000 | 1000 | **147284** | Complete | 0.2 | 32 | 38 | 154204 | 11.7 | 31 | 49 | 151942 | Complete | 0.2 | 30 | 50 | Agg. |
| | 30 | 4000 | 750 | 163500 | GeomDiff | 0.4 | 0 | 218 | **155522** | 10.3 | 11 | 141 | 163500 | GeomDiff | 0.3 | 0 | 218 | DB-KM |
| | 30 | 4000 | 1000 | **175269** | Complete | 0.2 | 23 | 72 | 179125 | 10.2 | 22 | 81 | 177423 | Complete | 0.2 | 19 | 92 | Agg. |
| | 50 | 3000 | 750 | **95678** | Complete | 0.4 | 22 | 10 | 100059 | 7.4 | 23 | 13 | 96083 | Complete | 0.3 | 22 | 11 | Agg. |
| | 50 | 3000 | 1000 | **98178** | Complete | 0.5 | 22 | 10 | 105135 | 7.4 | 24 | 12 | 98833 | Complete | 0.4 | 22 | 11 | Agg. |
| | 50 | 4000 | 750 | **117678** | Complete | 0.4 | 22 | 10 | 122144 | 7.8 | 19 | 36 | 118083 | Complete | 0.3 | 22 | 11 | Agg. |
| | 50 | 4000 | 1000 | **120178** | Complete | 0.3 | 22 | 10 | 126309 | 7.3 | 23 | 13 | 120833 | Complete | 0.3 | 22 | 11 | Agg. |
| | 100 | 3000 | 750 | **72472** | GeomDiff | 1.9 | 9 | 9 | 74713 | 3.4 | 9 | 6 | **72472** | GeomDiff | 1.6 | 9 | 9 | Agg.DB-Agg. |
| | 100 | 3000 | 1000 | **74722** | GeomDiff | 1.8 | 9 | 9 | 76213 | 3.5 | 9 | 6 | **74722** | GeomDiff | 1.6 | 9 | 9 | Agg.DB-Agg. |
| | 100 | 4000 | 750 | **81472** | GeomDiff | 1.6 | 9 | 9 | 81876 | 3.6 | 8 | 9 | **81472** | GeomDiff | 1.6 | 9 | 9 | Agg.DB-Agg. |
| | 100 | 4000 | 1000 | **83722** | GeomDiff | 0.9 | 9 | 9 | 85213 | 3.0 | 9 | 6 | **83722** | GeomDiff | 1.5 | 9 | 9 | Agg.DB-Agg. |
| | 200 | 3000 | 750 | **71441** | GeomDiff | 1.7 | 9 | 3 | 89038 | 1.4 | 5 | 0 | **71441** | GeomDiff | 2.4 | 9 | 3 | Agg.DB-Agg. |
| | 200 | 3000 | 1000 | **72191** | GeomDiff | 1.4 | 9 | 3 | 88177 | 1.5 | 5 | 0 | **72191** | GeomDiff | 1.5 | 9 | 3 | Agg.DB-Agg. |
| | 200 | 4000 | 750 | **79870** | GeomDiff | 1.4 | 7 | 3 | 94038 | 1.3 | 5 | 0 | **79870** | GeomDiff | 1.7 | 7 | 3 | Agg.DB-Agg. |
| | 200 | 4000 | 1000 | **80620** | GeomDiff | 1.5 | 7 | 3 | 94038 | 1.6 | 5 | 0 | **80620** | GeomDiff | 1.6 | 7 | 3 | Agg.DB-Agg. |

Table F.3: Results of the Model based Heuristics on Mbola (Fixed Cost)

| | | | | MB-I | | | | | MB-II | | | | | MB-III | | | | BestMethod |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | Cost | Time | Gap | M | N | Cost | Time | Gap | M | N | Cost | Time | M | N | |
| MBOLA - 1 | 30 | 3000 | 750 | **107026** | 4.1 | 0 | 3 | 61 | **107026** | 7.5 | 0 | 3 | 129 | 150959 | 2.1 | 41 | 26 | MB-I, MB-II |
| | 30 | 3000 | 1000 | **132626** | 4.3 | 0 | 4 | 57 | **132626** | 5.8 | 0 | 13 | 89 | 157459 | 1.7 | 41 | 26 | MB-I, MB-II |
| | 30 | 4000 | 750 | **108581** | 3.6 | 0 | 1 | 71 | **108581** | 9.9 | 0 | 1 | 139 | 191959 | 1.7 | 41 | 26 | MB-I, MB-II |
| | 30 | 4000 | 1000 | **142276** | 3.7 | 0 | 3 | 61 | **142276** | 7.1 | 0 | 3 | 129 | 198459 | 1.1 | 41 | 26 | MB-I, MB-II |
| | 50 | 3000 | 750 | 101597 | 4.2 | 0 | 3 | 60 | **100920** | 5.0 | 0 | 10 | 84 | 135861 | 1.7 | 38 | 10 | MB-II |
| | 50 | 3000 | 1000 | 118532 | 13.1 | 0 | 6 | 48 | **117720** | 11.8 | 0 | 17 | 56 | 138361 | 1.6 | 38 | 10 | MB-II |
| | 50 | 4000 | 750 | **106692** | 12.3 | 0 | 1 | 71 | **106692** | 9.6 | 0 | 3 | 122 | 173861 | 1.8 | 38 | 10 | MB-I, MB-II |
| | 50 | 4000 | 1000 | 132596 | 3.4 | 0 | 3 | 60 | **131784** | 5.0 | 0 | 11 | 79 | 176361 | 0.9 | 38 | 10 | MB-II |
| | 100 | 3000 | 750 | 88651 | 14.1 | 0 | 3 | 60 | **88303** | 31.4 | 0 | 10 | 45 | 100214 | 1.2 | 21 | 3 | MB-II |
| | 100 | 3000 | 1000 | 96453 | 17.4 | 0 | 8 | 36 | **95411** | 30.4 | 0 | 14 | 22 | 100964 | 1.6 | 21 | 3 | MB-II |
| | 100 | 4000 | 750 | 96578 | 14.7 | 0 | 1 | 71 | **96385** | 8.3 | 0 | 7 | 62 | 121214 | 1.2 | 21 | 3 | MB-II |
| | 100 | 4000 | 1000 | 109244 | 12.2 | 0 | 3 | 60 | **108551** | 32.0 | 0 | 12 | 30 | 121964 | 1.4 | 21 | 3 | MB-II |
| | 200 | 3000 | 750 | **81715** | 410.8 | 0 | 3 | 59 | **81715** | 550.0 | 0 | 10 | 19 | 88757 | 1.2 | 15 | 2 | MB-I, MB-II |
| | 200 | 3000 | 1000 | **85674** | 117.0 | 0 | 8 | 30 | **85674** | 115.5 | 0 | 11 | 15 | 89257 | 0.8 | 15 | 2 | MB-I, MB-II |
| | 200 | 4000 | 750 | **90321** | 594.1 | 0 | 2 | 64 | **90321** | 686.1 | 0 | 7 | 30 | 102986 | 0.9 | 14 | 2 | MB-I, MB-II |
| | 200 | 4000 | 1000 | **95701** | 606.9 | 0 | 5 | 44 | **95701** | 591.7 | 0 | 9 | 19 | 103486 | 1.1 | 14 | 2 | MB-I, MB-II |
| MBOLA - 2 | 30 | 3000 | 750 | 55945 | 6.0 | 0 | 3 | 61 | **55836** | 4.6 | 0 | 3 | 61 | 83827 | 1.5 | 22 | 20 | MB-II |
| | 30 | 3000 | 1000 | 70432 | 2.1 | 0 | 4 | 57 | **70323** | 3.3 | 0 | 4 | 57 | 88827 | 0.7 | 22 | 20 | MB-II |
| | 30 | 4000 | 750 | **57642** | 3.2 | 0 | 1 | 71 | **57642** | 3.6 | 0 | 1 | 71 | 105827 | 0.7 | 22 | 20 | MB-I, MB-II |
| | 30 | 4000 | 1000 | 74195 | 1.9 | 0 | 3 | 61 | **74086** | 4.2 | 0 | 3 | 61 | 110827 | 0.6 | 22 | 20 | MB-II |
| | 50 | 3000 | 750 | **55272** | 1.9 | 0 | 3 | 60 | **55272** | 3.5 | 0 | 3 | 60 | 78151 | 0.9 | 21 | 14 | MB-I, MB-II |
| | 50 | 3000 | 1000 | **68749** | 11.1 | 0 | 6 | 48 | **68749** | 16.4 | 0 | 6 | 48 | 81651 | 1.1 | 21 | 14 | MB-I, MB-II |
| | 50 | 4000 | 750 | **57624** | 2.1 | 0 | 1 | 71 | **57624** | 4.0 | 0 | 1 | 71 | 99151 | 1.2 | 21 | 14 | MB-I, MB-II |
| | 50 | 4000 | 1000 | **73272** | 1.3 | 0 | 3 | 60 | **73272** | 3.7 | 0 | 3 | 60 | 102651 | 0.6 | 21 | 14 | MB-I, MB-II |
| | 100 | 3000 | 750 | **55272** | 5.7 | 0 | 3 | 60 | **55272** | 2.4 | 0 | 3 | 60 | 75396 | 0.5 | 20 | 8 | MB-I, MB-II |
| | 100 | 3000 | 1000 | **66818** | 1.4 | 0 | 8 | 36 | **66818** | 2.6 | 0 | 8 | 36 | 77396 | 0.5 | 20 | 8 | MB-I, MB-II |
| | 100 | 4000 | 750 | **57624** | 2.1 | 0 | 1 | 71 | **57624** | 4.0 | 0 | 1 | 71 | 95396 | 0.7 | 20 | 8 | MB-I, MB-II |
| | 100 | 4000 | 1000 | **73272** | 2.8 | 0 | 3 | 60 | **73272** | 3.1 | 0 | 3 | 60 | 97396 | 0.5 | 20 | 8 | MB-I, MB-II |
| | 200 | 3000 | 750 | **55121** | 2.9 | 0 | 3 | 59 | **55121** | 3.3 | 0 | 3 | 59 | 73092 | 0.5 | 15 | 2 | MB-I, MB-II |
| | 200 | 3000 | 1000 | 64569 | 15.3 | 0 | 8 | 30 | **64253** | 14.4 | 0 | 8 | 27 | 73592 | 0.9 | 15 | 2 | MB-II |
| | 200 | 4000 | 750 | **57527** | 3.0 | 0 | 2 | 64 | **57527** | 3.1 | 0 | 2 | 64 | 87113 | 0.7 | 12 | 2 | MB-I, MB-II |
| | 200 | 4000 | 1000 | 71583 | 1.9 | 0 | 5 | 44 | **71267** | 2.4 | 0 | 5 | 41 | 87613 | 0.5 | 12 | 2 | MB-II |

| | | | | MB-I | | | | | MB-II | | | | | Unicost Post Process (MB-III) | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | Cost | Time | Gap | M | N | Cost | Time | Gap | M | N | Cost | Time | M | N | |
| MBOLA - 3 | 30 | 3000 | 750 | **34967** | 2.9 | 0 | 1 | 42 | **34967** | 4.5 | 0 | 1 | 42 | 54180 | 1.3 | 15 | 10 | MB-I, MB-II |
| | 30 | 3000 | 1000 | **44723** | 1.1 | 0 | 2 | 38 | **44723** | 15.3 | 0 | 2 | 38 | 56680 | 0.7 | 15 | 10 | MB-I, MB-II |
| | 30 | 4000 | 750 | **35250** | 1.7 | 0 | 0 | 47 | **35250** | 3.0 | 0 | 0 | 47 | 69180 | 0.8 | 15 | 10 | MB-I, MB-II |
| | 30 | 4000 | 1000 | **46467** | 1.6 | 0 | 1 | 42 | **46467** | 1.8 | 0 | 1 | 42 | 71680 | 0.4 | 15 | 10 | MB-I, MB-II |
| | 50 | 3000 | 750 | **34369** | 1.7 | 0 | 1 | 41 | **34369** | 2.4 | 0 | 1 | 41 | 52425 | 0.6 | 15 | 5 | MB-I, MB-II |
| | 50 | 3000 | 1000 | **43539** | 10.7 | 0 | 3 | 33 | **43539** | 11.4 | 0 | 3 | 33 | 53675 | 0.9 | 15 | 5 | MB-I, MB-II |
| | 50 | 4000 | 750 | **35250** | 2.3 | 0 | 0 | 47 | **35250** | 2.8 | 0 | 0 | 47 | 67425 | 1.0 | 15 | 5 | MB-I, MB-II |
| | 50 | 4000 | 1000 | **45619** | 2.0 | 0 | 1 | 41 | **45619** | 2.5 | 0 | 1 | 41 | 68675 | 0.4 | 15 | 5 | MB-I, MB-II |
| | 100 | 3000 | 750 | **34369** | 1.3 | 0 | 1 | 41 | **34369** | 6.3 | 0 | 1 | 41 | 49323 | 0.5 | 14 | 2 | MB-I, MB-II |
| | 100 | 3000 | 1000 | **42486** | 3.7 | 0 | 4 | 28 | **42486** | 1.5 | 0 | 4 | 28 | 49823 | 0.5 | 14 | 2 | MB-I, MB-II |
| | 100 | 4000 | 750 | **35250** | 2.1 | 0 | 0 | 47 | **35250** | 18.4 | 0 | 0 | 47 | 63323 | 0.4 | 14 | 2 | MB-I, MB-II |
| | 100 | 4000 | 1000 | **45619** | 1.2 | 0 | 1 | 41 | **45619** | 1.7 | 0 | 1 | 41 | 63823 | 0.4 | 14 | 2 | MB-I, MB-II |
| | 200 | 3000 | 750 | **34110** | 1.3 | 0 | 2 | 33 | **34110** | 3.7 | 0 | 2 | 33 | 47301 | 0.4 | 11 | 1 | MB-I, MB-II |
| | 200 | 3000 | 1000 | **40785** | 1.4 | 0 | 4 | 24 | **40785** | 3.1 | 0 | 4 | 24 | 47551 | 0.5 | 11 | 1 | MB-I, MB-II |
| | 200 | 4000 | 750 | **35250** | 2.7 | 0 | 0 | 47 | **35250** | 2.6 | 0 | 0 | 47 | 57267 | 0.7 | 10 | 1 | MB-I, MB-II |
| | 200 | 4000 | 1000 | **44360** | 5.0 | 0 | 2 | 33 | **44360** | 2.0 | 0 | 2 | 33 | 57517 | 0.4 | 10 | 1 | MB-I, MB-II |
| MBOLA - 4 | 30 | 3000 | 750 | **46177** | 4.5 | 0 | 1 | 57 | **46177** | 11.1 | 0 | 1 | 57 | 69211 | 1.4 | 19 | 12 | MB-I, MB-II |
| | 30 | 3000 | 1000 | **59772** | 2.3 | 0 | 2 | 53 | **59772** | 3.0 | 0 | 2 | 53 | 72211 | 0.5 | 19 | 12 | MB-I, MB-II |
| | 30 | 4000 | 750 | **46500** | 1.7 | 0 | 0 | 62 | **46500** | 14.2 | 0 | 0 | 62 | 88211 | 1.0 | 19 | 12 | MB-I, MB-II |
| | 30 | 4000 | 1000 | **61427** | 1.5 | 0 | 1 | 57 | **61427** | 2.2 | 0 | 1 | 57 | 91211 | 0.5 | 19 | 12 | MB-I, MB-II |
| | 50 | 3000 | 750 | **43822** | 2.1 | 0 | 2 | 48 | **43822** | 2.5 | 0 | 2 | 48 | 58567 | 0.7 | 16 | 6 | MB-I, MB-II |
| | 50 | 3000 | 1000 | **52680** | 10.9 | 0 | 7 | 27 | **52680** | 11.7 | 0 | 7 | 27 | 60067 | 0.9 | 16 | 6 | MB-I, MB-II |
| | 50 | 4000 | 750 | **45822** | 1.6 | 0 | 2 | 48 | **45822** | 4.0 | 0 | 2 | 48 | 74567 | 1.0 | 16 | 6 | MB-I, MB-II |
| | 50 | 4000 | 1000 | **57530** | 1.6 | 0 | 3 | 43 | **57530** | 5.7 | 0 | 3 | 43 | 76067 | 0.4 | 16 | 6 | MB-I, MB-II |
| | 100 | 3000 | 750 | 40579 | 2.6 | 0 | 4 | 29 | **40322** | 2.5 | 0 | 4 | 28 | 49556 | 0.5 | 12 | 4 | MB-II |
| | 100 | 3000 | 1000 | 45414 | 9.4 | 0 | 8 | 12 | **45245** | 3.4 | 0 | 8 | 11 | 50556 | 0.5 | 12 | 4 | MB-II |
| | 100 | 4000 | 750 | **43845** | 2.8 | 0 | 2 | 42 | **43845** | 9.4 | 0 | 2 | 42 | 61556 | 0.4 | 12 | 4 | MB-I, MB-II |
| | 100 | 4000 | 1000 | **51322** | 5.2 | 0 | 4 | 28 | **51322** | 3.3 | 0 | 4 | 28 | 62556 | 0.4 | 12 | 4 | MB-I, MB-II |
| | 200 | 3000 | 750 | **39471** | 7.1 | 0 | 4 | 25 | **39471** | 9.1 | 0 | 4 | 25 | 42296 | 0.4 | 8 | 3 | MB-I, MB-II |
| | 200 | 3000 | 1000 | **42272** | 4.8 | 0 | 7 | 6 | **42272** | 7.7 | 0 | 7 | 6 | 43046 | 0.5 | 8 | 3 | MB-I, MB-II |
| | 200 | 4000 | 750 | **43166** | 16.3 | 0 | 3 | 32 | **43166** | 16.8 | 0 | 3 | 32 | 49998 | 0.4 | 7 | 3 | MB-I, MB-II |
| | 200 | 4000 | 1000 | **48441** | 10.0 | 0 | 5 | 14 | **48441** | 14.4 | 0 | 5 | 14 | 50748 | 0.3 | 7 | 3 | MB-I, MB-II |

Table F.4: Results of the Clustering based Heuristics on Mbola (Fixed Cost)

| | | | | Agglomerative (Agg) | | | | | DBSCAN - KMeans (DB-KM) | | | | DBSCAN - Agglomerative (DB-Agg) | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | Cost | Type | Time | M | N | Cost | Time | M | N | Cost | Type | Time | M | N | |
| MBOLA - 1 | 30 | 3000 | 750 | 108750 | GeomDiff | 0.2 | 0 | 145 | **107581** | 0.27 | 1 | 139 | **107581** | GeomDiff | 0.3 | 1 | 139 | DB-KM, DB-Agg. |
| | 30 | 3000 | 1000 | 145000 | GeomDiff | 0.1 | 0 | 145 | **139243** | 0.09 | 5 | 123 | **139243** | GeomDiff | 0.1 | 5 | 123 | DB-KM, DB-Agg. |
| | 30 | 4000 | 750 | 108750 | GeomDiff | 0.1 | 0 | 145 | **108581** | 0.05 | 1 | 139 | **108581** | GeomDiff | 0.0 | 1 | 139 | DB-KM, DB-Agg. |
| | 30 | 4000 | 1000 | 145000 | GeomDiff | 0.1 | 0 | 145 | **143331** | 0.14 | 1 | 139 | **143331** | GeomDiff | 0.2 | 1 | 139 | DB-KM, DB-Agg. |
| | 50 | 3000 | 750 | 108750 | GeomDiff | 0.1 | 0 | 145 | **102969** | 0.61 | 10 | 89 | 104284 | GeomDiff | 0.2 | 7 | 105 | DB-KM |
| | 50 | 3000 | 1000 | **120456** | Comp | 0.1 | 15 | 67 | 122819 | 0.44 | 13 | 77 | 122819 | GeomDiff | 0.1 | 13 | 77 | Agg. |
| | 50 | 4000 | 750 | 108750 | GeomDiff | 0.1 | 0 | 145 | **108410** | 0.2 | 2 | 132 | 108579 | GeomDiff | 0.1 | 1 | 138 | DB-KM |
| | 50 | 4000 | 1000 | 145000 | GeomDiff | 0.1 | 0 | 145 | **134484** | 0.44 | 10 | 88 | 137534 | GeomDiff | 0.2 | 7 | 105 | DB-KM |
| | 100 | 3000 | 750 | 108750 | GeomDiff | 0.2 | 0 | 145 | 94389 | 5.14 | 11 | 62 | **93097** | Comp | 0.1 | 11 | 56 | DB-Agg. |
| | 100 | 3000 | 1000 | **102771** | Comp | 0.1 | 17 | 29 | 102812 | 5.42 | 16 | 33 | 102778 | Comp | 0.1 | 17 | 29 | Agg. |
| | 100 | 4000 | 750 | 108750 | GeomDiff | 0.2 | 0 | 145 | **99280** | 3.48 | 6 | 81 | 104895 | Comp | 0.1 | 2 | 122 | DB-KM |
| | 100 | 4000 | 1000 | 117391 | Comp | 0.1 | 13 | 46 | **115545** | 3.88 | 12 | 48 | 117356 | Comp | 0.1 | 12 | 50 | DB-KM |
| | 200 | 3000 | 750 | **84723** | GeomDiff | 0.7 | 10 | 17 | 86322 | 2.14 | 8 | 19 | **84723** | GeomDiff | 0.7 | 10 | 17 | Agg., DB-Agg. |
| | 200 | 3000 | 1000 | **88182** | GeomDiff | 0.7 | 11 | 13 | 91195 | 2.59 | 10 | 13 | **88182** | GeomDiff | 0.6 | 11 | 13 | Agg., DB-Agg. |
| | 200 | 4000 | 750 | **93782** | GeomDiff | 0.7 | 8 | 22 | 94322 | 2.44 | 8 | 19 | **93782** | GeomDiff | 0.6 | 8 | 22 | Agg., DB-Agg. |
| | 200 | 4000 | 1000 | **98368** | GeomDiff | 0.7 | 9 | 17 | 100985 | 2.02 | 9 | 17 | **98368** | GeomDiff | 0.6 | 9 | 17 | Agg., DB-Agg. |
| MBOLA - 2 | 30 | 3000 | 750 | 57750 | GeomDiff | 0.2 | 0 | 77 | 56236 | 0.16 | 2 | 66 | **55836** | Comp | 0.1 | 3 | 61 | DB-Agg. |
| | 30 | 3000 | 1000 | 77000 | GeomDiff | 0.1 | 0 | 77 | 71973 | 0.03 | 3 | 62 | **70323** | Comp | 0.0 | 4 | 57 | DB-Agg. |
| | 30 | 4000 | 750 | 57750 | GeomDiff | 0.0 | 0 | 77 | **57642** | 0.05 | 1 | 71 | **57642** | GeomDiff | 0.0 | 1 | 71 | DB-KM, DB-Agg. |
| | 30 | 4000 | 1000 | 77000 | GeomDiff | 0.0 | 0 | 77 | 74736 | 0.02 | 2 | 66 | **74086** | Comp | 0.1 | 3 | 61 | DB-Agg. |
| | 50 | 3000 | 750 | 57750 | GeomDiff | 0.1 | 0 | 77 | **55272** | 0.08 | 3 | 60 | **55272** | GeomDiff | 0.1 | 3 | 60 | DB-KM, DB-Agg. |
| | 50 | 3000 | 1000 | 77000 | GeomDiff | 0.0 | 0 | 77 | **69510** | 0 | 4 | 56 | **69510** | GeomDiff | 0.0 | 4 | 56 | DB-KM, DB-Agg. |
| | 50 | 4000 | 750 | 57750 | GeomDiff | 0.1 | 0 | 77 | **57624** | 0 | 1 | 71 | **57624** | GeomDiff | 0.1 | 1 | 71 | DB-KM, DB-Agg. |
| | 50 | 4000 | 1000 | 77000 | GeomDiff | 0.0 | 0 | 77 | **73272** | 0.05 | 3 | 60 | **73272** | GeomDiff | 0.0 | 3 | 60 | DB-KM, DB-Agg. |
| | 100 | 3000 | 750 | 57750 | GeomDiff | 0.0 | 0 | 77 | **55272** | 0.09 | 3 | 60 | **55272** | GeomDiff | 0.1 | 3 | 60 | DB-KM, DB-Agg. |
| | 100 | 3000 | 1000 | 77000 | GeomDiff | 0.1 | 0 | 77 | **67952** | 0.05 | 7 | 43 | 68087 | GeomDiff | 0.0 | 6 | 47 | DB-KM |
| | 100 | 4000 | 750 | 57750 | GeomDiff | 0.1 | 0 | 77 | **57624** | 0 | 1 | 71 | **57624** | GeomDiff | 0.1 | 1 | 71 | DB-KM, DB-Agg. |
| | 100 | 4000 | 1000 | 77000 | GeomDiff | 0.0 | 0 | 77 | **73272** | 0 | 3 | 60 | **73272** | GeomDiff | 0.1 | 3 | 60 | DB-KM, DB-Agg. |
| | 200 | 3000 | 750 | 57750 | GeomDiff | 0.1 | 0 | 77 | **55984** | 0.05 | 3 | 54 | **55984** | GeomDiff | 0.1 | 3 | 54 | DB-KM, DB-Agg. |
| | 200 | 3000 | 1000 | 64977 | GeomDiff | 0.2 | 8 | 27 | **64513** | 0 | 8 | 25 | **64513** | GeomDiff | 0.0 | 8 | 25 | DB-KM, DB-Agg. |
| | 200 | 4000 | 750 | 57750 | GeomDiff | 0.2 | 0 | 77 | **57624** | 0.05 | 1 | 71 | **57624** | GeomDiff | 0.0 | 1 | 71 | DB-KM, DB-Agg. |
| | 200 | 4000 | 1000 | 77000 | GeomDiff | 0.1 | 0 | 77 | **71527** | 0 | 5 | 39 | **71527** | GeomDiff | 0.1 | 5 | 39 | DB-KM, DB-Agg. |

| | | | | Agglomerative (Agg) | | | | | DBSCAN - KMeans (DB-KM) | | | | DBSCAN - Agglomerative (DB-Agg) | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | Cost | Type | Time | M | N | Cost | Time | M | N | Cost | Type | Time | M | N | |
| MBOLA - 3 | 30 | 3000 | 750 | **35250** | GeomDiff | 0.1 | 0 | 47 | **35250** | 0.11 | 0 | 47 | **35250** | GeomDiff | 0.1 | 0 | 47 | Agg., DB-KM, DB-Agg. |
| | 30 | 3000 | 1000 | 47000 | GeomDiff | 0.0 | 0 | 47 | **46256** | 0.03 | 1 | 43 | **46256** | GeomDiff | 0.0 | 1 | 43 | DB-KM, DB-Agg. |
| | 30 | 4000 | 750 | **35250** | GeomDiff | 0.0 | 0 | 47 | **35250** | 0 | 0 | 47 | **35250** | GeomDiff | 0.0 | 0 | 47 | Agg., DB-KM, DB-Agg. |
| | 30 | 4000 | 1000 | **47000** | GeomDiff | 0.0 | 0 | 47 | **47000** | 0.02 | 0 | 47 | **47000** | GeomDiff | 0.0 | 0 | 47 | Agg., DB-KM, DB-Agg. |
| | 50 | 3000 | 750 | 35250 | GeomDiff | 0.1 | 0 | 47 | **34369** | 0.09 | 1 | 41 | **34369** | GeomDiff | 0.2 | 1 | 41 | DB-KM, DB-Agg. |
| | 50 | 3000 | 1000 | 47000 | GeomDiff | 0.0 | 0 | 47 | **43875** | 0 | 2 | 37 | **43875** | GeomDiff | 0.1 | 2 | 37 | DB-KM, DB-Agg. |
| | 50 | 4000 | 750 | **35250** | GeomDiff | 0.1 | 0 | 47 | **35250** | 0.03 | 0 | 47 | **35250** | GeomDiff | 0.0 | 0 | 47 | Agg., DB-KM, DB-Agg. |
| | 50 | 4000 | 1000 | 47000 | GeomDiff | 0.0 | 0 | 47 | **45619** | 0 | 1 | 41 | **45619** | GeomDiff | 0.0 | 1 | 41 | DB-KM, DB-Agg. |
| | 100 | 3000 | 750 | 35250 | GeomDiff | 0.0 | 0 | 47 | **34369** | 0 | 1 | 41 | **34369** | GeomDiff | 0.0 | 1 | 41 | DB-KM, DB-Agg. |
| | 100 | 3000 | 1000 | 47000 | GeomDiff | 0.0 | 0 | 47 | **42486** | 0.05 | 4 | 28 | **42486** | GeomDiff | 0.0 | 4 | 28 | DB-KM, DB-Agg. |
| | 100 | 4000 | 750 | **35250** | GeomDiff | 0.1 | 0 | 47 | **35250** | 0 | 0 | 47 | **35250** | GeomDiff | 0.0 | 0 | 47 | Agg., DB-KM, DB-Agg. |
| | 100 | 4000 | 1000 | 47000 | GeomDiff | 0.0 | 0 | 47 | **45619** | 0 | 1 | 41 | **45619** | GeomDiff | 0.0 | 1 | 41 | DB-KM, DB-Agg. |
| | 200 | 3000 | 750 | 35250 | GeomDiff | 0.1 | 0 | 47 | **34110** | 0.23 | 2 | 33 | 34369 | GeomDiff | 0.2 | 1 | 41 | DB-KM |
| | 200 | 3000 | 1000 | 41189 | GeomDiff | 0.1 | 4 | 24 | **40785** | 0.06 | 4 | 24 | 41189 | GeomDiff | 0.1 | 4 | 24 | DB-KM |
| | 200 | 4000 | 750 | **35250** | GeomDiff | 0.1 | 0 | 47 | **35250** | 0.09 | 0 | 47 | **35250** | GeomDiff | 0.0 | 0 | 47 | Agg., DB-KM, DB-Agg. |
| | 200 | 4000 | 1000 | 47000 | GeomDiff | 0.1 | 0 | 47 | **44360** | 0.05 | 2 | 33 | 44478 | GeomDiff | 0.1 | 2 | 32 | DB-KM |
| MBOLA - 4 | 30 | 3000 | 750 | **46500** | GeomDiff | 0.2 | 0 | 62 | **46500** | 0.09 | 0 | 62 | **46500** | GeomDiff | 0.1 | 0 | 62 | Agg., DB-KM, DB-Agg. |
| | 30 | 3000 | 1000 | **62000** | GeomDiff | 0.1 | 0 | 62 | **62000** | 0.02 | 0 | 62 | **62000** | GeomDiff | 0.0 | 0 | 62 | Agg., DB-KM, DB-Agg. |
| | 30 | 4000 | 750 | **46500** | GeomDiff | 0.0 | 0 | 62 | **46500** | 0 | 0 | 62 | **46500** | GeomDiff | 0.0 | 0 | 62 | Agg., DB-KM, DB-Agg. |
| | 30 | 4000 | 1000 | **62000** | GeomDiff | 0.0 | 0 | 62 | **62000** | 0.02 | 0 | 62 | **62000** | GeomDiff | 0.0 | 0 | 62 | Agg., DB-KM, DB-Agg. |
| | 50 | 3000 | 750 | 46500 | GeomDiff | 0.1 | 0 | 62 | 45334 | 0.28 | 3 | 46 | **45207** | GeomDiff | 0.3 | 1 | 55 | DB-Agg. |
| | 50 | 3000 | 1000 | **54242** | Comp | 0.1 | 7 | 29 | 55727 | 0.05 | 5 | 38 | 55574 | GeomDiff | 0.1 | 4 | 41 | Agg. |
| | 50 | 4000 | 750 | **46500** | GeomDiff | 0.0 | 0 | 62 | **46500** | 0.02 | 0 | 62 | **46500** | GeomDiff | 0.1 | 0 | 62 | Agg., DB-KM, DB-Agg. |
| | 50 | 4000 | 1000 | 62000 | GeomDiff | 0.1 | 0 | 62 | **59834** | 0.12 | 3 | 46 | 59957 | GeomDiff | 0.1 | 1 | 55 | DB-KM |
| | 100 | 3000 | 750 | 46500 | GeomDiff | 0.1 | 0 | 62 | 41056 | 0.91 | 4 | 31 | **40416** | Comp | 0.1 | 4 | 28 | DB-Agg. |
| | 100 | 3000 | 1000 | **46143** | Comp | 0.0 | 7 | 16 | 47016 | 0.78 | 8 | 15 | **46143** | Comp | 0.0 | 7 | 16 | Agg., DB-Agg. |
| | 100 | 4000 | 750 | 46500 | GeomDiff | 0.1 | 0 | 62 | **44246** | 0.78 | 2 | 44 | 45112 | GeomDiff | 0.1 | 1 | 52 | DB-KM |
| | 100 | 4000 | 1000 | 62000 | GeomDiff | 0.1 | 0 | 62 | 52806 | 0.83 | 4 | 31 | **51416** | Comp | 0.1 | 4 | 28 | DB-Agg. |
| | 200 | 3000 | 750 | **39768** | GeomDiff | 0.2 | 4 | 22 | 41744 | 0.61 | 4 | 23 | **39768** | GeomDiff | 0.1 | 4 | 22 | Agg., DB-Agg. |
| | 200 | 3000 | 1000 | **42272** | GeomDiff | 0.2 | 7 | 6 | 43730 | 0.69 | 6 | 6 | **42272** | GeomDiff | 0.1 | 7 | 6 | Agg., DB-Agg. |
| | 200 | 4000 | 750 | 46500 | GeomDiff | 0.1 | 0 | 62 | **43893** | 0.84 | 2 | 38 | 45094 | GeomDiff | 0.1 | 1 | 52 | DB-KM |
| | 200 | 4000 | 1000 | **48735** | GeomDiff | 0.1 | 6 | 10 | 49486 | 0.92 | 6 | 6 | **48735** | GeomDiff | 0.1 | 6 | 10 | Agg., DB-Agg. |

Table F.5: Results of the Model based Heuristics on Potou (Fixed Cost)

| | | | | MB-I | | | | | MB-II | | | | | MB-III | | | | BestMethod |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | Cost | Time | Gap | M | N | Cost | Time | Gap | M | N | Cost | Time | M | N | |
| POTOU - 1 | 30 | 3000 | 750 | 175768 | 10824.9 | 0.63 | 31 | 75 | **173461** | 10856.0 | 0.8 | 31 | 70 | 205885 | 21.3 | 57 | 8 | MB-II |
| | 30 | 3000 | 1000 | 189816 | 7350.4 | 0 | 38 | 46 | **186001** | 2243.6 | 0 | 39 | 38 | 207885 | 14.2 | 57 | 8 | MB-II |
| | 30 | 4000 | 750 | 203895 | 10827.5 | 1.17 | 25 | 106 | **201827** | 10849.0 | 1.77 | 26 | 96 | 262885 | 20.0 | 57 | 8 | MB-II |
| | 30 | 4000 | 1000 | 225380 | 10820.2 | 0.75 | 31 | 74 | **221961** | 10831.3 | 0.7 | 31 | 70 | 264885 | 18.7 | 57 | 8 | MB-II |
| | 50 | 3000 | 750 | **137204** | 10818.7 | 3.87 | 24 | 27 | 138139 | 10832.0 | 5.16 | 25 | 26 | 145960 | 26.9 | 32 | 6 | MB-I |
| | 50 | 3000 | 1000 | 143135 | 10818.8 | 2.65 | 26 | 21 | **141509** | 10832.8 | 3.11 | 25 | 20 | 147460 | 27.8 | 32 | 6 | MB-II |
| | 50 | 4000 | 750 | **158240** | 10824.1 | 5.26 | 19 | 54 | 160799 | 10834.3 | 6.81 | 20 | 54 | 176893 | 26.0 | 31 | 6 | MB-I |
| | 50 | 4000 | 1000 | **167153** | 10818.6 | 3.62 | 24 | 26 | 168829 | 10833.5 | 5.41 | 25 | 26 | 178393 | 25.2 | 31 | 6 | MB-I |
| | 100 | 3000 | 750 | 121859 | 10834.6 | 11.37 | 17 | 17 | **120795** | 10841.5 | 11.79 | 17 | 15 | 126103 | 82.2 | 20 | 2 | MB-II |
| | 100 | 3000 | 1000 | 123813 | 10831.4 | 7.59 | 18 | 11 | **123575** | 10841.1 | 9.32 | 17 | 11 | 126603 | 72.2 | 20 | 2 | MB-II |
| | 100 | 4000 | 750 | 135912 | 10834.1 | 16.21 | 14 | 28 | **133554** | 10842.1 | 13.77 | 14 | 23 | 145214 | 101.5 | 18 | 2 | MB-II |
| | 100 | 4000 | 1000 | **139417** | 10833.2 | 10.41 | 16 | 16 | 139891 | 10842.0 | 12.07 | 16 | 16 | 145714 | 100.2 | 18 | 2 | MB-I |
| | 200 | 3000 | 750 | 125135 | 10884.0 | 18.62 | 21 | 12 | 123507 | 10888.8 | 19.89 | 20 | 13 | **122470** | 116.3 | 18 | 0 | MB-III |
| | 200 | 3000 | 1000 | 124368 | 10877.8 | 11.66 | 20 | 7 | 123432 | 10891.9 | 13.29 | 19 | 5 | **122470** | 115.4 | 18 | 0 | MB-III |
| | 200 | 4000 | 750 | **138462** | 10877.8 | 19.41 | 18 | 12 | 139474 | 10890.8 | 20.92 | 18 | 12 | 139980 | 193.7 | 17 | 0 | MB-I |
| | 200 | 4000 | 1000 | **137451** | 10880.1 | 16.76 | 16 | 12 | 139929 | 10888.9 | 17.04 | 17 | 10 | 139980 | 172.3 | 17 | 0 | MB-I |
| POTOU - 2 | 30 | 3000 | 750 | **73833** | 19.7 | 0 | 5 | 76 | 73884 | 25.1 | 0 | 5 | 76 | 103899 | 1.7 | 30 | 11 | MB-I |
| | 30 | 3000 | 1000 | **87929** | 2.1 | 0 | 12 | 48 | 87980 | 15.3 | 0 | 12 | 48 | 106649 | 1.1 | 30 | 11 | MB-I |
| | 30 | 4000 | 750 | **77104** | 4.0 | 0 | 2 | 91 | 77156 | 5.6 | 0 | 2 | 91 | 133899 | 1.0 | 30 | 11 | MB-I |
| | 30 | 4000 | 1000 | **97833** | 4.6 | 0 | 5 | 76 | 97884 | 5.1 | 0 | 5 | 76 | 136649 | 0.9 | 30 | 11 | MB-I |
| | 50 | 3000 | 750 | **67892** | 2.1 | 0 | 8 | 50 | **67892** | 17.2 | 0 | 8 | 50 | 89052 | 1.3 | 25 | 6 | MB-I, MB-II |
| | 50 | 3000 | 1000 | **77920** | 19.4 | 0 | 12 | 34 | **77920** | 17.4 | 0 | 12 | 34 | 90552 | 1.9 | 25 | 6 | MB-I, MB-II |
| | 50 | 4000 | 750 | 74429 | 2.4 | 0 | 4 | 73 | **74355** | 5.5 | 0 | 5 | 66 | 114052 | 1.2 | 25 | 6 | MB-II |
| | 50 | 4000 | 1000 | **88392** | 3.9 | 0 | 8 | 50 | **88392** | 3.3 | 0 | 8 | 50 | 115552 | 0.7 | 25 | 6 | MB-I, MB-II |
| | 100 | 3000 | 750 | 64106 | 8.4 | 0 | 8 | 36 | **63810** | 13.1 | 0 | 9 | 27 | 72599 | 0.6 | 17 | 0 | MB-II |
| | 100 | 3000 | 1000 | **67846** | 9.9 | 0 | 13 | 11 | **67846** | 15.6 | 0 | 13 | 11 | 72599 | 1.3 | 17 | 0 | MB-I, MB-II |
| | 100 | 4000 | 750 | 70405 | 3.2 | 0 | 5 | 55 | **70197** | 7.0 | 0 | 5 | 53 | 89599 | 0.8 | 17 | 0 | MB-II |
| | 100 | 4000 | 1000 | **79560** | 2.5 | 0 | 9 | 27 | **79560** | 5.4 | 0 | 9 | 27 | 89599 | 0.8 | 17 | 0 | MB-I, MB-II |
| | 200 | 3000 | 750 | **61364** | 23.5 | 0 | 9 | 17 | **61364** | 34.3 | 0 | 9 | 17 | 65264 | 0.7 | 14 | 0 | MB-I, MB-II |
| | 200 | 3000 | 1000 | **63451** | 20.1 | 0 | 12 | 4 | **63451** | 22.6 | 0 | 12 | 4 | 65264 | 0.7 | 14 | 0 | MB-I, MB-II |
| | 200 | 4000 | 750 | **68295** | 32.7 | 0 | 5 | 38 | **68295** | 42.2 | 0 | 5 | 38 | 76362 | 0.7 | 11 | 0 | MB-I, MB-II |
| | 200 | 4000 | 1000 | **73176** | 26.8 | 0 | 7 | 15 | **73176** | 28.0 | 0 | 7 | 15 | 76362 | 0.9 | 11 | 0 | MB-I, MB-II |

| | DLim | F1 | F2 | MB-I Cost | Time | Gap | M | N | MB-II Cost | Time | Gap | M | N | Unicost Post Process (MB-III) Cost | Time | M | N | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| POTOU - 3 | 30 | 3000 | 750 | 41894 | 3.1 | 0 | 6 | 28 | **41857** | 18.4 | 0 | 6 | 28 | 54338 | 1.5 | 16 | 3 | MB-II |
| | 30 | 3000 | 1000 | 46942 | 2.2 | 0 | 9 | 16 | **46875** | 2.8 | 0 | 9 | 16 | 55088 | 0.9 | 16 | 3 | MB-II |
| | 30 | 4000 | 750 | 47313 | 11.7 | 0 | 3 | 45 | **47201** | 5.9 | 0 | 4 | 39 | 70338 | 0.6 | 16 | 3 | MB-II |
| | 30 | 4000 | 1000 | 54894 | 2.3 | 0 | 6 | 28 | **54857** | 2.4 | 0 | 6 | 28 | 71088 | 0.6 | 16 | 3 | MB-II |
| | 50 | 3000 | 750 | **36472** | 0.9 | 0 | 7 | 13 | **36472** | 4.1 | 0 | 7 | 13 | 38326 | 0.9 | 10 | 2 | MB-I, MB-II |
| | 50 | 3000 | 1000 | **37732** | 8.0 | 0 | 9 | 4 | **37732** | 12.1 | 0 | 9 | 4 | 38826 | 1.1 | 10 | 2 | MB-I, MB-II |
| | 50 | 4000 | 750 | **42664** | 1.2 | 0 | 5 | 24 | **42664** | 1.9 | 0 | 5 | 24 | 48326 | 1.0 | 10 | 2 | MB-I, MB-II |
| | 50 | 4000 | 1000 | **46487** | 1.0 | 0 | 8 | 8 | **46487** | 5.0 | 0 | 8 | 8 | 48826 | 0.4 | 10 | 2 | MB-I, MB-II |
| | 100 | 3000 | 750 | **33736** | 0.9 | 0 | 8 | 1 | **33736** | 2.9 | 0 | 8 | 1 | 34905 | 0.5 | 9 | 0 | MB-I, MB-II |
| | 100 | 3000 | 1000 | **33986** | 1.0 | 0 | 8 | 1 | **33986** | 1.1 | 0 | 8 | 1 | 34905 | 0.5 | 9 | 0 | MB-I, MB-II |
| | 100 | 4000 | 750 | **39974** | 1.2 | 0 | 5 | 17 | **39974** | 1.7 | 0 | 5 | 17 | 43905 | 0.5 | 9 | 0 | MB-I, MB-II |
| | 100 | 4000 | 1000 | **41986** | 0.7 | 0 | 8 | 1 | **41986** | 1.1 | 0 | 8 | 1 | 43905 | 0.6 | 9 | 0 | MB-I, MB-II |
| | 200 | 3000 | 750 | **33309** | 8.3 | 0 | 8 | 0 | **33309** | 8.3 | 0 | 8 | 0 | **33309** | 0.5 | 8 | 0 | MB-I, MB-II, MB-III |
| | 200 | 3000 | 1000 | **33309** | 4.6 | 0 | 8 | 0 | **33309** | 6.0 | 0 | 8 | 0 | **33309** | 0.5 | 8 | 0 | MB-I, MB-II, MB-III |
| | 200 | 4000 | 750 | **38943** | 4.1 | 0 | 5 | 11 | **38943** | 4.8 | 0 | 5 | 11 | 40474 | 0.6 | 7 | 0 | MB-I, MB-II |
| | 200 | 4000 | 1000 | 40757 | 12.3 | 0 | 7 | 1 | 40757 | 14.3 | 0 | 7 | 1 | **40474** | 0.9 | 7 | 0 | MB-III |
| POTOU - 4 | 30 | 3000 | 750 | **71176** | 28.7 | 0 | 12 | 37 | **71176** | 105.0 | 0 | 12 | 37 | 86863 | 2.2 | 25 | 3 | MB-I, MB-II |
| | 30 | 3000 | 1000 | 78067 | 40.8 | 0 | 15 | 25 | **78058** | 87.2 | 0 | 15 | 25 | 87613 | 1.5 | 25 | 3 | MB-II |
| | 30 | 4000 | 750 | **79691** | 27.1 | 0 | 7 | 62 | **79691** | 72.1 | 0 | 7 | 62 | 111863 | 1.2 | 25 | 3 | MB-I, MB-II |
| | 30 | 4000 | 1000 | **92426** | 45.5 | 0 | 12 | 37 | **92426** | 109.1 | 0 | 12 | 37 | 112613 | 1.8 | 25 | 3 | MB-I, MB-II |
| | 50 | 3000 | 750 | **53900** | 58.8 | 0 | 10 | 15 | 54018 | 152.9 | 0 | 10 | 14 | 62328 | 1.3 | 16 | 1 | MB-I |
| | 50 | 3000 | 1000 | **57518** | 37.6 | 0 | 10 | 14 | **57518** | 71.5 | 0 | 10 | 14 | 62578 | 1.5 | 16 | 1 | MB-I, MB-II |
| | 50 | 4000 | 750 | **63218** | 118.8 | 0 | 8 | 26 | 63336 | 216.0 | 0 | 8 | 25 | 78328 | 1.4 | 16 | 1 | MB-I |
| | 50 | 4000 | 1000 | **67518** | 59.1 | 0 | 10 | 14 | **67518** | 174.3 | 0 | 10 | 14 | 78578 | 1.3 | 16 | 1 | MB-I, MB-II |
| | 100 | 3000 | 750 | **43018** | 33.1 | 0 | 7 | 4 | **43018** | 68.8 | 0 | 7 | 4 | 44812 | 1.1 | 8 | 0 | MB-I, MB-II |
| | 100 | 3000 | 1000 | 43640 | 18.7 | 0 | 8 | 1 | **43628** | 31.1 | 0 | 8 | 1 | 44812 | 1.5 | 8 | 0 | MB-II |
| | 100 | 4000 | 750 | **49774** | 77.2 | 0 | 6 | 9 | **49774** | 90.4 | 0 | 6 | 9 | 52812 | 1.1 | 8 | 0 | MB-I, MB-II |
| | 100 | 4000 | 1000 | **50702** | 41.0 | 0 | 7 | 2 | **50702** | 41.2 | 0 | 7 | 2 | 52812 | 1.1 | 8 | 0 | MB-I, MB-II |
| | 200 | 3000 | 750 | **42049** | 52.6 | 0 | 6 | 0 | **42049** | 96.5 | 0 | 6 | 0 | **42049** | 1.7 | 6 | 0 | MB-I, MB-II, MB-III |
| | 200 | 3000 | 1000 | **42049** | 33.7 | 0 | 6 | 0 | **42049** | 102.0 | 0 | 6 | 0 | **42049** | 1.4 | 6 | 0 | MB-I, MB-II, MB-III |
| | 200 | 4000 | 750 | **48049** | 66.5 | 0 | 6 | 0 | **48049** | 254.6 | 0 | 6 | 0 | **48049** | 1.3 | 6 | 0 | MB-I, MB-II, MB-III |
| | 200 | 4000 | 1000 | **48049** | 68.5 | 0 | 6 | 0 | **48049** | 110.7 | 0 | 6 | 0 | **48049** | 1.4 | 6 | 0 | MB-I, MB-II, MB-III |

Table F.6: Results of the Clustering based Heuristics on Potou (Fixed Cost)

| | | | | Agglomerative (Agg) | | | | | DBSCAN - KMeans (DB-KM) | | | | DBSCAN - Agglomerative (DB-Agg) | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | Cost | Type | Time | M | N | Cost | Time | M | N | Cost | Type | Time | M | N | |
| POTOU - 1 | 30 | 3000 | 750 | **196767** | Complete | 1.6 | 34 | 98 | 216336 | 20.5 | 39 | 108 | 197478 | Complete | 1.2 | 32 | 108 | Agg. |
| | 30 | 3000 | 1000 | **219641** | Complete | 1.4 | 41 | 74 | 237724 | 17.3 | 49 | 70 | 222146 | Complete | 1.0 | 40 | 80 | Agg. |
| | 30 | 4000 | 750 | **222794** | Complete | 0.8 | 24 | 145 | 232066 | 13.8 | 26 | 147 | **222794** | Complete | 0.6 | 24 | 145 | Agg., DB-Agg. |
| | 30 | 4000 | 1000 | **255267** | Complete | 0.9 | 34 | 98 | 260482 | 14.3 | 37 | 91 | 256478 | Complete | 0.5 | 32 | 108 | Agg. |
| | 50 | 3000 | 750 | **146546** | Complete | 0.8 | 28 | 26 | 154151 | 9.8 | 32 | 25 | **146546** | Complete | 0.7 | 28 | 26 | Agg., DB-Agg. |
| | 50 | 3000 | 1000 | **152583** | Complete | 0.9 | 29 | 22 | 155193 | 9.7 | 31 | 23 | 153046 | Complete | 0.6 | 28 | 26 | Agg. |
| | 50 | 4000 | 750 | **169756** | Complete | 0.7 | 20 | 67 | 179840 | 9.0 | 24 | 64 | 170160 | Complete | 0.5 | 19 | 74 | Agg. |
| | 50 | 4000 | 1000 | **181046** | Complete | 0.6 | 28 | 26 | 191135 | 9.8 | 31 | 28 | **181046** | Complete | 0.8 | 28 | 26 | Agg., DB-Agg. |
| | 100 | 3000 | 750 | 126158 | Complete | 1.1 | 15 | 15 | 123851 | 3.7 | 13 | 15 | **123345** | GeomDiff | 2.9 | 14 | 22 | DB-Agg. |
| | 100 | 3000 | 1000 | 129224 | Complete | 0.9 | 16 | 10 | 127601 | 4.1 | 13 | 15 | **126121** | GeomDiff | 2.9 | 15 | 15 | DB-Agg. |
| | 100 | 4000 | 750 | 139111 | Complete | 1.1 | 13 | 24 | **136797** | 3.7 | 12 | 22 | 137345 | GeomDiff | 2.5 | 14 | 22 | DB-KM |
| | 100 | 4000 | 1000 | 144908 | Complete | 0.9 | 15 | 15 | **140601** | 3.3 | 13 | 15 | 142845 | GeomDiff | 2.8 | 14 | 22 | DB-KM |
| | 200 | 3000 | 750 | **121999** | Ward | 1.5 | 16 | 11 | 151362 | 1.4 | 7 | 8 | 122274 | GeomDiff | 4.1 | 15 | 8 | Agg. |
| | 200 | 3000 | 1000 | **123529** | GeomDiff | 4.6 | 16 | 3 | 152797 | 1.3 | 8 | 3 | **123529** | GeomDiff | 5.1 | 16 | 3 | Agg., DB-Agg. |
| | 200 | 4000 | 750 | **136755** | Ward | 1.6 | 13 | 8 | 159063 | 1.6 | 7 | 8 | **136755** | Ward | 1.8 | 13 | 8 | Agg., DB-Agg. |
| | 200 | 4000 | 1000 | **138755** | Ward | 1.8 | 13 | 8 | 160161 | 1.5 | 7 | 8 | **138755** | Ward | 1.2 | 13 | 8 | Agg., DB-Agg. |
| POTOU - 2 | 30 | 3000 | 750 | 77250 | GeomDiff | 0.2 | 0 | 103 | **74517** | 0.2 | 5 | 77 | 74900 | GeomDiff | 0.1 | 4 | 82 | DB-KM |
| | 30 | 3000 | 1000 | 103000 | GeomDiff | 0.1 | 0 | 103 | 91451 | 0.1 | 8 | 65 | **91391** | GeomDiff | 0.1 | 8 | 65 | DB-Agg. |
| | 30 | 4000 | 750 | 77250 | GeomDiff | 0.1 | 0 | 103 | **77171** | 0.1 | 1 | 97 | **77171** | GeomDiff | 0.1 | 1 | 97 | DB-KM, DB-Agg. |
| | 30 | 4000 | 1000 | 103000 | GeomDiff | 0.1 | 0 | 103 | **99400** | 0.0 | 4 | 82 | **99400** | GeomDiff | 0.0 | 4 | 82 | DB-KM, DB-Agg. |
| | 50 | 3000 | 750 | 77250 | GeomDiff | 0.1 | 0 | 103 | **70949** | 0.2 | 8 | 57 | 70979 | Ward | 0.0 | 8 | 57 | DB-KM |
| | 50 | 3000 | 1000 | **79505** | Complete | 0.1 | 13 | 33 | 82244 | 0.1 | 12 | 41 | 82260 | Ward | 0.0 | 12 | 41 | Agg. |
| | 50 | 4000 | 750 | 77250 | GeomDiff | 0.1 | 0 | 103 | **75940** | 0.3 | 2 | 89 | **75940** | GeomDiff | 0.1 | 2 | 89 | DB-KM, DB-Agg. |
| | 50 | 4000 | 1000 | 103000 | GeomDiff | 0.1 | 0 | 103 | 94381 | 0.2 | 7 | 63 | **93229** | Ward | 0.0 | 8 | 57 | DB-Agg. |
| | 100 | 3000 | 750 | 65538 | Complete | 0.1 | 8 | 35 | **64491** | 0.0 | 7 | 44 | 64562 | GeomDiff | 0.1 | 8 | 39 | DB-KM |
| | 100 | 3000 | 1000 | **69932** | Complete | 0.1 | 14 | 9 | 70325 | 0.0 | 13 | 17 | 70266 | Ward | 0.1 | 13 | 17 | Agg. |
| | 100 | 4000 | 750 | 77250 | GeomDiff | 0.1 | 0 | 103 | **70289** | 0.1 | 5 | 54 | 70899 | GeomDiff | 0.1 | 4 | 64 | DB-KM |
| | 100 | 4000 | 1000 | **82189** | Complete | 0.1 | 9 | 30 | 82272 | 0.0 | 9 | 34 | 82312 | GeomDiff | 0.1 | 8 | 39 | Agg. |
| | 200 | 3000 | 750 | 63162 | Complete | 0.1 | 7 | 14 | 62595 | 1.9 | 7 | 14 | **62553** | Ward | 0.1 | 8 | 22 | DB-Agg. |
| | 200 | 3000 | 1000 | 64778 | Complete | 0.1 | 10 | 2 | 68596 | 1.8 | 10 | 2 | **64100** | Ward | 0.1 | 12 | 2 | DB-Agg. |
| | 200 | 4000 | 750 | 68895 | Ward | 0.1 | 4 | 46 | 71524 | 1.6 | 5 | 25 | **68874** | Ward | 0.1 | 4 | 37 | DB-Agg. |
| | 200 | 4000 | 1000 | 74234 | Complete | 0.1 | 7 | 10 | 75939 | 1.6 | 7 | 12 | **73663** | Ward | 0.1 | 7 | 14 | DB-Agg. |

| | | | | Agglomerative (Agg) | | | | | DBSCAN - KMeans (DB-KM) | | | | DBSCAN - Agglomerative (DB-Agg) | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | Cost | Type | Time | M | N | Cost | Time | M | N | Cost | Type | Time | M | N | |
| POTOU - 3 | 30 | 3000 | 750 | 49500 | GeomDiff | 0.2 | 0 | 66 | 41845 | 0.2 | 6 | 28 | **41191** | Complete | 0.1 | 6 | 27 | DB-Agg. |
| | 30 | 3000 | 1000 | 49104 | Complete | 0.1 | 8 | 22 | 47206 | 0.1 | 7 | 23 | **47185** | Complete | 0.2 | 7 | 23 | DB-Agg. |
| | 30 | 4000 | 750 | 49500 | GeomDiff | 0.1 | 0 | 66 | **46707** | 0.1 | 4 | 38 | 48104 | GeomDiff | 0.1 | 3 | 46 | DB-KM |
| | 30 | 4000 | 1000 | 66000 | GeomDiff | 0.0 | 0 | 66 | 56892 | 0.1 | 7 | 26 | **53941** | Complete | 0.0 | 6 | 27 | DB-Agg. |
| | 50 | 3000 | 750 | **36472** | Complete | 0.1 | 7 | 13 | 37446 | 0.1 | 7 | 16 | 37446 | GeomDiff | 0.1 | 7 | 16 | Agg. |
| | 50 | 3000 | 1000 | **37732** | Complete | 0.0 | 9 | 4 | 40691 | 0.0 | 8 | 12 | 40691 | GeomDiff | 0.1 | 8 | 12 | Agg. |
| | 50 | 4000 | 750 | **42664** | Complete | 0.1 | 5 | 24 | 43639 | 0.0 | 5 | 27 | 43639 | GeomDiff | 0.0 | 5 | 27 | Agg. |
| | 50 | 4000 | 1000 | **46487** | Complete | 0.0 | 8 | 8 | 48446 | 0.1 | 7 | 16 | 48446 | GeomDiff | 0.0 | 7 | 16 | Agg. |
| | 100 | 3000 | 750 | **34286** | GeomDiff | 0.1 | 8 | 3 | **34286** | 0.1 | 8 | 3 | **34286** | GeomDiff | 0.1 | 8 | 3 | Agg., DB-KM, DB-Agg. |
| | 100 | 3000 | 1000 | **34905** | GeomDiff | 0.1 | 9 | 0 | **34905** | 0.0 | 9 | 0 | **34905** | GeomDiff | 0.1 | 9 | 0 | Agg., DB-KM, DB-Agg. |
| | 100 | 4000 | 750 | **40524** | GeomDiff | 0.1 | 5 | 19 | **40524** | 0.0 | 5 | 19 | 41986 | GeomDiff | 0.1 | 4 | 28 | Agg., DB-KM |
| | 100 | 4000 | 1000 | **43036** | GeomDiff | 0.1 | 8 | 3 | **43036** | 0.2 | 8 | 3 | **43036** | GeomDiff | 0.1 | 8 | 3 | Agg., DB-KM, DB-Agg. |
| | 200 | 3000 | 750 | **33309** | GeomDiff | 0.1 | 8 | 0 | 39373 | 0.0 | 6 | 0 | 39373 | GeomDiff | 0.0 | 6 | 0 | Agg. |
| | 200 | 3000 | 1000 | **33309** | GeomDiff | 0.1 | 8 | 0 | 39373 | 0.0 | 6 | 0 | 39373 | GeomDiff | 0.0 | 6 | 0 | Agg. |
| | 200 | 4000 | 750 | **38910** | GeomDiff | 0.2 | 5 | 10 | 43808 | 0.0 | 4 | 10 | 43808 | GeomDiff | 0.0 | 4 | 10 | Agg. |
| | 200 | 4000 | 1000 | **40474** | GeomDiff | 0.1 | 7 | 0 | 45373 | 0.0 | 6 | 0 | 45373 | GeomDiff | 0.0 | 6 | 0 | Agg. |
| POTOU - 4 | 30 | 3000 | 750 | 77666 | Complete | 0.1 | 13 | 44 | **72606** | 2.1 | 12 | 40 | 76830 | GeomDiff | 0.5 | 12 | 47 | DB-KM |
| | 30 | 3000 | 1000 | 84800 | Complete | 0.1 | 17 | 27 | **80902** | 1.8 | 14 | 32 | 86148 | GeomDiff | 0.2 | 15 | 35 | DB-KM |
| | 30 | 4000 | 750 | 96000 | GeomDiff | 0.1 | 0 | 128 | **84955** | 2.8 | 5 | 82 | 88192 | Complete | 0.1 | 4 | 93 | DB-KM |
| | 30 | 4000 | 1000 | 101666 | Complete | 0.1 | 13 | 44 | **96156** | 2.1 | 12 | 42 | 100580 | GeomDiff | 0.1 | 12 | 47 | DB-KM |
| | 50 | 3000 | 750 | 60131 | Complete | 0.1 | 14 | 8 | **59411** | 2.3 | 12 | 16 | 59706 | GeomDiff | 0.2 | 14 | 7 | DB-KM |
| | 50 | 3000 | 1000 | 62131 | Complete | 0.1 | 14 | 8 | 62768 | 1.9 | 12 | 15 | **61456** | GeomDiff | 0.2 | 14 | 7 | DB-Agg. |
| | 50 | 4000 | 750 | 70082 | Complete | 0.1 | 9 | 32 | 67911 | 1.7 | 9 | 28 | **67253** | GeomDiff | 0.1 | 8 | 33 | DB-Agg. |
| | 50 | 4000 | 1000 | 76131 | Complete | 0.1 | 14 | 8 | 77504 | 1.3 | 13 | 14 | **75456** | GeomDiff | 0.1 | 14 | 7 | DB-Agg. |
| | 100 | 3000 | 750 | **43633** | GeomDiff | 0.3 | 8 | 1 | 46744 | 0.5 | 8 | 0 | **43633** | GeomDiff | 0.2 | 8 | 1 | Agg., DB-Agg. |
| | 100 | 3000 | 1000 | **43883** | GeomDiff | 0.3 | 8 | 1 | 46107 | 0.9 | 8 | 0 | **43883** | GeomDiff | 0.2 | 8 | 1 | Agg., DB-Agg. |
| | 100 | 4000 | 750 | 51633 | GeomDiff | 0.3 | 8 | 1 | **51393** | 1.2 | 8 | 1 | 51633 | GeomDiff | 0.2 | 8 | 1 | DB-KM |
| | 100 | 4000 | 1000 | 51883 | GeomDiff | 0.3 | 8 | 1 | **51643** | 0.7 | 8 | 1 | 51883 | GeomDiff | 0.2 | 8 | 1 | DB-KM |
| | 200 | 3000 | 750 | **42049** | GeomDiff | 0.5 | 6 | 0 | 50620 | 0.7 | 4 | 0 | **42049** | GeomDiff | 0.5 | 6 | 0 | Agg., DB-Agg. |
| | 200 | 3000 | 1000 | **42049** | GeomDiff | 0.5 | 6 | 0 | 50620 | 0.5 | 4 | 0 | **42049** | GeomDiff | 0.5 | 6 | 0 | Agg., DB-Agg. |
| | 200 | 4000 | 750 | **48049** | GeomDiff | 0.5 | 6 | 0 | 50707 | 0.8 | 5 | 0 | **48049** | GeomDiff | 0.5 | 6 | 0 | Agg., DB-Agg. |
| | 200 | 4000 | 1000 | **48049** | GeomDiff | 0.5 | 6 | 0 | 54620 | 0.5 | 4 | 0 | **48049** | GeomDiff | 0.5 | 6 | 0 | Agg., DB-Agg. |

Table F.7: Results of the Model based Heuristics on Ruhiira (Fixed Cost)

| | | | | MB-I | | | | | MB-II | | | | | MB-III | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | Cost | Type | Time | M | N | Cost | Time | M | N | Cost | Type | Time | M | N | |
| RUHIIRA - 1 | 30 | 3000 | 750 | **100374** | 6.0 | 0 | 1 | 129 | **100374** | 9.6 | 0 | 1 | 129 | 160545 | 2.4 | 42 | 37 | MB-I, MB-II |
| | 30 | 3000 | 1000 | **131233** | 4.3 | 0 | 3 | 121 | **131233** | 6.0 | 0 | 3 | 121 | 169795 | 1.6 | 42 | 37 | MB-I, MB-II |
| | 30 | 4000 | 750 | **101374** | 5.3 | 0 | 1 | 129 | **101374** | 6.8 | 0 | 1 | 129 | 202545 | 1.6 | 42 | 37 | MB-I, MB-II |
| | 30 | 4000 | 1000 | **133624** | 4.0 | 0 | 1 | 129 | **133624** | 8.0 | 0 | 1 | 129 | 211795 | 1.5 | 42 | 37 | MB-I, MB-II |
| | 50 | 3000 | 750 | **98577** | 5.3 | 0 | 4 | 112 | **98577** | 9.0 | 0 | 4 | 112 | 145511 | 1.9 | 40 | 18 | MB-I, MB-II |
| | 50 | 3000 | 1000 | **124062** | 12.4 | 0 | 9 | 92 | **124062** | 29.8 | 0 | 9 | 92 | 150011 | 1.9 | 40 | 18 | MB-I, MB-II |
| | 50 | 4000 | 750 | **100110** | 4.2 | 0 | 1 | 127 | **100110** | 9.7 | 0 | 1 | 127 | 185511 | 1.5 | 40 | 18 | MB-I, MB-II |
| | 50 | 4000 | 1000 | **130577** | 8.4 | 0 | 4 | 112 | **130577** | 9.3 | 0 | 4 | 112 | 190011 | 1.9 | 40 | 18 | MB-I, MB-II |
| | 100 | 3000 | 750 | 95490 | 4.6 | 0 | 6 | 92 | **95059** | 19.4 | 0 | 8 | 80 | 117187 | 1.1 | 28 | 5 | MB-II |
| | 100 | 3000 | 1000 | 110920 | 3.2 | 0 | 14 | 49 | **110838** | 6.0 | 0 | 14 | 47 | 118437 | 1.1 | 28 | 5 | MB-II |
| | 100 | 4000 | 750 | **99315** | 4.6 | 0 | 2 | 117 | **99315** | 8.3 | 0 | 2 | 117 | 145187 | 1.1 | 28 | 5 | MB-I, MB-II |
| | 100 | 4000 | 1000 | 122839 | 3.9 | 0 | 9 | 74 | **122757** | 8.6 | 0 | 9 | 72 | 146437 | 1.0 | 28 | 5 | MB-II |
| | 200 | 3000 | 750 | **91594** | 12.1 | 0 | 8 | 55 | **91594** | 16.5 | 0 | 8 | 55 | 105924 | 1.1 | 19 | 0 | MB-I, MB-II |
| | 200 | 3000 | 1000 | 100479 | 24.8 | 0 | 13 | 21 | **100348** | 19.4 | 0 | 12 | 21 | 105924 | 1.0 | 19 | 0 | MB-II |
| | 200 | 4000 | 750 | **97637** | 20.3 | 0 | 3 | 96 | **97637** | 33.5 | 0 | 3 | 96 | 122621 | 1.0 | 17 | 0 | MB-I, MB-II |
| | 200 | 4000 | 1000 | 111405 | 12.8 | 0 | 8 | 45 | **111010** | 13.0 | 0 | 9 | 34 | 122621 | 1.6 | 17 | 0 | MB-II |
| RUHIIRA - 2 | 30 | 3000 | 750 | **176463** | 34.7 | 0 | 4 | 217 | **176463** | 27.1 | 0 | 4 | 217 | 265108 | 6.3 | 70 | 58 | MB-I, MB-II |
| | 30 | 3000 | 1000 | 226965 | 12.3 | 0 | 10 | 193 | **226282** | 20.9 | 0 | 11 | 189 | 279608 | 4.6 | 70 | 58 | MB-II |
| | 30 | 4000 | 750 | **179924** | 16.7 | 0 | 3 | 222 | **179924** | 21.6 | 0 | 3 | 222 | 335108 | 5.2 | 70 | 58 | MB-I, MB-II |
| | 30 | 4000 | 1000 | **234713** | 13.2 | 0 | 4 | 217 | **234713** | 25.4 | 0 | 4 | 217 | 349608 | 4.8 | 70 | 58 | MB-I, MB-II |
| | 50 | 3000 | 750 | 171694 | 14.1 | 0 | 9 | 184 | **171425** | 21.6 | 0 | 11 | 174 | 245932 | 5.3 | 68 | 25 | MB-II |
| | 50 | 3000 | 1000 | **209818** | 13.7 | 0 | 19 | 140 | **209818** | 17.3 | 0 | 19 | 140 | 252182 | 5.1 | 68 | 25 | MB-I, MB-II |
| | 50 | 4000 | 750 | **176947** | 14.0 | 0 | 4 | 210 | **176947** | 19.6 | 0 | 4 | 210 | 313932 | 4.6 | 68 | 25 | MB-I, MB-II |
| | 50 | 4000 | 1000 | **225536** | 12.0 | 0 | 12 | 168 | **225536** | 19.3 | 0 | 12 | 168 | 320182 | 4.1 | 68 | 25 | MB-I, MB-II |
| | 100 | 3000 | 750 | **159153** | 34.7 | 0 | 14 | 122 | **159153** | 53.0 | 0 | 14 | 122 | 194032 | 3.0 | 42 | 3 | MB-I, MB-II |
| | 100 | 3000 | 1000 | 178630 | 10.7 | 0 | 28 | 50 | **178618** | 27.5 | 0 | 28 | 49 | 194782 | 2.8 | 42 | 3 | MB-II |
| | 100 | 4000 | 750 | **168884** | 16.9 | 0 | 7 | 166 | **168884** | 42.4 | 0 | 7 | 166 | 236032 | 3.1 | 42 | 3 | MB-I, MB-II |
| | 100 | 4000 | 1000 | 202298 | 27.9 | 0 | 18 | 93 | **202298** | 80.2 | 0 | 17 | 96 | 236782 | 2.9 | 42 | 3 | MB-II |
| | 200 | 3000 | 750 | **151140** | 165.3 | 0 | 14 | 77 | **151140** | 215.6 | 0 | 14 | 77 | 163422 | 2.9 | 28 | 0 | MB-I, MB-II |
| | 200 | 3000 | 1000 | **158852** | 40.8 | 0 | 23 | 18 | **158852** | 56.1 | 0 | 23 | 18 | 163422 | 3.0 | 28 | 0 | MB-I, MB-II |
| | 200 | 4000 | 750 | **163071** | 236.7 | 0 | 8 | 121 | **163071** | 278.7 | 0 | 8 | 121 | 191422 | 3.5 | 28 | 0 | MB-I, MB-II |
| | 200 | 4000 | 1000 | **179623** | 226.6 | 0 | 16 | 46 | **179623** | 184.5 | 0 | 16 | 46 | 191422 | 3.4 | 28 | 0 | MB-I, MB-II |

| | | | | MB-I | | | | | MB-II | | | | | Unicost Post Process (MB-III) | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | Cost | Time | Gap | M | N | Cost | Time | Gap | M | N | Cost | Time | M | N | |
| RUHIIRA - 3 | 30 | 3000 | 750 | **188616** | 18.5 | 0 | 12 | 196 | **188616** | 23.1 | 0 | 12 | 196 | 271180 | 7.6 | 73 | 50 | MB-I, MB-II |
| | 30 | 3000 | 1000 | **232482** | 15.8 | 0 | 20 | 164 | **232482** | 23.2 | 0 | 20 | 164 | 283680 | 6.1 | 73 | 50 | MB-I, MB-II |
| | 30 | 4000 | 750 | **197850** | 16.4 | 0 | 8 | 216 | **197850** | 136.8 | 0 | 8 | 216 | 344180 | 7.0 | 73 | 50 | MB-I, MB-II |
| | 30 | 4000 | 1000 | **249616** | 15.5 | 0 | 12 | 196 | **249616** | 91.7 | 0 | 12 | 196 | 356680 | 6.3 | 73 | 50 | MB-I, MB-II |
| | 50 | 3000 | 750 | 176717 | 17.9 | 0 | 16 | 153 | **176412** | 38.7 | 0 | 17 | 148 | 243836 | 5.3 | 67 | 23 | MB-II |
| | 50 | 3000 | 1000 | 206228 | 15.3 | 0 | 28 | 102 | **206097** | 36.6 | 0 | 28 | 102 | 249586 | 5.4 | 67 | 23 | MB-II |
| | 50 | 4000 | 750 | **188699** | 17.3 | 0 | 9 | 192 | **188699** | 21.7 | 0 | 9 | 192 | 310836 | 4.9 | 67 | 23 | MB-I, MB-II |
| | 50 | 4000 | 1000 | 229405 | 16.0 | 0 | 20 | 132 | **229275** | 78.4 | 0 | 20 | 132 | 316586 | 4.9 | 67 | 23 | MB-II |
| | 100 | 3000 | 750 | 156786 | 45.0 | 0 | 20 | 79 | **156564** | 69.7 | 0 | 20 | 78 | 183874 | 5.4 | 40 | 6 | MB-II |
| | 100 | 3000 | 1000 | 172326 | 32.3 | 0 | 26 | 51 | **172028** | 67.2 | 0 | 25 | 53 | 185374 | 4.3 | 40 | 6 | MB-II |
| | 100 | 4000 | 750 | 173377 | 73.3 | 0 | 14 | 116 | **173082** | 77.2 | 0 | 13 | 120 | 223874 | 6.6 | 40 | 6 | MB-II |
| | 100 | 4000 | 1000 | 195597 | 48.8 | 0 | 21 | 71 | **195443** | 86.6 | 0 | 21 | 70 | 225374 | 5.0 | 40 | 6 | MB-II |
| | 200 | 3000 | 750 | **148939** | 186.1 | 0 | 18 | 38 | **148939** | 368.9 | 0 | 18 | 38 | 160973 | 3.8 | 27 | 1 | MB-I, MB-II |
| | 200 | 3000 | 1000 | **155652** | 140.3 | 0 | 21 | 22 | **155652** | 112.0 | 0 | 21 | 22 | 161223 | 3.6 | 27 | 1 | MB-I, MB-II |
| | 200 | 4000 | 750 | **164533** | 228.4 | 0 | 12 | 80 | **164533** | 392.7 | 0 | 12 | 80 | 188006 | 3.6 | 24 | 0 | MB-I, MB-II |
| | 200 | 4000 | 1000 | **173975** | 155.7 | 0 | 16 | 32 | 174004 | 312.6 | 0 | 16 | 30 | 188006 | 3.7 | 24 | 0 | MB-I |
| RUHIIRA - 4 | 30 | 3000 | 750 | **180546** | 13.4 | 0 | 1 | 236 | **180546** | 20.9 | 0 | 1 | 236 | 265244 | 6.4 | 65 | 78 | MB-I, MB-II |
| | 30 | 3000 | 1000 | **236606** | 14.6 | 0 | 5 | 220 | **236606** | 24.2 | 0 | 5 | 220 | 284744 | 5.0 | 65 | 78 | MB-I, MB-II |
| | 30 | 4000 | 750 | **181500** | 12.7 | 0 | 0 | 242 | **181500** | 17.9 | 0 | 0 | 242 | 330244 | 5.2 | 65 | 78 | MB-I, MB-II |
| | 30 | 4000 | 1000 | **240546** | 12.1 | 0 | 1 | 236 | **240546** | 20.1 | 0 | 1 | 236 | 349744 | 4.9 | 65 | 78 | MB-I, MB-II |
| | 50 | 3000 | 750 | 179424 | 12.4 | 0 | 1 | 234 | **179133** | 23.2 | 990 | 4 | 219 | 257918 | 5.1 | 69 | 38 | MB-II |
| | 50 | 3000 | 1000 | 223680 | 15.2 | 0 | 21 | 149 | **223482** | 19.6 | 990 | 21 | 149 | 267418 | 5.1 | 69 | 38 | MB-II |
| | 50 | 4000 | 750 | **180424** | 10.5 | 0 | 1 | 234 | **180424** | 20.5 | 990 | 1 | 234 | 326918 | 4.3 | 69 | 38 | MB-I, MB-II |
| | 50 | 4000 | 1000 | **237421** | 13.7 | 0 | 6 | 209 | **237421** | 20.6 | 990 | 6 | 209 | 336418 | 4.3 | 69 | 38 | MB-I, MB-II |
| | 100 | 3000 | 750 | 166978 | 11.4 | 0 | 10 | 147 | **166795** | 15.6 | 0 | 11 | 141 | 218612 | 3.2 | 53 | 4 | MB-II |
| | 100 | 3000 | 1000 | 193764 | 11.8 | 0 | 24 | 81 | **193327** | 22.7 | 0 | 24 | 80 | 219612 | 3.1 | 53 | 4 | MB-II |
| | 100 | 4000 | 750 | **174337** | 12.8 | 0 | 6 | 176 | **174337** | 19.0 | 0 | 6 | 176 | 271612 | 2.9 | 53 | 4 | MB-I, MB-II |
| | 100 | 4000 | 1000 | 213165 | 11.1 | 0 | 15 | 121 | **212728** | 14.7 | 0 | 15 | 120 | 272612 | 3.2 | 53 | 4 | MB-II |
| | 200 | 3000 | 750 | **160430** | 42.4 | 0 | 13 | 97 | **160430** | 68.0 | 0 | 13 | 97 | 178631 | 3.9 | 31 | 1 | MB-I, MB-II |
| | 200 | 3000 | 1000 | **172532** | 33.5 | 0 | 21 | 33 | **172532** | 50.0 | 0 | 21 | 33 | 178881 | 3.9 | 31 | 1 | MB-I, MB-II |
| | 200 | 4000 | 750 | **170253** | 35.7 | 0 | 7 | 149 | **170253** | 58.1 | 0 | 7 | 149 | 206152 | 3.3 | 27 | 1 | MB-I, MB-II |
| | 200 | 4000 | 1000 | **192816** | 91.2 | 0 | 18 | 43 | **192816** | 197.7 | 0 | 18 | 43 | 206402 | 2.9 | 27 | 1 | MB-I, MB-II |

Table F.8: Results of the Clustering based Heuristics on Ruhiira (Fixed Cost)

| | | | | Agglomerative (Agg) | | | | | DBSCAN - KMeans (DB-KM) | | | | DBSCAN - Agglomerative (DB-Agg) | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | Cost | Type | Time | M | N | Cost | Time | M | N | Cost | Type | Time | M | N | |
| RUHIIRA - 1 | 30 | 3000 | 750 | 102000 | GeomDiff | 0.2 | 0 | 136 | **99717** | 0.2 | 1 | 128 | **99717** | GeomDiff | 0.3 | 1 | 128 | DB-KM, DB-Agg. |
| | 30 | 3000 | 1000 | 136000 | GeomDiff | 0.1 | 0 | 136 | **130979** | 0.1 | 2 | 124 | 131717 | GeomDiff | 0.0 | 1 | 128 | DB-KM |
| | 30 | 4000 | 750 | 102000 | GeomDiff | 0.1 | 0 | 136 | **100717** | 0.1 | 1 | 128 | **100717** | GeomDiff | 0.1 | 1 | 128 | DB-KM, DB-Agg. |
| | 30 | 4000 | 1000 | 136000 | GeomDiff | 0.1 | 0 | 136 | **132717** | 0.0 | 1 | 128 | **132717** | GeomDiff | 0.0 | 1 | 128 | DB-KM, DB-Agg. |
| | 50 | 3000 | 750 | 102000 | GeomDiff | 0.1 | 0 | 136 | 98662 | 0.1 | 3 | 117 | **98643** | GeomDiff | 0.2 | 3 | 117 | DB-Agg. |
| | 50 | 3000 | 1000 | 136000 | GeomDiff | 0.1 | 0 | 136 | **125493** | 0.0 | 6 | 104 | 126718 | GeomDiff | 0.1 | 5 | 109 | DB-KM |
| | 50 | 4000 | 750 | 102000 | GeomDiff | 0.1 | 0 | 136 | 100119 | 0.1 | 1 | 127 | **100110** | GeomDiff | 0.1 | 1 | 127 | DB-Agg. |
| | 50 | 4000 | 1000 | 136000 | GeomDiff | 0.1 | 0 | 136 | 130902 | 0.0 | 3 | 117 | **130893** | GeomDiff | 0.1 | 3 | 117 | DB-Agg. |
| | 100 | 3000 | 750 | 102000 | GeomDiff | 0.1 | 0 | 136 | **96640** | 0.4 | 7 | 92 | 97300 | GeomDiff | 0.1 | 5 | 103 | DB-KM |
| | 100 | 3000 | 1000 | **113086** | Ward | 0.1 | 15 | 52 | 113509 | 0.7 | 15 | 54 | 113531 | GeomDiff | 0.1 | 14 | 57 | Agg. |
| | 100 | 4000 | 750 | 102000 | GeomDiff | 0.1 | 0 | 136 | **99463** | 0.9 | 1 | 125 | **99463** | GeomDiff | 0.1 | 1 | 125 | DB-KM, DB-Agg. |
| | 100 | 4000 | 1000 | 136000 | GeomDiff | 0.1 | 0 | 136 | **126038** | 1.0 | 10 | 76 | 126574 | GeomDiff | 0.1 | 7 | 91 | DB-KM |
| | 200 | 3000 | 750 | 102000 | GeomDiff | 0.3 | 0 | 136 | 95391 | 3.8 | 6 | 60 | **92295** | GeomDiff | 0.3 | 7 | 61 | DB-Agg. |
| | 200 | 3000 | 1000 | 101359 | GeomDiff | 0.5 | 15 | 19 | 105873 | 4.2 | 13 | 11 | **100871** | GeomDiff | 0.3 | 14 | 18 | DB-Agg. |
| | 200 | 4000 | 750 | 102000 | GeomDiff | 0.3 | 0 | 136 | **99782** | 3.3 | 1 | 117 | 102000 | GeomDiff | 0.2 | 0 | 136 | DB-KM |
| | 200 | 4000 | 1000 | 114181 | GeomDiff | 0.3 | 10 | 43 | 115299 | 2.7 | 9 | 30 | **113435** | GeomDiff | 0.3 | 10 | 37 | DB-Agg. |
| RUHIIRA - 2 | 30 | 3000 | 750 | 182250 | GeomDiff | 0.5 | 0 | 243 | **177523** | 0.2 | 3 | 223 | **177523** | GeomDiff | 0.2 | 3 | 223 | DB-KM, DB-Agg. |
| | 30 | 3000 | 1000 | 243000 | GeomDiff | 0.3 | 0 | 243 | **231029** | 0.1 | 7 | 208 | **231029** | GeomDiff | 0.1 | 7 | 208 | DB-KM, DB-Agg. |
| | 30 | 4000 | 750 | 182250 | GeomDiff | 0.2 | 0 | 243 | **180634** | 0.1 | 2 | 229 | **180634** | GeomDiff | 0.1 | 2 | 229 | DB-KM, DB-Agg. |
| | 30 | 4000 | 1000 | 243000 | GeomDiff | 0.3 | 0 | 243 | **236273** | 0.1 | 3 | 223 | **236273** | GeomDiff | 0.1 | 3 | 223 | DB-KM, DB-Agg. |
| | 50 | 3000 | 750 | 182250 | GeomDiff | 0.4 | 0 | 243 | 174379 | 0.5 | 10 | 185 | **171782** | Complete | 0.0 | 8 | 189 | DB-Agg. |
| | 50 | 3000 | 1000 | 243000 | GeomDiff | 0.3 | 0 | 243 | 216640 | 0.5 | 17 | 157 | **214962** | Complete | 0.1 | 15 | 161 | DB-Agg. |
| | 50 | 4000 | 750 | 182250 | GeomDiff | 0.3 | 0 | 243 | **180633** | 0.5 | 2 | 229 | 182165 | GeomDiff | 0.1 | 1 | 237 | DB-KM |
| | 50 | 4000 | 1000 | 243000 | GeomDiff | 0.3 | 0 | 243 | 230105 | 0.3 | 9 | 189 | **227032** | Complete | 0.1 | 8 | 189 | DB-Agg. |
| | 100 | 3000 | 750 | 182250 | GeomDiff | 0.6 | 0 | 243 | **161434** | 4.2 | 13 | 133 | 161885 | Complete | 0.1 | 11 | 148 | DB-KM |
| | 100 | 3000 | 1000 | 185044 | Complete | 0.4 | 29 | 63 | 186001 | 3.3 | 28 | 67 | **184552** | Ward | 0.3 | 25 | 80 | DB-Agg. |
| | 100 | 4000 | 750 | 182250 | GeomDiff | 0.6 | 0 | 243 | **171799** | 4.0 | 6 | 183 | 176598 | Ward | 0.1 | 4 | 207 | DB-KM |
| | 100 | 4000 | 1000 | 243000 | GeomDiff | 0.4 | 0 | 243 | 208690 | 3.3 | 18 | 110 | **208275** | GeomDiff | 0.2 | 16 | 121 | DB-Agg. |
| | 200 | 3000 | 750 | **154768** | GeomDiff | 1.2 | 16 | 70 | 160073 | 4.5 | 13 | 75 | **154768** | GeomDiff | 0.7 | 16 | 70 | Agg., DB-Agg. |
| | 200 | 3000 | 1000 | 162343 | Ward | 0.5 | 27 | 10 | 168154 | 4.6 | 22 | 13 | **162285** | Ward | 0.3 | 26 | 13 | DB-Agg. |
| | 200 | 4000 | 750 | 182250 | GeomDiff | 0.8 | 0 | 243 | **169017** | 4.9 | 6 | 138 | 170066 | GeomDiff | 0.6 | 6 | 167 | DB-KM |
| | 200 | 4000 | 1000 | 186362 | Complete | 0.3 | 17 | 42 | 187259 | 5.2 | 18 | 34 | **185642** | Complete | 0.2 | 18 | 42 | DB-Agg. |

| | | | | Agglomerative (Agg) | | | | | DBSCAN - KMeans (DB-KM) | | | | DBSCAN - Agglomerative (DB-Agg) | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | Cost | Type | Time | M | N | Cost | Time | M | N | Cost | Type | Time | M | N | |
| RUHIRA - 3 | 30 | 3000 | 750 | 203250 | GeomDiff | 0.6 | 0 | 271 | **191733** | 0.7 | 9 | 215 | 191739 | GeomDiff | 0.3 | 9 | 215 | DB-KM |
| | 30 | 3000 | 1000 | 271000 | GeomDiff | 0.5 | 0 | 271 | **240455** | 0.5 | 12 | 200 | 242228 | Ward | 0.1 | 11 | 205 | DB-KM |
| | 30 | 4000 | 750 | 203250 | GeomDiff | 0.5 | 0 | 271 | **199568** | 0.5 | 7 | 225 | 199574 | GeomDiff | 0.1 | 7 | 225 | DB-KM |
| | 30 | 4000 | 1000 | 271000 | GeomDiff | 0.3 | 0 | 271 | **252829** | 0.3 | 10 | 209 | 254489 | GeomDiff | 0.1 | 9 | 215 | DB-KM |
| | 50 | 3000 | 750 | 203250 | GeomDiff | 0.6 | 0 | 271 | **181787** | 1.3 | 16 | 166 | 183625 | GeomDiff | 0.2 | 15 | 173 | DB-KM |
| | 50 | 3000 | 1000 | **211374** | Complete | 0.4 | 26 | 116 | 218641 | 0.8 | 25 | 130 | 216174 | GeomDiff | 0.1 | 24 | 131 | Agg. |
| | 50 | 4000 | 750 | 203250 | GeomDiff | 0.6 | 0 | 271 | **193087** | 0.5 | 9 | 201 | 196499 | GeomDiff | 0.1 | 6 | 225 | DB-KM |
| | 50 | 4000 | 1000 | 271000 | GeomDiff | 0.6 | 0 | 271 | 239816 | 0.8 | 17 | 161 | **239260** | GeomDiff | 0.1 | 17 | 161 | DB-Agg. |
| | 100 | 3000 | 750 | **159899** | Complete | 0.4 | 21 | 79 | 161913 | 4.4 | 20 | 92 | 159930 | Complete | 0.1 | 20 | 90 | Agg. |
| | 100 | 3000 | 1000 | **176054** | Complete | 0.4 | 26 | 55 | 176676 | 3.5 | 27 | 56 | 177842 | Complete | 0.1 | 25 | 64 | Agg. |
| | 100 | 4000 | 750 | 203250 | GeomDiff | 0.6 | 0 | 271 | **176194** | 3.5 | 13 | 132 | 180858 | Complete | 0.1 | 11 | 157 | DB-KM |
| | 100 | 4000 | 1000 | **200649** | Complete | 0.3 | 21 | 79 | 202248 | 2.4 | 23 | 74 | 201964 | Complete | 0.1 | 22 | 79 | Agg. |
| | 200 | 3000 | 750 | **152707** | Ward | 0.4 | 21 | 23 | 162499 | 3.9 | 16 | 31 | 156234 | Ward | 0.4 | 19 | 32 | Agg. |
| | 200 | 3000 | 1000 | **157451** | Ward | 0.4 | 22 | 17 | 168295 | 4.4 | 18 | 15 | 161407 | Ward | 0.3 | 21 | 16 | Agg. |
| | 200 | 4000 | 750 | **168074** | Ward | 0.4 | 14 | 70 | 172824 | 3.9 | 9 | 99 | 169962 | Ward | 0.4 | 12 | 88 | Agg. |
| | 200 | 4000 | 1000 | **178648** | Complete | 0.2 | 17 | 32 | 186217 | 4.4 | 18 | 24 | 183012 | Ward | 0.4 | 19 | 31 | Agg. |
| RUHIRA - 4 | 30 | 3000 | 750 | **181500** | GeomDiff | 0.6 | 0 | 242 | **181500** | 0.2 | 0 | 242 | **181500** | GeomDiff | 0.2 | 0 | 242 | Agg., DB-KM, DB-Agg. |
| | 30 | 3000 | 1000 | 242000 | GeomDiff | 0.3 | 0 | 242 | **238892** | 0.1 | 4 | 226 | **238892** | GeomDiff | 0.1 | 4 | 226 | DB-KM, DB-Agg. |
| | 30 | 4000 | 750 | **181500** | GeomDiff | 0.2 | 0 | 242 | **181500** | 0.0 | 0 | 242 | **181500** | GeomDiff | 0.0 | 0 | 242 | Agg., DB-KM, DB-Agg. |
| | 30 | 4000 | 1000 | **242000** | GeomDiff | 0.3 | 0 | 242 | **242000** | 0.1 | 0 | 242 | **242000** | GeomDiff | 0.1 | 0 | 242 | Agg., DB-KM, DB-Agg. |
| | 50 | 3000 | 750 | 181500 | GeomDiff | 0.5 | 0 | 242 | **179163** | 0.4 | 3 | 224 | **179163** | GeomDiff | 0.3 | 3 | 224 | DB-KM, DB-Agg. |
| | 50 | 3000 | 1000 | 242000 | GeomDiff | 0.3 | 0 | 242 | **229579** | 0.2 | 12 | 188 | 230054 | GeomDiff | 0.1 | 11 | 192 | DB-KM |
| | 50 | 4000 | 750 | 181500 | GeomDiff | 0.3 | 0 | 242 | **180424** | 0.0 | 1 | 234 | **180424** | GeomDiff | 0.1 | 1 | 234 | DB-KM, DB-Agg. |
| | 50 | 4000 | 1000 | 242000 | GeomDiff | 0.2 | 0 | 242 | **238163** | 0.1 | 3 | 224 | **238163** | GeomDiff | 0.1 | 3 | 224 | DB-KM, DB-Agg. |
| | 100 | 3000 | 750 | 181500 | GeomDiff | 0.5 | 0 | 242 | **172616** | 2.9 | 10 | 166 | 173482 | Complete | 0.1 | 5 | 194 | DB-KM |
| | 100 | 3000 | 1000 | 201390 | Complete | 0.4 | 28 | 80 | 206167 | 2.9 | 29 | 89 | **200908** | Complete | 0.1 | 27 | 87 | DB-Agg. |
| | 100 | 4000 | 750 | 181500 | GeomDiff | 0.5 | 0 | 242 | **177931** | 2.6 | 3 | 210 | 178496 | Complete | 0.1 | 1 | 228 | DB-KM |
| | 100 | 4000 | 1000 | 242000 | GeomDiff | 0.4 | 0 | 242 | 224568 | 3.6 | 14 | 150 | **224000** | Complete | 0.2 | 11 | 161 | DB-Agg. |
| | 200 | 3000 | 750 | 181500 | GeomDiff | 0.8 | 0 | 242 | **168541** | 9.4 | 10 | 109 | 174348 | Complete | 0.3 | 2 | 205 | DB-KM |
| | 200 | 3000 | 1000 | **176329** | Complete | 0.5 | 24 | 25 | 182786 | 8.1 | 21 | 29 | **176329** | Complete | 0.3 | 24 | 25 | Agg., DB-Agg. |
| | 200 | 4000 | 750 | 181500 | GeomDiff | 0.7 | 0 | 242 | **175506** | 8.6 | 3 | 188 | 176348 | Complete | 0.3 | 2 | 205 | DB-KM |
| | 200 | 4000 | 1000 | **196440** | Complete | 0.3 | 17 | 59 | 200037 | 7.7 | 17 | 63 | **196440** | Complete | 0.3 | 17 | 59 | Agg., DB-Agg. |

# Appendix G

# Computational Results of the Variable Cost Problem on Real Instances

Table G.1: Results of the Model based Heuristics on Tiby (Variable Cost)

| | | | | MB-I | | | | | MB-II | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F3 | F2 | Cost | Time | Gap | M | N | Cost | Time | Gap | M | N | |
| TIBY - 1 | 30 | 500 | 750 | **229381** | 38.4 | 0 | 198 | 7 | 229425 | 51.1 | 0 | 198 | 7 | MB-I |
| | 30 | 500 | 1000 | **230499** | 39.1 | 0 | 198 | 5 | 230543 | 46.9 | 0 | 198 | 5 | MB-I |
| | 30 | 600 | 750 | **271113** | 33.4 | 0 | 195 | 13 | 271135 | 47.0 | 0 | 196 | 10 | MB-I |
| | 30 | 600 | 1000 | **272499** | 35.3 | 0 | 198 | 5 | 272543 | 45.2 | 0 | 198 | 5 | MB-I |
| | 50 | 500 | 750 | 228620 | 32.6 | 0 | 202 | 4 | 228586 | 40.5 | 0 | 202 | 4 | MB-II |
| | 50 | 500 | 1000 | 229365 | 33.1 | 0 | 202 | 3 | 229331 | 41.9 | 0 | 202 | 3 | MB-II |
| | 50 | 600 | 750 | **270675** | 34.2 | 0 | 201 | 6 | **270675** | 40.7 | 0 | 201 | 6 | MB-I, MB-II |
| | 50 | 600 | 1000 | 271565 | 31.7 | 0 | 202 | 3 | **271531** | 40.7 | 0 | 202 | 3 | MB-II |
| | 100 | 500 | 750 | **228522** | 41.6 | 0 | 202 | 3 | **228522** | 48.2 | 0 | 202 | 3 | MB-I, MB-II |
| | 100 | 500 | 1000 | 229208 | 44.1 | 0 | 203 | 2 | **229133** | 52.9 | 0 | 202 | 2 | MB-II |
| | 100 | 600 | 750 | **270619** | 48.8 | 0 | 201 | 5 | **270619** | 46.1 | 0 | 201 | 5 | MB-I, MB-II |
| | 100 | 600 | 1000 | **271472** | 39.8 | 0 | 202 | 3 | **271472** | 51.0 | 0 | 202 | 3 | MB-I, MB-II |
| | 200 | 500 | 750 | **228522** | 133.5 | 0 | 202 | 3 | **228522** | 152.4 | 0 | 202 | 3 | MB-I, MB-II |
| | 200 | 500 | 1000 | **229133** | 130.2 | 0 | 203 | 2 | **229133** | 151.1 | 0 | 203 | 2 | MB-I, MB-II |
| | 200 | 600 | 750 | **270619** | 126.2 | 0 | 201 | 5 | **270619** | 144.3 | 0 | 201 | 5 | MB-I, MB-II |
| | 200 | 600 | 1000 | **271433** | 128.6 | 0 | 203 | 2 | **271433** | 149.4 | 0 | 203 | 2 | MB-I, MB-II |
| TIBY - 2 | 30 | 500 | 750 | **212862** | 34.1 | 0 | 188 | 1 | **212862** | 41.1 | 0 | 188 | 1 | MB-I, MB-II |
| | 30 | 500 | 1000 | **212819** | 31.6 | 0 | 188 | 0 | **212819** | 41.3 | 0 | 188 | 0 | MB-I, MB-II |
| | 30 | 600 | 750 | 252534 | 28.2 | 0 | 185 | 6 | **252442** | 40.9 | 0 | 186 | 4 | MB-II |
| | 30 | 600 | 1000 | **252519** | 31.3 | 0 | 188 | 0 | **252519** | 39.9 | 0 | 188 | 0 | MB-I, MB-II |
| | 50 | 500 | 750 | **212395** | 27.8 | 0 | 190 | 0 | **212395** | 35.3 | 0 | 190 | 0 | MB-I, MB-II |
| | 50 | 500 | 1000 | **212395** | 27.6 | 0 | 190 | 0 | **212395** | 35.7 | 0 | 190 | 0 | MB-I, MB-II |
| | 50 | 600 | 750 | **252050** | 27.4 | 0 | 190 | 1 | **252050** | 33.5 | 0 | 190 | 1 | MB-I, MB-II |
| | 50 | 600 | 1000 | **252095** | 27.9 | 0 | 190 | 0 | **252095** | 34.6 | 0 | 190 | 0 | MB-I, MB-II |
| | 100 | 500 | 750 | **212367** | 37.8 | 0 | 190 | 0 | **212367** | 43.3 | 0 | 190 | 0 | MB-I, MB-II |
| | 100 | 500 | 1000 | **212367** | 37.0 | 0 | 190 | 0 | **212367** | 43.6 | 0 | 190 | 0 | MB-I, MB-II |
| | 100 | 600 | 750 | **252050** | 40.1 | 0 | 190 | 1 | **252050** | 42.9 | 0 | 190 | 1 | MB-I, MB-II |
| | 100 | 600 | 1000 | **252067** | 40.2 | 0 | 190 | 0 | **252067** | 45.1 | 0 | 190 | 0 | MB-I, MB-II |
| | 200 | 500 | 750 | **212367** | 118.0 | 0 | 190 | 0 | **212367** | 269.2 | 0 | 190 | 0 | MB-I, MB-II |
| | 200 | 500 | 1000 | **212367** | 115.0 | 0 | 190 | 0 | **212367** | 267.6 | 0 | 190 | 0 | MB-I, MB-II |
| | 200 | 600 | 750 | **252050** | 115.3 | 0 | 190 | 1 | **252050** | 270.6 | 0 | 190 | 1 | MB-I, MB-II |
| | 200 | 600 | 1000 | **252067** | 117.2 | 0 | 190 | 0 | **252067** | 267.3 | 0 | 190 | 0 | MB-I, MB-II |

| | | | | MB-I | | | | | MB-II | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F3 | F2 | Cost | Time | Gap | M | N | Cost | Time | Gap | M | N | Best Method |
| TIBY - 3 | 30 | 500 | 750 | 222476 | 38.5 | 0 | 191 | 5 | **222269** | 39.4 | 0 | 192 | 4 | MB-II |
| | 30 | 500 | 1000 | 223185 | 29.3 | 0 | 191 | 3 | **223153** | 37.6 | 0 | 192 | 3 | MB-II |
| | 30 | 600 | 750 | 263065 | 31.5 | 0 | 186 | 15 | **262947** | 39.1 | 0 | 187 | 15 | MB-II |
| | 30 | 600 | 1000 | 263785 | 27.6 | 0 | 191 | 3 | **263753** | 37.1 | 0 | 192 | 3 | MB-II |
| | 50 | 500 | 750 | 221855 | 26.7 | 0 | 194 | 3 | **221809** | 32.9 | 0 | 193 | 3 | MB-II |
| | 50 | 500 | 1000 | 222094 | 26.3 | 0 | 194 | 0 | **222048** | 34.6 | 0 | 193 | 0 | MB-II |
| | 50 | 600 | 750 | **262389** | 24.6 | 0 | 192 | 8 | **262389** | 33.5 | 0 | 192 | 8 | MB-I, MB-II |
| | 50 | 600 | 1000 | 263174 | 28.7 | 0 | 194 | 2 | **262941** | 33.7 | 0 | 193 | 1 | MB-II |
| | 100 | 500 | 750 | **221730** | 28.8 | 0 | 194 | 1 | **221730** | 41.6 | 0 | 194 | 1 | MB-I, MB-II |
| | 100 | 500 | 1000 | **221830** | 31.6 | 0 | 195 | 0 | **221830** | 36.1 | 0 | 195 | 0 | MB-I, MB-II |
| | 100 | 600 | 750 | **262334** | 32.4 | 0 | 192 | 8 | **262334** | 37.5 | 0 | 192 | 8 | MB-I, MB-II |
| | 100 | 600 | 1000 | **262730** | 31.7 | 0 | 195 | 0 | **262730** | 36.3 | 0 | 195 | 0 | MB-I, MB-II |
| | 200 | 500 | 750 | **221723** | 57.0 | 0 | 194 | 0 | **221723** | 65.2 | 0 | 194 | 0 | MB-I, MB-II |
| | 200 | 500 | 1000 | **221723** | 56.3 | 0 | 194 | 0 | **221723** | 64.9 | 0 | 194 | 0 | MB-I, MB-II |
| | 200 | 600 | 750 | **262334** | 57.4 | 0 | 192 | 8 | **262334** | 66.4 | 0 | 192 | 8 | MB-I, MB-II |
| | 200 | 600 | 1000 | **262623** | 56.0 | 0 | 194 | 0 | **262623** | 64.9 | 0 | 194 | 0 | MB-I, MB-II |
| TIBY - 4 | 30 | 500 | 750 | **118009** | 8.1 | 0 | 102 | 3 | 118036 | 9.8 | 0 | 102 | 3 | MB-I |
| | 30 | 500 | 1000 | **118759** | 5.8 | 0 | 102 | 3 | 118786 | 10.0 | 0 | 102 | 3 | MB-I |
| | 30 | 600 | 750 | **139555** | 7.0 | 0 | 101 | 8 | **139555** | 11.1 | 0 | 101 | 8 | MB-I, MB-II |
| | 30 | 600 | 1000 | **140259** | 6.3 | 0 | 102 | 3 | 140286 | 8.9 | 0 | 102 | 3 | MB-I |
| | 50 | 500 | 750 | **117751** | 6.2 | 0 | 104 | 2 | **117751** | 7.9 | 0 | 104 | 2 | MB-I, MB-II |
| | 50 | 500 | 1000 | 118040 | 12.5 | 0 | 104 | 1 | **117954** | 9.4 | 0 | 104 | 1 | MB-II |
| | 50 | 600 | 750 | **139378** | 5.2 | 0 | 102 | 6 | **139378** | 9.3 | 0 | 102 | 6 | MB-I, MB-II |
| | 50 | 600 | 1000 | 139740 | 7.7 | 0 | 104 | 1 | **139654** | 9.2 | 0 | 104 | 1 | MB-II |
| | 100 | 500 | 750 | **117704** | 8.0 | 0 | 104 | 1 | **117704** | 12.9 | 0 | 104 | 1 | MB-I, MB-II |
| | 100 | 500 | 1000 | **117954** | 10.4 | 0 | 104 | 1 | **117954** | 10.8 | 0 | 104 | 1 | MB-I, MB-II |
| | 100 | 600 | 750 | **139353** | 11.1 | 0 | 103 | 4 | **139353** | 11.3 | 0 | 103 | 4 | MB-I, MB-II |
| | 100 | 600 | 1000 | **139654** | 12.2 | 0 | 104 | 1 | **139654** | 10.5 | 0 | 104 | 1 | MB-I, MB-II |
| | 200 | 500 | 750 | **117704** | 27.0 | 0 | 104 | 1 | **117704** | 25.3 | 0 | 104 | 1 | MB-I, MB-II |
| | 200 | 500 | 1000 | **117954** | 26.6 | 0 | 104 | 1 | **117954** | 25.2 | 0 | 104 | 1 | MB-I, MB-II |
| | 200 | 600 | 750 | **139353** | 26.7 | 0 | 103 | 4 | **139353** | 24.4 | 0 | 103 | 4 | MB-I, MB-II |
| | 200 | 600 | 1000 | **139654** | 28.1 | 0 | 104 | 1 | **139654** | 25.1 | 0 | 104 | 1 | MB-I, MB-II |

Table G.2: Results of the Clustering based Heuristics on Tiby (Variable Cost)

| | | | | Agglomerative (Agg) | | | | | DBSCAN - KMeans (DB-KM) | | | | DBSCAN - Agglomerative (DB-Agg) | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F3 | Cost | Type | Time | M | N | Cost | Time | M | N | Cost | Type | Time | M | N | |
| TIBY - 1 | 30 | 500 | 750 | **233840** | Ward | 1.9 | 137 | 14 | 244028 | 24.73 | 93 | 27 | 235779 | Ward | 0.6 | 141 | 33 | Agg. |
| | 30 | 500 | 1000 | **236754** | Ward | 1.4 | 133 | 11 | 250891 | 20.25 | 93 | 27 | 243122 | Ward | 0.7 | 132 | 28 | Agg. |
| | 30 | 600 | 750 | **274521** | Ward | 0.8 | 142 | 21 | 283595 | 20.16 | 93 | 27 | 274740 | Ward | 0.7 | 145 | 36 | Agg. |
| | 30 | 600 | 1000 | **278154** | Ward | 1.2 | 133 | 11 | 291070 | 19.19 | 92 | 27 | 282822 | Ward | 0.6 | 132 | 28 | Agg. |
| | 50 | 500 | 750 | **233839** | Ward | 1.1 | 137 | 14 | 258211 | 17.5 | 56 | 6 | **233839** | Ward | 1.0 | 137 | 14 | Agg., DB-Agg. |
| | 50 | 500 | 1000 | **236754** | Ward | 0.8 | 133 | 11 | 259131 | 17.84 | 56 | 6 | **236754** | Ward | 1.0 | 133 | 11 | Agg., DB-Agg. |
| | 50 | 600 | 750 | 274521 | Ward | 0.7 | 142 | 21 | 300111 | 17.55 | 56 | 6 | **274439** | Ward | 1.0 | 144 | 25 | DB-Agg. |
| | 50 | 600 | 1000 | **278154** | Ward | 1.0 | 133 | 11 | 301611 | 18.42 | 56 | 6 | **278154** | Ward | 0.7 | 133 | 11 | Agg., DB-Agg. |
| | 100 | 500 | 750 | **233839** | Ward | 1.3 | 137 | 14 | 300427 | 7.25 | 18 | 33 | **233839** | Ward | 1.0 | 137 | 14 | Agg., DB-Agg. |
| | 100 | 500 | 1000 | **236754** | Ward | 1.2 | 133 | 11 | 299758 | 8.45 | 20 | 3 | **236754** | Ward | 1.4 | 133 | 11 | Agg., DB-Agg. |
| | 100 | 600 | 750 | **274521** | Ward | 1.6 | 142 | 21 | 318750 | 7.06 | 0 | 425 | **274521** | Ward | 1.1 | 142 | 21 | Agg., DB-Agg. |
| | 100 | 600 | 1000 | **278154** | Ward | 1.7 | 133 | 11 | 341958 | 7.81 | 20 | 3 | **278154** | Ward | 1.1 | 133 | 11 | Agg., DB-Agg. |
| | 200 | 500 | 750 | **233839** | Ward | 1.9 | 137 | 14 | 318750 | 2.81 | 0 | 425 | **233839** | Ward | 1.5 | 137 | 14 | Agg., DB-Agg. |
| | 200 | 500 | 1000 | **236754** | Ward | 2.1 | 133 | 11 | 373969 | 2.94 | 6 | 1 | **236754** | Ward | 2.1 | 133 | 11 | Agg., DB-Agg. |
| | 200 | 600 | 750 | **274521** | Ward | 1.6 | 142 | 21 | 318750 | 2.81 | 0 | 425 | **274521** | Ward | 2.1 | 142 | 21 | Agg., DB-Agg. |
| | 200 | 600 | 1000 | **278154** | Ward | 1.9 | 133 | 11 | 409544 | 2.83 | 3 | 221 | **278154** | Ward | 1.6 | 133 | 11 | Agg., DB-Agg. |
| TIBY - 2 | 30 | 500 | 750 | **218417** | Ward | 1.8 | 120 | 12 | 226571 | 21.92 | 83 | 16 | 218894 | Ward | 0.8 | 125 | 20 | Agg. |
| | 30 | 500 | 1000 | **220737** | Ward | 1.3 | 105 | 4 | 230512 | 18.64 | 83 | 16 | 223894 | Ward | 1.0 | 125 | 20 | Agg. |
| | 30 | 600 | 750 | 256433 | Ward | 0.8 | 125 | 17 | 264631 | 17.77 | 84 | 16 | **256122** | Ward | 0.6 | 137 | 33 | DB-Agg. |
| | 30 | 600 | 1000 | **259770** | Ward | 0.6 | 113 | 8 | 268994 | 16.34 | 84 | 17 | 261594 | Ward | 0.6 | 125 | 20 | Agg. |
| | 50 | 500 | 750 | 218417 | Ward | 0.9 | 120 | 12 | 238502 | 15.59 | 47 | 1 | **218114** | Ward | 0.7 | 121 | 10 | DB-Agg. |
| | 50 | 500 | 1000 | 220702 | Ward | 0.6 | 105 | 4 | 238752 | 15.03 | 47 | 1 | **220067** | Ward | 0.9 | 114 | 6 | DB-Agg. |
| | 50 | 600 | 750 | 256433 | Ward | 0.7 | 125 | 17 | 278102 | 14.5 | 47 | 1 | **256330** | Ward | 0.9 | 126 | 15 | DB-Agg. |
| | 50 | 600 | 1000 | 259769 | Ward | 0.8 | 113 | 8 | 278352 | 15.38 | 47 | 1 | **259167** | Ward | 0.9 | 114 | 6 | DB-Agg. |
| | 100 | 500 | 750 | **218417** | Ward | 1.4 | 120 | 12 | 269875 | 6.69 | 18 | 0 | **218417** | Ward | 1.3 | 120 | 12 | Agg., DB-Agg. |
| | 100 | 500 | 1000 | **220702** | Ward | 1.3 | 105 | 4 | 270373 | 7.2 | 18 | 0 | **220702** | Ward | 1.1 | 105 | 4 | Agg., DB-Agg. |
| | 100 | 600 | 750 | **256433** | Ward | 1.1 | 125 | 17 | 296910 | 7.23 | 3 | 340 | **256433** | Ward | 1.0 | 125 | 17 | Agg., DB-Agg. |
| | 100 | 600 | 1000 | **259769** | Ward | 1.4 | 113 | 8 | 309575 | 8.17 | 18 | 0 | **259769** | Ward | 1.4 | 113 | 8 | Agg., DB-Agg. |
| | 200 | 500 | 750 | **218417** | Ward | 1.8 | 120 | 12 | 297750 | 1.7 | 0 | 397 | **218417** | Ward | 1.3 | 120 | 12 | Agg., DB-Agg. |
| | 200 | 500 | 1000 | **220702** | Ward | 2.1 | 105 | 4 | 337301 | 1.91 | 5 | 0 | **220702** | Ward | 1.9 | 105 | 4 | Agg., DB-Agg. |
| | 200 | 600 | 750 | **256433** | Ward | 1.6 | 125 | 17 | 297750 | 1.83 | 0 | 397 | **256433** | Ward | 1.5 | 125 | 17 | Agg., DB-Agg. |
| | 200 | 600 | 1000 | **259769** | Ward | 1.8 | 113 | 8 | 376415 | 1.52 | 4 | 76 | **259769** | Ward | 1.7 | 113 | 8 | Agg., DB-Agg. |

| | | | | Agglomerative (Agg) | | | | | DBSCAN - KMeans (DB-KM) | | | | DBSCAN - Agglomerative (DB-Agg) | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F3 | Cost | Type | Time | M | N | Cost | Time | M | N | Cost | Type | Time | M | N | |
| TIBY - 3 | 30 | 500 | 750 | **227366** | Ward | 1.4 | 129 | 15 | 234749 | 17.75 | 102 | 31 | 229679 | Ward | 0.5 | 132 | 36 | Agg. |
| | 30 | 500 | 1000 | **231045** | Ward | 1.1 | 124 | 13 | 243265 | 13.11 | 100 | 32 | 238407 | Ward | 0.3 | 127 | 34 | Agg. |
| | 30 | 600 | 750 | **265581** | Ward | 1.2 | 143 | 34 | 273033 | 13.16 | 99 | 33 | 266979 | Ward | 0.3 | 132 | 36 | Agg. |
| | 30 | 600 | 1000 | **270516** | Ward | 0.5 | 129 | 15 | 281048 | 13.08 | 100 | 33 | 275872 | Ward | 0.3 | 130 | 35 | Agg. |
| | 50 | 500 | 750 | **227305** | Ward | 1.0 | 129 | 15 | 246425 | 16.97 | 65 | 7 | 227959 | Ward | 1.2 | 127 | 14 | Agg. |
| | 50 | 500 | 1000 | **230841** | GeomDiff | 2.0 | 109 | 6 | 247768 | 15.92 | 65 | 8 | 231459 | Ward | 1.2 | 127 | 14 | Agg. |
| | 50 | 600 | 750 | **265581** | Ward | 0.6 | 143 | 34 | 285294 | 15.88 | 65 | 12 | 266639 | Ward | 1.1 | 138 | 31 | Agg. |
| | 50 | 600 | 1000 | **270455** | Ward | 0.7 | 129 | 15 | 287736 | 17.38 | 66 | 8 | 270959 | Ward | 1.3 | 127 | 14 | Agg. |
| | 100 | 500 | 750 | 227305 | Ward | 0.6 | 129 | 15 | 281006 | 9.05 | 27 | 19 | **227059** | Ward | 1.9 | 131 | 15 | DB-Agg. |
| | 100 | 500 | 1000 | 230841 | GeomDiff | 1.3 | 109 | 6 | 281349 | 8.45 | 28 | 0 | **230519** | GeomDiff | 1.9 | 111 | 6 | DB-Agg. |
| | 100 | 600 | 750 | 265581 | Ward | 0.9 | 143 | 34 | 304617 | 9.31 | 8 | 335 | **265525** | Ward | 0.7 | 143 | 33 | DB-Agg. |
| | 100 | 600 | 1000 | 270455 | Ward | 0.9 | 129 | 15 | 322170 | 9 | 28 | 0 | **270209** | Ward | 1.0 | 131 | 15 | DB-Agg. |
| | 200 | 500 | 750 | **227305** | Ward | 1.3 | 129 | 15 | 306750 | 3.91 | 0 | 409 | 235988 | Ward | 1.6 | 116 | 50 | Agg. |
| | 200 | 500 | 1000 | **230841** | GeomDiff | 3.0 | 109 | 6 | 338342 | 3.62 | 10 | 0 | 240330 | GeomDiff | 4.2 | 98 | 6 | Agg. |
| | 200 | 600 | 750 | **265581** | Ward | 1.6 | 143 | 34 | 306750 | 3.73 | 0 | 409 | 270340 | Ward | 1.6 | 128 | 65 | Agg. |
| | 200 | 600 | 1000 | **270455** | Ward | 1.1 | 129 | 15 | 378911 | 3.19 | 9 | 38 | 280092 | Ward | 1.2 | 117 | 15 | Agg. |
| TIBY - 4 | 30 | 500 | 750 | **120272** | Ward | 0.4 | 78 | 11 | 126486 | 15.47 | 46 | 16 | 121399 | Ward | 0.3 | 77 | 18 | Agg. |
| | 30 | 500 | 1000 | **122954** | Ward | 0.4 | 75 | 10 | 129399 | 10.73 | 48 | 14 | 125678 | Ward | 0.2 | 75 | 17 | Agg. |
| | 30 | 600 | 750 | **140972** | Ward | 0.4 | 78 | 11 | 146735 | 11.25 | 46 | 16 | 141399 | Ward | 0.2 | 77 | 18 | Agg. |
| | 30 | 600 | 1000 | **143722** | Ward | 0.4 | 78 | 11 | 149777 | 9.86 | 48 | 14 | 145778 | Ward | 0.2 | 75 | 17 | Agg. |
| | 50 | 500 | 750 | 120272 | Ward | 0.4 | 78 | 11 | 131824 | 7.95 | 28 | 4 | **120035** | Ward | 0.4 | 78 | 9 | DB-Agg. |
| | 50 | 500 | 1000 | 122954 | Ward | 0.2 | 75 | 10 | 132824 | 7.7 | 28 | 4 | **122285** | Ward | 0.5 | 78 | 9 | DB-Agg. |
| | 50 | 600 | 750 | 140972 | Ward | 0.2 | 78 | 11 | 152236 | 8.23 | 29 | 4 | **140935** | Ward | 0.2 | 78 | 9 | DB-Agg. |
| | 50 | 600 | 1000 | 143722 | Ward | 0.2 | 78 | 11 | 153847 | 7.95 | 28 | 4 | **143185** | Ward | 0.1 | 78 | 9 | DB-Agg. |
| | 100 | 500 | 750 | 120272 | Ward | 0.3 | 78 | 11 | 153025 | 3.33 | 11 | 1 | **120170** | Ward | 0.3 | 78 | 10 | DB-Agg. |
| | 100 | 500 | 1000 | 122954 | Ward | 0.3 | 75 | 10 | 153275 | 3.33 | 11 | 1 | **122603** | Ward | 0.8 | 75 | 9 | DB-Agg. |
| | 100 | 600 | 750 | 140972 | Ward | 0.4 | 78 | 11 | 163303 | 3.08 | 3 | 208 | **140970** | Ward | 0.3 | 78 | 10 | DB-Agg. |
| | 100 | 600 | 1000 | 143722 | Ward | 0.3 | 78 | 11 | 174975 | 3.77 | 11 | 1 | **143470** | Ward | 0.4 | 78 | 10 | DB-Agg. |
| | 200 | 500 | 750 | **120272** | Ward | 0.4 | 78 | 11 | 163500 | 1.44 | 0 | 218 | **120272** | Ward | 0.5 | 78 | 11 | Agg., DB-Agg. |
| | 200 | 500 | 1000 | **122954** | Ward | 0.6 | 75 | 10 | 183038 | 1.84 | 5 | 0 | **122954** | Ward | 1.2 | 75 | 10 | Agg., DB-Agg. |
| | 200 | 600 | 750 | **140972** | Ward | 0.5 | 78 | 11 | 163500 | 1.67 | 0 | 218 | **140972** | Ward | 0.6 | 78 | 11 | Agg., DB-Agg. |
| | 200 | 600 | 1000 | **143722** | Ward | 0.4 | 78 | 11 | 198325 | 1.72 | 3 | 69 | **143722** | Ward | 0.6 | 78 | 11 | Agg., DB-Agg. |

Table G.3: Results of the Model based Heuristics on Mbola (Variable Cost)

| | | | | MB-I | | | | | MB-II | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F3 | F2 | Cost | Time | Gap | M | N | Cost | Time | Gap | M | N | |
| MBOLA - 1 | 30 | 500 | 750 | 85210 | 4.5 | 0 | 54 | 22 | **85083** | 6.9 | 0 | 54 | 23 | MB-II |
| | 30 | 500 | 1000 | 90710 | 3.1 | 0 | 54 | 22 | **90604** | 4.3 | 0 | 54 | 22 | MB-II |
| | 30 | 600 | 750 | 97364 | 4.8 | 0 | 53 | 27 | **97278** | 4.4 | 0 | 53 | 26 | MB-II |
| | 30 | 600 | 1000 | 103010 | 3.1 | 0 | 54 | 22 | **102904** | 4.6 | 0 | 54 | 22 | MB-II |
| | 50 | 500 | 750 | 84179 | 10.5 | 0 | 57 | 15 | **84116** | 5.3 | 0 | 57 | 14 | MB-II |
| | 50 | 500 | 1000 | 85986 | 11.2 | 0 | 59 | 7 | **85737** | 19.5 | 0 | 60 | 6 | MB-II |
| | 50 | 600 | 750 | 97171 | 6.3 | 0 | 52 | 28 | **97143** | 7.5 | 0 | 52 | 27 | MB-II |
| | 50 | 600 | 1000 | 99853 | 3.2 | 0 | 59 | 8 | **99786** | 4.9 | 0 | 59 | 7 | MB-II |
| | 100 | 500 | 750 | **83539** | 7.1 | 0 | 60 | 8 | **83539** | 7.8 | 0 | 60 | 8 | MB-I, MB-II |
| | 100 | 500 | 1000 | 84896 | 3.0 | 0 | 61 | 4 | **84867** | 3.9 | 0 | 61 | 4 | MB-II |
| | 100 | 600 | 750 | 96872 | 4.4 | 0 | 58 | 17 | **96845** | 2.9 | 0 | 58 | 16 | MB-II |
| | 100 | 600 | 1000 | **98954** | 2.8 | 0 | 60 | 5 | **98954** | 3.9 | 0 | 60 | 5 | MB-I, MB-II |
| | 200 | 500 | 750 | **83539** | 6.8 | 0 | 60 | 8 | **83539** | 3.0 | 0 | 60 | 8 | MB-I, MB-II |
| | 200 | 500 | 1000 | **84810** | 3.1 | 0 | 62 | 4 | **84810** | 3.2 | 0 | 62 | 4 | MB-I, MB-II |
| | 200 | 600 | 750 | **96872** | 2.6 | 0 | 58 | 17 | **96872** | 2.9 | 0 | 58 | 17 | MB-I, MB-II |
| | 200 | 600 | 1000 | **98910** | 3.2 | 0 | 62 | 4 | **98910** | 3.2 | 0 | 62 | 4 | MB-I, MB-II |
| MBOLA - 2 | 30 | 500 | 750 | **45926** | 1.6 | 0 | 27 | 20 | **45926** | 2.4 | 0 | 27 | 20 | MB-I, MB-II |
| | 30 | 500 | 1000 | **50926** | 1.2 | 0 | 27 | 20 | **50926** | 1.3 | 0 | 27 | 20 | MB-I, MB-II |
| | 30 | 600 | 750 | **51626** | 1.1 | 0 | 27 | 20 | **51626** | 1.3 | 0 | 27 | 20 | MB-I, MB-II |
| | 30 | 600 | 1000 | **56626** | 0.8 | 0 | 27 | 20 | **56626** | 1.1 | 0 | 27 | 20 | MB-I, MB-II |
| | 50 | 500 | 750 | **45463** | 1.2 | 0 | 29 | 15 | **45463** | 1.8 | 0 | 29 | 15 | MB-I, MB-II |
| | 50 | 500 | 1000 | 49242 | 9.7 | 0 | 29 | 14 | **49102** | 11.2 | 0 | 29 | 13 | MB-II |
| | 50 | 600 | 750 | **51626** | 1.3 | 0 | 27 | 20 | **51626** | 1.2 | 0 | 27 | 20 | MB-I, MB-II |
| | 50 | 600 | 1000 | **55413** | 1.5 | 0 | 29 | 15 | **55413** | 1.7 | 0 | 29 | 15 | MB-I, MB-II |
| | 100 | 500 | 750 | **45314** | 2.2 | 0 | 30 | 13 | **45314** | 1.4 | 0 | 30 | 13 | MB-I, MB-II |
| | 100 | 500 | 1000 | 48012 | 1.1 | 0 | 31 | 8 | **47850** | 3.4 | 0 | 32 | 7 | MB-II |
| | 100 | 600 | 750 | **51626** | 1.0 | 0 | 27 | 20 | **51626** | 1.2 | 0 | 27 | 20 | MB-I, MB-II |
| | 100 | 600 | 1000 | **54833** | 1.1 | 0 | 31 | 9 | 54855 | 1.5 | 0 | 31 | 10 | MB-I |
| | 200 | 500 | 750 | **45314** | 1.5 | 0 | 30 | 13 | **45314** | 1.5 | 0 | 30 | 13 | MB-I, MB-II |
| | 200 | 500 | 1000 | **47850** | 8.4 | 0 | 32 | 7 | **47850** | 8.5 | 0 | 32 | 7 | MB-I, MB-II |
| | 200 | 600 | 750 | **51626** | 1.3 | 0 | 27 | 20 | **51626** | 1.3 | 0 | 27 | 20 | MB-I, MB-II |
| | 200 | 600 | 1000 | **54770** | 1.1 | 0 | 32 | 8 | **54770** | 1.2 | 0 | 32 | 8 | MB-I, MB-II |

| | DLim | F3 | F2 | MB-I Cost | MB-I Time | MB-I Gap | MB-I M | MB-I N | MB-II Cost | MB-II Time | MB-II Gap | MB-II M | MB-II N | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| MBOLA - 3 | 30 | 500 | 750 | **27584** | 1.9 | 0 | 16 | 10 | **27584** | 2.6 | 0 | 16 | 10 | MB-I, MB-II |
| | 30 | 500 | 1000 | **30084** | 0.7 | 0 | 16 | 10 | **30084** | 2.2 | 0 | 16 | 10 | MB-I, MB-II |
| | 30 | 600 | 750 | **31284** | 1.1 | 0 | 16 | 10 | **31284** | 1.1 | 0 | 16 | 10 | MB-I, MB-II |
| | 30 | 600 | 1000 | **33784** | 1.2 | 0 | 16 | 10 | **33784** | 0.9 | 0 | 16 | 10 | MB-I, MB-II |
| | 50 | 500 | 750 | **27410** | 1.1 | 0 | 17 | 8 | **27410** | 0.9 | 0 | 17 | 8 | MB-I, MB-II |
| | 50 | 500 | 1000 | 29167 | 8.5 | 0 | 18 | 7 | **29046** | 9.4 | 0 | 18 | 6 | MB-II |
| | 50 | 600 | 750 | **31284** | 0.6 | 0 | 16 | 10 | **31284** | 0.9 | 0 | 16 | 10 | MB-I, MB-II |
| | 50 | 600 | 1000 | **33167** | 1.0 | 0 | 18 | 7 | **33167** | 0.9 | 0 | 18 | 7 | MB-I, MB-II |
| | 100 | 500 | 750 | **27410** | 1.1 | 0 | 17 | 8 | **27410** | 3.3 | 0 | 17 | 8 | MB-I, MB-II |
| | 100 | 500 | 1000 | **28227** | 1.0 | 0 | 18 | 2 | **28227** | 1.2 | 0 | 18 | 2 | MB-I, MB-II |
| | 100 | 600 | 750 | **31284** | 0.8 | 0 | 16 | 10 | **31284** | 1.1 | 0 | 16 | 10 | MB-I, MB-II |
| | 100 | 600 | 1000 | **32727** | 1.0 | 0 | 18 | 2 | **32727** | 1.2 | 0 | 18 | 2 | MB-I, MB-II |
| | 200 | 500 | 750 | **27410** | 1.1 | 0 | 17 | 8 | **27410** | 1.0 | 0 | 17 | 8 | MB-I, MB-II |
| | 200 | 500 | 1000 | **28227** | 1.2 | 0 | 18 | 2 | **28227** | 1.3 | 0 | 18 | 2 | MB-I, MB-II |
| | 200 | 600 | 750 | **31284** | 0.9 | 0 | 16 | 10 | **31284** | 1.0 | 0 | 16 | 10 | MB-I, MB-II |
| | 200 | 600 | 1000 | **32727** | 2.3 | 0 | 18 | 2 | **32727** | 1.1 | 0 | 18 | 2 | MB-I, MB-II |
| MBOLA - 4 | 30 | 500 | 750 | **36715** | 1.8 | 0 | 22 | 11 | **36715** | 2.4 | 0 | 22 | 11 | MB-I, MB-II |
| | 30 | 500 | 1000 | **39465** | 1.0 | 0 | 22 | 11 | **39465** | 4.7 | 0 | 22 | 11 | MB-I, MB-II |
| | 30 | 600 | 750 | 41805 | 1.4 | 0 | 21 | 15 | 41805 | 2.1 | 0 | 21 | 15 | MB-I, MB-II |
| | 30 | 600 | 1000 | **44565** | 1.1 | 0 | 22 | 11 | **44565** | 1.6 | 0 | 22 | 11 | MB-I, MB-II |
| | 50 | 500 | 750 | 36228 | 1.3 | 0 | 25 | 6 | **36214** | 1.5 | 0 | 25 | 6 | MB-II |
| | 50 | 500 | 1000 | 37486 | 6.3 | 0 | 26 | 5 | **37472** | 8.7 | 0 | 26 | 5 | MB-II |
| | 50 | 600 | 750 | 41733 | 4.2 | 0 | 22 | 13 | **41657** | 1.1 | 0 | 23 | 11 | MB-II |
| | 50 | 600 | 1000 | 43186 | 1.2 | 0 | 26 | 5 | **43172** | 1.4 | 0 | 26 | 5 | MB-II |
| | 100 | 500 | 750 | **36186** | 1.2 | 0 | 25 | 6 | **36186** | 1.9 | 0 | 25 | 6 | MB-I, MB-II |
| | 100 | 500 | 1000 | **37445** | 1.2 | 0 | 26 | 5 | **37445** | 1.4 | 0 | 26 | 5 | MB-I, MB-II |
| | 100 | 600 | 750 | **41657** | 1.6 | 0 | 23 | 11 | **41657** | 1.5 | 0 | 23 | 11 | MB-I, MB-II |
| | 100 | 600 | 1000 | **43145** | 2.4 | 0 | 26 | 5 | **43145** | 1.4 | 0 | 26 | 5 | MB-I, MB-II |
| | 200 | 500 | 750 | **36186** | 0.8 | 0 | 25 | 6 | **36186** | 1.3 | 0 | 25 | 6 | MB-I, MB-II |
| | 200 | 500 | 1000 | **37445** | 0.8 | 0 | 26 | 5 | **37445** | 1.5 | 0 | 26 | 5 | MB-I, MB-II |
| | 200 | 600 | 750 | **41657** | 1.0 | 0 | 23 | 11 | **41657** | 1.0 | 0 | 23 | 11 | MB-I, MB-II |
| | 200 | 600 | 1000 | **43145** | 0.8 | 0 | 26 | 5 | **43145** | 1.6 | 0 | 26 | 5 | MB-I, MB-II |

Table G.4: Results of the Clustering based Heuristics on Mbola (Variable Cost)

| | | | | Agglomerative (Agg) | | | | | DBSCAN - KMeans (DB-KM) | | | | DBSCAN - Agglomerative (DB-Agg) | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F3 | Cost | Type | Time | M | N | Cost | Time | M | N | Cost | Type | Time | M | N | |
| MBOLA - 1 | 30 | 500 | 750 | **85809** | Complete | 0.1 | 45 | 26 | 90478 | 0.2 | 32 | 54 | 90376 | Ward | 0.1 | 33 | 54 | Agg. |
| | 30 | 500 | 1000 | **92309** | Complete | 0.1 | 45 | 26 | 103959 | 0.2 | 32 | 54 | 103876 | Ward | 0.0 | 33 | 54 | Agg. |
| | 30 | 600 | 750 | **97633** | Ward | 0.1 | 45 | 27 | 99578 | 0.1 | 32 | 54 | 99476 | Ward | 0.0 | 33 | 54 | Agg. |
| | 30 | 600 | 1000 | **104209** | Complete | 0.1 | 45 | 26 | 113059 | 0.1 | 32 | 54 | 112976 | Ward | 0.1 | 33 | 54 | Agg. |
| | 50 | 500 | 750 | **85027** | Ward | 0.1 | 47 | 14 | 89069 | 0.5 | 35 | 26 | 87395 | Ward | 0.0 | 42 | 27 | Agg. |
| | 50 | 500 | 1000 | **88275** | Ward | 0.1 | 46 | 12 | 95437 | 0.5 | 35 | 26 | 93933 | Ward | 0.1 | 41 | 26 | Agg. |
| | 50 | 600 | 750 | **97565** | Ward | 0.1 | 47 | 21 | 100941 | 0.5 | 34 | 33 | 99166 | Ward | 0.0 | 41 | 34 | Agg. |
| | 50 | 600 | 1000 | **101575** | Ward | 0.1 | 46 | 12 | 107572 | 0.3 | 35 | 26 | 105833 | Ward | 0.0 | 41 | 26 | Agg. |
| | 100 | 500 | 750 | 85027 | Ward | 0.2 | 47 | 14 | 98801 | 4.3 | 20 | 40 | **84521** | Ward | 0.1 | 50 | 12 | DB-Agg. |
| | 100 | 500 | 1000 | 88262 | Ward | 0.2 | 46 | 12 | 98402 | 5.8 | 28 | 6 | **86955** | Ward | 0.1 | 50 | 9 | DB-Agg. |
| | 100 | 600 | 750 | 97565 | Ward | 0.2 | 47 | 21 | 106648 | 3.9 | 13 | 96 | **97452** | Ward | 0.1 | 50 | 19 | DB-Agg. |
| | 100 | 600 | 1000 | 101562 | Ward | 0.2 | 46 | 12 | 113805 | 3.2 | 27 | 5 | **100555** | Ward | 0.1 | 50 | 9 | DB-Agg. |
| | 200 | 500 | 750 | 85027 | Ward | 0.3 | 47 | 14 | 106105 | 2.6 | 5 | 131 | **84996** | Ward | 0.3 | 47 | 13 | DB-Agg. |
| | 200 | 500 | 1000 | 88262 | Ward | 0.4 | 46 | 12 | 122747 | 2.5 | 13 | 23 | **88246** | Ward | 0.3 | 47 | 13 | DB-Agg. |
| | 200 | 600 | 750 | **97565** | Ward | 0.3 | 47 | 21 | 107505 | 2.2 | 5 | 131 | 97635 | Ward | 0.3 | 47 | 20 | Agg. |
| | 200 | 600 | 1000 | 101562 | Ward | 0.4 | 46 | 12 | 134165 | 2.5 | 10 | 70 | **101446** | Ward | 0.3 | 47 | 13 | DB-Agg. |
| MBOLA - 2 | 30 | 500 | 750 | **46327** | GeomDiff | 0.2 | 22 | 20 | 46348 | 0.3 | 22 | 20 | **46327** | GeomDiff | 0.1 | 22 | 20 | Agg., DB-Agg. |
| | 30 | 500 | 1000 | **51327** | GeomDiff | 0.1 | 22 | 20 | 51348 | 0.1 | 22 | 20 | **51327** | GeomDiff | 0.0 | 22 | 20 | Agg., DB-Agg. |
| | 30 | 600 | 750 | **51902** | GeomDiff | 0.0 | 23 | 22 | 52048 | 0.0 | 22 | 20 | 52027 | GeomDiff | 0.0 | 22 | 20 | Agg. |
| | 30 | 600 | 1000 | **57027** | GeomDiff | 0.1 | 22 | 20 | 57048 | 0.0 | 22 | 20 | **57027** | GeomDiff | 0.0 | 22 | 20 | Agg., DB-Agg. |
| | 50 | 500 | 750 | **46145** | GeomDiff | 0.1 | 22 | 17 | 46402 | 0.0 | 21 | 18 | 46402 | GeomDiff | 0.0 | 21 | 18 | Agg. |
| | 50 | 500 | 1000 | **49642** | GeomDiff | 0.0 | 22 | 13 | 50902 | 0.1 | 21 | 18 | 50902 | GeomDiff | 0.2 | 21 | 18 | Agg. |
| | 50 | 600 | 750 | **51902** | GeomDiff | 0.1 | 23 | 22 | 52302 | 0.0 | 21 | 18 | 52302 | GeomDiff | 0.0 | 21 | 18 | Agg. |
| | 50 | 600 | 1000 | **56042** | GeomDiff | 0.0 | 22 | 13 | 56802 | 0.0 | 21 | 18 | 56802 | GeomDiff | 0.0 | 21 | 18 | Agg. |
| | 100 | 500 | 750 | **46116** | GeomDiff | 0.1 | 22 | 16 | 46906 | 0.1 | 21 | 11 | 46754 | GeomDiff | 0.1 | 21 | 13 | Agg. |
| | 100 | 500 | 1000 | **49359** | GeomDiff | 0.0 | 22 | 8 | 49816 | 0.0 | 21 | 11 | 49656 | GeomDiff | 0.0 | 21 | 11 | Agg. |
| | 100 | 600 | 750 | **51902** | GeomDiff | 0.0 | 23 | 22 | 53155 | 0.1 | 20 | 16 | 52803 | GeomDiff | 0.1 | 20 | 18 | Agg. |
| | 100 | 600 | 1000 | **56216** | GeomDiff | 0.1 | 22 | 16 | 56256 | 0.2 | 21 | 11 | 56256 | GeomDiff | 0.1 | 21 | 11 | Agg. |
| | 200 | 500 | 750 | **46116** | GeomDiff | 0.1 | 22 | 16 | 52224 | 0.1 | 12 | 36 | 52098 | GeomDiff | 0.1 | 12 | 37 | Agg. |
| | 200 | 500 | 1000 | **49305** | GeomDiff | 0.1 | 22 | 8 | 59228 | 0.0 | 15 | 16 | 59228 | GeomDiff | 0.1 | 15 | 16 | Agg. |
| | 200 | 600 | 750 | **51902** | GeomDiff | 0.1 | 23 | 22 | 55438 | 0.1 | 9 | 50 | 55212 | GeomDiff | 0.0 | 9 | 51 | Agg. |
| | 200 | 600 | 1000 | **56205** | GeomDiff | 0.1 | 22 | 8 | 64362 | 0.1 | 14 | 28 | 64362 | GeomDiff | 0.1 | 14 | 28 | Agg. |

| | | | | Agglomerative (Agg) | | | | | DBSCAN - KMeans (DB-KM) | | | | DBSCAN - Agglomerative (DB-Agg) | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F3 | Cost | Type | Time | M | N | Cost | Time | M | N | Cost | Type | Time | M | N | |
| MBOLA - 3 | 30 | 500 | 750 | **27680** | GeomDiff | 0.1 | 15 | 10 | 28020 | 0.1 | 14 | 12 | 28020 | GeomDiff | 0.1 | 14 | 12 | Agg. |
| | 30 | 500 | 1000 | **30180** | GeomDiff | 0.0 | 15 | 10 | 31020 | 0.0 | 14 | 12 | 31020 | GeomDiff | 0.0 | 14 | 12 | Agg. |
| | 30 | 600 | 750 | **31380** | GeomDiff | 0.0 | 15 | 10 | 31520 | 0.0 | 14 | 12 | 31520 | GeomDiff | 0.0 | 14 | 12 | Agg. |
| | 30 | 600 | 1000 | **33880** | GeomDiff | 0.0 | 15 | 10 | 34520 | 0.0 | 14 | 12 | 34520 | GeomDiff | 0.0 | 14 | 12 | Agg. |
| | 50 | 500 | 750 | **27506** | GeomDiff | 0.1 | 16 | 8 | 28086 | 0.1 | 14 | 10 | 28086 | GeomDiff | 0.1 | 14 | 10 | Agg. |
| | 50 | 500 | 1000 | **29225** | GeomDiff | 0.0 | 16 | 6 | 30586 | 0.0 | 14 | 10 | 30586 | GeomDiff | 0.0 | 14 | 10 | Agg. |
| | 50 | 600 | 750 | **31380** | GeomDiff | 0.0 | 15 | 10 | 31786 | 0.1 | 14 | 10 | 31786 | GeomDiff | 0.1 | 14 | 10 | Agg. |
| | 50 | 600 | 1000 | **33325** | GeomDiff | 0.1 | 16 | 6 | 34286 | 0.0 | 14 | 10 | 34286 | GeomDiff | 0.0 | 14 | 10 | Agg. |
| | 100 | 500 | 750 | **27506** | Ward | 0.1 | 16 | 8 | 28879 | 0.0 | 14 | 3 | 28879 | GeomDiff | 0.0 | 14 | 3 | Agg. |
| | 100 | 500 | 1000 | **28653** | GeomDiff | 0.0 | 16 | 3 | 29629 | 0.0 | 14 | 3 | 29629 | GeomDiff | 0.0 | 14 | 3 | Agg. |
| | 100 | 600 | 750 | **31380** | GeomDiff | 0.1 | 15 | 10 | 32800 | 0.1 | 11 | 13 | 32800 | GeomDiff | 0.1 | 11 | 13 | Agg. |
| | 100 | 600 | 1000 | **33053** | GeomDiff | 0.0 | 16 | 3 | 34029 | 0.0 | 14 | 3 | 34029 | GeomDiff | 0.0 | 14 | 3 | Agg. |
| | 200 | 500 | 750 | **27506** | Ward | 0.1 | 16 | 8 | 30830 | 0.2 | 10 | 14 | 28944 | GeomDiff | 0.3 | 13 | 9 | Agg. |
| | 200 | 500 | 1000 | **28653** | GeomDiff | 0.1 | 16 | 3 | 32770 | 0.1 | 12 | 2 | 30571 | GeomDiff | 0.1 | 14 | 3 | Agg. |
| | 200 | 600 | 750 | **31380** | GeomDiff | 0.1 | 15 | 10 | 33637 | 0.1 | 7 | 24 | 32670 | GeomDiff | 0.1 | 11 | 14 | Agg. |
| | 200 | 600 | 1000 | **33053** | GeomDiff | 0.1 | 16 | 3 | 37616 | 0.1 | 10 | 14 | 34873 | GeomDiff | 0.0 | 13 | 7 | Agg. |
| MBOLA - 4 | 30 | 500 | 750 | **36801** | GeomDiff | 0.1 | 21 | 12 | 38814 | 0.1 | 16 | 25 | 38814 | GeomDiff | 0.1 | 16 | 25 | Agg. |
| | 30 | 500 | 1000 | **39572** | Complete | 0.0 | 21 | 11 | 45064 | 0.0 | 16 | 25 | 45064 | GeomDiff | 0.0 | 16 | 25 | Agg. |
| | 30 | 600 | 750 | **41770** | Complete | 0.0 | 21 | 15 | 42514 | 0.0 | 16 | 25 | 42514 | GeomDiff | 0.0 | 16 | 25 | Agg. |
| | 30 | 600 | 1000 | **44672** | Complete | 0.0 | 21 | 11 | 48764 | 0.0 | 16 | 25 | 48764 | GeomDiff | 0.0 | 16 | 25 | Agg. |
| | 50 | 500 | 750 | **36596** | GeomDiff | 0.1 | 21 | 10 | 38503 | 0.3 | 15 | 12 | 36924 | GeomDiff | 0.2 | 20 | 11 | Agg. |
| | 50 | 500 | 1000 | **38729** | Complete | 0.0 | 19 | 6 | 41503 | 0.1 | 15 | 12 | 39674 | GeomDiff | 0.1 | 20 | 11 | Agg. |
| | 50 | 600 | 750 | **41770** | Ward | 0.0 | 21 | 13 | 43221 | 0.0 | 16 | 11 | 42006 | Ward | 0.0 | 20 | 14 | Agg. |
| | 50 | 600 | 1000 | **44296** | GeomDiff | 0.0 | 21 | 10 | 45971 | 0.0 | 16 | 11 | 44774 | GeomDiff | 0.0 | 20 | 11 | Agg. |
| | 100 | 500 | 750 | **36596** | GeomDiff | 0.1 | 21 | 10 | 40853 | 0.5 | 13 | 5 | 39463 | GeomDiff | 0.1 | 17 | 5 | Agg. |
| | 100 | 500 | 1000 | **38523** | GeomDiff | 0.1 | 19 | 5 | 42103 | 0.8 | 13 | 5 | 40713 | GeomDiff | 0.0 | 17 | 5 | Agg. |
| | 100 | 600 | 750 | **41770** | Ward | 0.0 | 21 | 13 | 45261 | 1.0 | 9 | 28 | 43866 | Ward | 0.0 | 13 | 29 | Agg. |
| | 100 | 600 | 1000 | **44223** | GeomDiff | 0.1 | 19 | 5 | 47803 | 0.5 | 13 | 5 | 46413 | GeomDiff | 0.1 | 17 | 5 | Agg. |
| | 200 | 500 | 750 | **36596** | GeomDiff | 0.1 | 21 | 10 | 46094 | 0.6 | 1 | 52 | 39594 | GeomDiff | 0.1 | 15 | 17 | Agg. |
| | 200 | 500 | 1000 | **38523** | GeomDiff | 0.2 | 19 | 5 | 52759 | 1.0 | 7 | 3 | 41130 | GeomDiff | 0.1 | 16 | 4 | Agg. |
| | 200 | 600 | 750 | **41770** | Ward | 0.1 | 21 | 13 | 46500 | 0.7 | 0 | 62 | 43473 | Ward | 0.1 | 14 | 30 | Agg. |
| | 200 | 600 | 1000 | **44223** | GeomDiff | 0.2 | 19 | 5 | 57845 | 0.9 | 5 | 26 | 46930 | GeomDiff | 0.1 | 16 | 4 | Agg. |

Table G.5: Results of the Model based Heuristics on Potou (Variable Cost)

| | | | | MB-I | | | | | MB-II | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F3 | F2 | Cost | Time | Gap | M | N | Cost | Time | Gap | M | N | |
| POTOU - 1 | 30 | 500 | 750 | 223227 | 31.0 | 0 | 195 | 8 | **223160** | 38.9 | 0 | 195 | 7 | MB-II |
| | 30 | 500 | 1000 | **224910** | 30.1 | 0 | 195 | 7 | **224910** | 37.3 | 0 | 195 | 7 | MB-I, MB-II |
| | 30 | 600 | 750 | **264356** | 35.3 | 0 | 195 | 10 | **264356** | 38.6 | 0 | 195 | 10 | MB-I, MB-II |
| | 30 | 600 | 1000 | **266210** | 28.1 | 0 | 195 | 7 | **266210** | 37.1 | 0 | 195 | 7 | MB-I, MB-II |
| | 50 | 500 | 750 | **223135** | 35.3 | 0 | 196 | 8 | **223135** | 46.0 | 0 | 196 | 8 | MB-I, MB-II |
| | 50 | 500 | 1000 | **224637** | 37.8 | 0 | 197 | 5 | **224637** | 47.1 | 0 | 197 | 5 | MB-I, MB-II |
| | 50 | 600 | 750 | **264338** | 32.5 | 0 | 196 | 9 | **264338** | 45.7 | 0 | 196 | 9 | MB-I, MB-II |
| | 50 | 600 | 1000 | 266335 | 35.0 | 0 | 196 | 8 | **266295** | 45.2 | 0 | 196 | 7 | MB-II |
| | 100 | 500 | 750 | **223007** | 49.5 | 0 | 196 | 6 | **223007** | 58.3 | 0 | 196 | 6 | MB-I, MB-II |
| | 100 | 500 | 1000 | **223867** | 48.3 | 0 | 197 | 2 | **223867** | 59.8 | 0 | 197 | 2 | MB-I, MB-II |
| | 100 | 600 | 750 | **264297** | 48.6 | 0 | 196 | 9 | **264297** | 56.2 | 0 | 196 | 9 | MB-I, MB-II |
| | 100 | 600 | 1000 | **265635** | 48.7 | 0 | 197 | 3 | 265834 | 56.3 | 0 | 196 | 5 | MB-I |
| | 200 | 500 | 750 | **223007** | 104.9 | 0 | 196 | 6 | **223007** | 115.4 | 0 | 196 | 6 | MB-I, MB-II |
| | 200 | 500 | 1000 | **223681** | 105.3 | 0 | 198 | 1 | **223681** | 113.5 | 0 | 198 | 1 | MB-I, MB-II |
| | 200 | 600 | 750 | **264297** | 99.0 | 0 | 196 | 9 | **264297** | 110.4 | 0 | 196 | 9 | MB-I, MB-II |
| | 200 | 600 | 1000 | **265549** | 100.6 | 0 | 198 | 2 | **265549** | 111.5 | 0 | 198 | 2 | MB-I, MB-II |
| POTOU - 2 | 30 | 500 | 750 | 58695 | 5.9 | 0 | 41 | 11 | **58581** | 3.4 | 0 | 42 | 11 | MB-II |
| | 30 | 500 | 1000 | 61445 | 1.6 | 0 | 41 | 11 | **61331** | 2.3 | 0 | 42 | 11 | MB-II |
| | 30 | 600 | 750 | 67895 | 2.0 | 0 | 41 | 11 | **67781** | 2.1 | 0 | 42 | 11 | MB-II |
| | 30 | 600 | 1000 | 70645 | 1.5 | 0 | 41 | 11 | **70531** | 2.3 | 0 | 42 | 11 | MB-II |
| | 50 | 500 | 750 | 58300 | 2.2 | 0 | 43 | 8 | **58240** | 3.1 | 0 | 44 | 7 | MB-II |
| | 50 | 500 | 1000 | 60051 | 9.5 | 0 | 44 | 7 | **59742** | 8.7 | 0 | 44 | 6 | MB-II |
| | 50 | 600 | 750 | **68032** | 1.8 | 0 | 39 | 16 | **68032** | 2.2 | 0 | 39 | 16 | MB-I, MB-II |
| | 50 | 600 | 1000 | 69651 | 2.8 | 0 | 44 | 7 | **69590** | 2.7 | 0 | 44 | 7 | MB-II |
| | 100 | 500 | 750 | **58220** | 9.2 | 0 | 44 | 6 | **58220** | 2.3 | 0 | 44 | 6 | MB-I, MB-II |
| | 100 | 500 | 1000 | 59556 | 6.4 | 0 | 44 | 5 | **59399** | 6.9 | 0 | 46 | 3 | MB-II |
| | 100 | 600 | 750 | **67740** | 1.9 | 0 | 43 | 9 | **67740** | 2.3 | 0 | 43 | 9 | MB-I, MB-II |
| | 100 | 600 | 1000 | 69356 | 1.9 | 0 | 44 | 5 | **69293** | 2.3 | 0 | 45 | 4 | MB-II |
| | 200 | 500 | 750 | **58220** | 2.8 | 0 | 44 | 6 | **58220** | 3.1 | 0 | 44 | 6 | MB-I, MB-II |
| | 200 | 500 | 1000 | **59269** | 1.6 | 0 | 46 | 1 | **59269** | 2.3 | 0 | 46 | 1 | MB-I, MB-II |
| | 200 | 600 | 750 | **67740** | 1.3 | 0 | 43 | 9 | **67740** | 2.1 | 0 | 43 | 9 | MB-I, MB-II |
| | 200 | 600 | 1000 | **69293** | 1.7 | 0 | 45 | 4 | **69293** | 1.7 | 0 | 45 | 4 | MB-I, MB-II |

| | | | | MB-I | | | | | MB-II | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F3 | F2 | Cost | Time | Gap | M | N | Cost | Time | Gap | M | N | |
| POTOU - 3 | 30 | 500 | 750 | **36268** | 2.6 | 0 | 30 | 2 | **36268** | 2.4 | 0 | 30 | 2 | MB-I, MB-II |
| | 30 | 500 | 1000 | **36307** | 1.6 | 0 | 31 | 0 | **36307** | 1.9 | 0 | 31 | 0 | MB-I, MB-II |
| | 30 | 600 | 750 | **42615** | 1.1 | 0 | 30 | 3 | **42615** | 1.0 | 0 | 30 | 3 | MB-I, MB-II |
| | 30 | 600 | 1000 | **42907** | 1.8 | 0 | 31 | 0 | **42907** | 2.1 | 0 | 31 | 0 | MB-I, MB-II |
| | 50 | 500 | 750 | **36232** | 2.0 | 0 | 30 | 2 | **36232** | 1.9 | 0 | 30 | 2 | MB-I, MB-II |
| | 50 | 500 | 1000 | **36243** | 8.6 | 0 | 31 | 0 | **36243** | 9.5 | 0 | 31 | 0 | MB-I, MB-II |
| | 50 | 600 | 750 | **42579** | 0.6 | 0 | 30 | 3 | **42579** | 0.9 | 0 | 30 | 3 | MB-I, MB-II |
| | 50 | 600 | 1000 | **42843** | 1.4 | 0 | 31 | 0 | **42843** | 3.2 | 0 | 31 | 0 | MB-I, MB-II |
| | 100 | 500 | 750 | **36195** | 1.6 | 0 | 30 | 0 | **36195** | 1.3 | 0 | 30 | 0 | MB-I, MB-II |
| | 100 | 500 | 1000 | **36195** | 1.8 | 0 | 30 | 0 | **36195** | 1.7 | 0 | 30 | 0 | MB-I, MB-II |
| | 100 | 600 | 750 | **42579** | 0.8 | 0 | 30 | 3 | **42579** | 1.1 | 0 | 30 | 3 | MB-I, MB-II |
| | 100 | 600 | 1000 | **42795** | 1.6 | 0 | 30 | 0 | **42795** | 1.8 | 0 | 30 | 0 | MB-I, MB-II |
| | 200 | 500 | 750 | **36195** | 1.7 | 0 | 30 | 0 | **36195** | 1.5 | 0 | 30 | 0 | MB-I, MB-II |
| | 200 | 500 | 1000 | **36195** | 0.8 | 0 | 30 | 0 | **36195** | 1.0 | 0 | 30 | 0 | MB-I, MB-II |
| | 200 | 600 | 750 | **42579** | 0.7 | 0 | 30 | 3 | **42579** | 1.3 | 0 | 30 | 3 | MB-I, MB-II |
| | 200 | 600 | 1000 | **42795** | 3.4 | 0 | 30 | 0 | **42795** | 9.1 | 0 | 30 | 0 | MB-I, MB-II |
| POTOU - 4 | 30 | 500 | 750 | 69783 | 5.1 | 0 | 59 | 2 | **69693** | 6.1 | 0 | 59 | 2 | MB-II |
| | 30 | 500 | 1000 | 70283 | 2.7 | 0 | 59 | 2 | **70193** | 4.2 | 0 | 59 | 2 | MB-II |
| | 30 | 600 | 750 | 82330 | 1.9 | 0 | 58 | 8 | **82267** | 2.9 | 0 | 58 | 6 | MB-II |
| | 30 | 600 | 1000 | 82883 | 2.9 | 0 | 59 | 2 | **82793** | 4.4 | 0 | 59 | 2 | MB-II |
| | 50 | 500 | 750 | 69766 | 3.6 | 0 | 60 | 2 | **69683** | 5.4 | 0 | 60 | 2 | MB-II |
| | 50 | 500 | 1000 | 69836 | 10.5 | 0 | 61 | 0 | **69628** | 10.7 | 0 | 62 | 0 | MB-II |
| | 50 | 600 | 750 | 82216 | 2.4 | 0 | 59 | 7 | **82166** | 2.8 | 0 | 60 | 6 | MB-II |
| | 50 | 600 | 1000 | 82636 | 7.8 | 0 | 61 | 0 | **82428** | 7.0 | 0 | 62 | 0 | MB-II |
| | 100 | 500 | 750 | **69509** | 3.9 | 0 | 62 | 1 | **69509** | 5.6 | 0 | 62 | 1 | MB-I, MB-II |
| | 100 | 500 | 1000 | **69544** | 2.2 | 0 | 63 | 0 | **69544** | 2.6 | 0 | 63 | 0 | MB-I, MB-II |
| | 100 | 600 | 750 | **82117** | 2.3 | 0 | 60 | 4 | **82117** | 2.3 | 0 | 60 | 4 | MB-I, MB-II |
| | 100 | 600 | 1000 | **82344** | 1.8 | 0 | 63 | 0 | **82344** | 2.3 | 0 | 63 | 0 | MB-I, MB-II |
| | 200 | 500 | 750 | **69509** | 6.6 | 0 | 62 | 1 | **69509** | 8.5 | 0 | 62 | 1 | MB-I, MB-II |
| | 200 | 500 | 1000 | **69544** | 3.5 | 0 | 63 | 0 | **69544** | 3.2 | 0 | 63 | 0 | MB-I, MB-II |
| | 200 | 600 | 750 | **82117** | 2.3 | 0 | 60 | 4 | **82117** | 2.8 | 0 | 60 | 4 | MB-I, MB-II |
| | 200 | 600 | 1000 | **82344** | 3.6 | 0 | 63 | 0 | **82344** | 3.2 | 0 | 63 | 0 | MB-I, MB-II |

Table G.6: Results of the Clustering based Heuristics on Potou (Variable Cost)

| | | | | Agglomerative (Agg) | | | | | DBSCAN - KMeans (DB-KM) | | | | DBSCAN - Agglomerative (DB-Agg) | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F3 | Cost | Type | Time | M | N | Cost | Time | M | N | Cost | Type | Time | M | N | |
| POTOU - 1 | 30 | 500 | 750 | 229914 | Ward | 1.7 | 121 | 32 | 237685 | 21.3 | 72 | 21 | **229744** | Ward | 1.4 | 118 | 27 | DB-Agg. |
| | 30 | 500 | 1000 | **234068** | Ward | 0.7 | 90 | 11 | 242444 | 15.3 | 73 | 20 | 236494 | Ward | 1.3 | 118 | 27 | Agg. |
| | 30 | 600 | 750 | **268714** | Ward | 1.2 | 121 | 32 | 277472 | 16.3 | 73 | 20 | 268768 | Ward | 0.7 | 127 | 36 | Agg. |
| | 30 | 600 | 1000 | **274968** | Ward | 0.9 | 90 | 11 | 282835 | 15.0 | 72 | 21 | 275794 | Ward | 0.7 | 118 | 27 | Agg. |
| | 50 | 500 | 750 | **229914** | Ward | 0.8 | 121 | 32 | 251929 | 9.1 | 38 | 9 | 229975 | Ward | 1.3 | 119 | 22 | Agg. |
| | 50 | 500 | 1000 | **233461** | GeomDiff | 1.2 | 85 | 8 | 254474 | 9.3 | 39 | 8 | 234579 | Ward | 0.7 | 100 | 14 | Agg. |
| | 50 | 600 | 750 | **268714** | Ward | 1.6 | 121 | 32 | 293660 | 9.0 | 39 | 8 | 269735 | Ward | 0.6 | 128 | 36 | Agg. |
| | 50 | 600 | 1000 | **274613** | GeomDiff | 1.1 | 91 | 12 | 295649 | 9.5 | 39 | 8 | 275179 | Ward | 0.7 | 100 | 14 | Agg. |
| | 100 | 500 | 750 | **229914** | Ward | 1.6 | 121 | 32 | 284558 | 3.5 | 15 | 36 | 232884 | Ward | 1.2 | 112 | 37 | Agg. |
| | 100 | 500 | 1000 | **233461** | GeomDiff | 3.5 | 85 | 8 | 286796 | 3.7 | 17 | 5 | 239358 | GeomDiff | 4.4 | 83 | 7 | Agg. |
| | 100 | 600 | 750 | **268714** | Ward | 1.2 | 121 | 32 | 314117 | 3.7 | 5 | 367 | 270351 | Ward | 1.3 | 121 | 41 | Agg. |
| | 100 | 600 | 1000 | **274613** | GeomDiff | 3.1 | 91 | 12 | 328296 | 3.9 | 17 | 5 | 280337 | Ward | 1.1 | 95 | 11 | Agg. |
| | 200 | 500 | 750 | 229914 | Ward | 1.4 | 121 | 32 | 315000 | 1.3 | 0 | 420 | **227792** | Ward | 1.4 | 121 | 13 | DB-Agg. |
| | 200 | 500 | 1000 | 233461 | GeomDiff | 4.8 | 85 | 8 | 337420 | 1.2 | 9 | 1 | **233274** | GeomDiff | 4.4 | 86 | 4 | DB-Agg. |
| | 200 | 600 | 750 | 268714 | Ward | 1.6 | 121 | 32 | 315000 | 1.4 | 0 | 420 | **268255** | Complete | 1.1 | 126 | 20 | DB-Agg. |
| | 200 | 600 | 1000 | 274613 | GeomDiff | 5.5 | 91 | 12 | 379320 | 1.4 | 9 | 1 | **274612** | Ward | 1.8 | 103 | 12 | DB-Agg. |
| POTOU - 2 | 30 | 500 | 750 | **59789** | Complete | 0.1 | 31 | 13 | 61421 | 0.1 | 26 | 22 | 61305 | Ward | 0.1 | 27 | 22 | Agg. |
| | 30 | 500 | 1000 | **63039** | Complete | 0.0 | 31 | 13 | 66899 | 0.1 | 26 | 22 | 66805 | Ward | 0.0 | 27 | 22 | Agg. |
| | 30 | 600 | 750 | **68495** | Complete | 0.1 | 34 | 19 | 69540 | 0.1 | 26 | 22 | 69405 | Ward | 0.0 | 27 | 22 | Agg. |
| | 30 | 600 | 1000 | **72039** | Complete | 0.1 | 31 | 13 | 75021 | 0.0 | 26 | 22 | 74905 | Ward | 0.0 | 27 | 22 | Agg. |
| | 50 | 500 | 750 | **59673** | Ward | 0.1 | 31 | 12 | 61878 | 0.1 | 23 | 16 | 60951 | GeomDiff | 0.1 | 26 | 16 | Agg. |
| | 50 | 500 | 1000 | **62262** | GeomDiff | 0.1 | 29 | 9 | 65552 | 0.5 | 24 | 16 | 64951 | GeomDiff | 0.0 | 26 | 16 | Agg. |
| | 50 | 600 | 750 | **68495** | Complete | 0.0 | 34 | 19 | 70595 | 0.0 | 23 | 16 | 69651 | GeomDiff | 0.1 | 26 | 16 | Agg. |
| | 50 | 600 | 1000 | **71611** | Complete | 0.1 | 30 | 10 | 74373 | 0.2 | 24 | 16 | 73651 | GeomDiff | 0.0 | 26 | 16 | Agg. |
| | 100 | 500 | 750 | **59673** | Ward | 0.1 | 31 | 12 | 68048 | 0.1 | 17 | 22 | 64145 | Ward | 0.1 | 23 | 26 | Agg. |
| | 100 | 500 | 1000 | **61952** | GeomDiff | 0.1 | 28 | 6 | 69239 | 0.1 | 18 | 5 | 65812 | Ward | 0.0 | 23 | 5 | Agg. |
| | 100 | 600 | 750 | **68495** | Complete | 0.1 | 34 | 19 | 74135 | 0.2 | 11 | 58 | 71282 | Complete | 0.1 | 23 | 33 | Agg. |
| | 100 | 600 | 1000 | **71509** | GeomDiff | 0.1 | 29 | 8 | 79327 | 0.0 | 18 | 5 | 75612 | Ward | 0.0 | 23 | 5 | Agg. |
| | 200 | 500 | 750 | 59673 | Ward | 0.1 | 31 | 12 | 74413 | 2.1 | 6 | 70 | **59433** | Ward | 0.1 | 32 | 10 | DB-Agg. |
| | 200 | 500 | 1000 | 61952 | GeomDiff | 0.3 | 28 | 6 | 87929 | 1.8 | 11 | 0 | **61346** | Ward | 0.1 | 32 | 7 | DB-Agg. |
| | 200 | 600 | 750 | **68495** | Complete | 0.1 | 34 | 19 | 76334 | 2.0 | 4 | 86 | 68620 | Complete | 0.1 | 33 | 19 | Agg. |
| | 200 | 600 | 1000 | 71509 | GeomDiff | 0.3 | 29 | 8 | 93461 | 1.5 | 9 | 28 | **70946** | Ward | 0.1 | 32 | 7 | DB-Agg. |

| | DLim | F1 | F3 | Agglomerative (Agg) Cost | Type | Time | M | N | DBSCAN - KMeans (DB-KM) Cost | Time | M | N | DBSCAN - Agglomerative (DB-Agg) Cost | Type | Time | M | N | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| POTOU - 3 | 30 | 500 | 750 | **37180** | GeomDiff | 0.3 | 22 | 6 | 38911 | 0.2 | 14 | 9 | 38594 | Ward | 0.1 | 16 | 9 | Agg. |
| | 30 | 500 | 1000 | **38185** | GeomDiff | 0.1 | 18 | 3 | 41084 | 0.1 | 14 | 9 | 40844 | Ward | 0.0 | 16 | 9 | Agg. |
| | 30 | 600 | 750 | **43121** | Complete | 0.0 | 24 | 7 | 44584 | 0.1 | 14 | 9 | 44294 | Ward | 0.0 | 16 | 9 | Agg. |
| | 30 | 600 | 1000 | **44485** | GeomDiff | 0.1 | 18 | 3 | 46784 | 0.0 | 14 | 9 | 46544 | Ward | 0.0 | 16 | 9 | Agg. |
| | 50 | 500 | 750 | **37180** | GeomDiff | 0.1 | 22 | 6 | 38828 | 0.0 | 12 | 3 | 38828 | GeomDiff | 0.1 | 12 | 3 | Agg. |
| | 50 | 500 | 1000 | **38015** | GeomDiff | 0.1 | 19 | 3 | 39578 | 0.1 | 12 | 3 | 39578 | GeomDiff | 0.0 | 12 | 3 | Agg. |
| | 50 | 600 | 750 | **43121** | Complete | 0.1 | 24 | 7 | 45128 | 0.0 | 12 | 3 | 45128 | GeomDiff | 0.0 | 12 | 3 | Agg. |
| | 50 | 600 | 1000 | **44315** | GeomDiff | 0.1 | 19 | 3 | 45878 | 0.0 | 12 | 3 | 45878 | GeomDiff | 0.0 | 12 | 3 | Agg. |
| | 100 | 500 | 750 | **37180** | GeomDiff | 0.1 | 22 | 6 | 40905 | 0.1 | 9 | 0 | 40589 | GeomDiff | 0.1 | 11 | 2 | Agg. |
| | 100 | 500 | 1000 | **37988** | GeomDiff | 0.1 | 16 | 1 | 40905 | 0.1 | 9 | 0 | 40592 | GeomDiff | 0.1 | 10 | 0 | Agg. |
| | 100 | 600 | 750 | **43121** | Complete | 0.0 | 24 | 7 | 46954 | 0.1 | 8 | 10 | 46420 | GeomDiff | 0.1 | 10 | 11 | Agg. |
| | 100 | 600 | 1000 | **44315** | GeomDiff | 0.1 | 19 | 3 | 47505 | 0.1 | 9 | 0 | 47192 | GeomDiff | 0.2 | 10 | 0 | Agg. |
| | 200 | 500 | 750 | **37180** | GeomDiff | 0.2 | 22 | 6 | 46070 | 0.0 | 4 | 36 | 46070 | GeomDiff | 0.0 | 4 | 36 | Agg. |
| | 200 | 500 | 1000 | **37988** | GeomDiff | 0.1 | 16 | 1 | 53196 | 0.0 | 5 | 23 | 53196 | GeomDiff | 0.0 | 5 | 23 | Agg. |
| | 200 | 600 | 750 | **43121** | Complete | 0.1 | 24 | 7 | 48637 | 0.1 | 3 | 46 | 48637 | GeomDiff | 0.1 | 3 | 46 | Agg. |
| | 200 | 600 | 1000 | **44315** | GeomDiff | 0.1 | 19 | 3 | 57496 | 0.1 | 5 | 23 | 57496 | GeomDiff | 0.1 | 5 | 23 | Agg. |
| POTOU - 4 | 30 | 500 | 750 | **72400** | GeomDiff | 0.4 | 36 | 14 | 74779 | 1.9 | 23 | 13 | 72952 | Complete | 0.1 | 35 | 14 | Agg. |
| | 30 | 500 | 1000 | **74549** | Ward | 0.1 | 30 | 7 | 78494 | 2.3 | 23 | 14 | 76452 | Complete | 0.0 | 35 | 14 | Agg. |
| | 30 | 600 | 750 | **83584** | Ward | 0.1 | 44 | 23 | 86024 | 2.0 | 24 | 13 | 84176 | Ward | 0.1 | 39 | 18 | Agg. |
| | 30 | 600 | 1000 | **86649** | Ward | 0.1 | 30 | 7 | 90165 | 1.5 | 22 | 14 | 87852 | Complete | 0.1 | 35 | 14 | Agg. |
| | 50 | 500 | 750 | 72400 | GeomDiff | 0.2 | 36 | 14 | 77313 | 1.9 | 17 | 6 | **72005** | GeomDiff | 0.2 | 37 | 11 | DB-Agg. |
| | 50 | 500 | 1000 | **74110** | Ward | 0.1 | 30 | 6 | 78757 | 1.5 | 16 | 5 | 74132 | GeomDiff | 0.1 | 31 | 6 | Agg. |
| | 50 | 600 | 750 | 83584 | Ward | 0.1 | 44 | 23 | 89361 | 2.0 | 17 | 5 | **83473** | Ward | 0.1 | 44 | 19 | DB-Agg. |
| | 50 | 600 | 1000 | 86310 | Ward | 0.1 | 30 | 6 | 90634 | 1.7 | 17 | 5 | **86300** | GeomDiff | 0.3 | 33 | 7 | DB-Agg. |
| | 100 | 500 | 750 | **72400** | GeomDiff | 0.3 | 36 | 14 | 82709 | 1.6 | 9 | 0 | 74871 | Complete | 0.1 | 33 | 13 | Agg. |
| | 100 | 500 | 1000 | **74110** | Ward | 0.2 | 30 | 6 | 85078 | 0.9 | 8 | 0 | 76587 | Ward | 0.1 | 25 | 6 | Agg. |
| | 100 | 600 | 750 | **83584** | Ward | 0.1 | 44 | 23 | 95433 | 0.5 | 3 | 100 | 85349 | Ward | 0.1 | 36 | 28 | Agg. |
| | 100 | 600 | 1000 | **86310** | Ward | 0.2 | 30 | 6 | 99632 | 0.6 | 8 | 0 | 88787 | Ward | 0.1 | 25 | 6 | Agg. |
| | 200 | 500 | 750 | **72400** | GeomDiff | 0.5 | 36 | 14 | 91138 | 1.1 | 3 | 61 | **72400** | GeomDiff | 0.5 | 36 | 14 | Agg., DB-Agg. |
| | 200 | 500 | 1000 | **74110** | Ward | 0.2 | 30 | 6 | 102620 | 0.7 | 4 | 0 | **74110** | Ward | 0.2 | 30 | 6 | Agg., DB-Agg. |
| | 200 | 600 | 750 | **83584** | Ward | 0.2 | 44 | 23 | 95661 | 1.2 | 1 | 121 | **83584** | Ward | 0.4 | 44 | 23 | Agg., DB-Agg. |
| | 200 | 600 | 1000 | **86310** | Ward | 0.3 | 30 | 6 | 114568 | 0.8 | 3 | 26 | **86310** | Ward | 0.2 | 30 | 6 | Agg., DB-Agg. |

Table G.7: Results of the Model based Heuristics on Ruhiira (Variable Cost)

| | | | | MB-I | | | | | MB-II | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F3 | F2 | Cost | Time | Gap | M | N | Cost | Time | Gap | M | N | |
| RUHIIRA - 1 | 30 | 500 | 750 | 83560 | 9.5 | 0 | 47 | 39 | **83489** | 10.0 | 0 | 47 | 38 | MB-II |
| | 30 | 500 | 1000 | 92088 | 2.4 | 0 | 47 | 35 | **91767** | 3.5 | 0 | 47 | 34 | MB-II |
| | 30 | 600 | 750 | 93329 | 2.8 | 0 | 45 | 42 | **93384** | 3.3 | 0 | 45 | 41 | MB-I |
| | 30 | 600 | 1000 | 102188 | 2.9 | 0 | 47 | 35 | **101967** | 4.3 | 0 | 47 | 34 | MB-II |
| | 50 | 500 | 750 | 81758 | 7.0 | 0 | 53 | 19 | **81739** | 11.1 | 0 | 53 | 18 | MB-II |
| | 50 | 500 | 1000 | **85802** | 10.5 | 0 | 53 | 16 | **85802** | 10.9 | 0 | 53 | 16 | MB-I, MB-II |
| | 50 | 600 | 750 | **93250** | 2.4 | 0 | 45 | 42 | **93250** | 3.7 | 0 | 45 | 42 | MB-I, MB-II |
| | 50 | 600 | 1000 | **98039** | 4.7 | 0 | 53 | 18 | **98039** | 6.2 | 0 | 53 | 18 | MB-I, MB-II |
| | 100 | 500 | 750 | **81612** | 3.0 | 0 | 54 | 17 | **81612** | 6.4 | 0 | 54 | 17 | MB-I, MB-II |
| | 100 | 500 | 1000 | 83879 | 2.5 | 0 | 59 | 7 | **83757** | 4.3 | 0 | 59 | 7 | MB-II |
| | 100 | 600 | 750 | **93001** | 3.6 | 0 | 50 | 31 | **93001** | 4.0 | 0 | 50 | 31 | MB-I, MB-II |
| | 100 | 600 | 1000 | 96909 | 2.9 | 0 | 57 | 9 | 97009 | 4.1 | 0 | 57 | 10 | MB-I |
| | 200 | 500 | 750 | **81553** | 2.1 | 0 | 57 | 13 | **81553** | 3.1 | 0 | 57 | 13 | MB-I, MB-II |
| | 200 | 500 | 1000 | **83367** | 2.3 | 0 | 62 | 3 | **83367** | 2.9 | 0 | 62 | 3 | MB-I, MB-II |
| | 200 | 600 | 750 | **93001** | 2.4 | 0 | 50 | 31 | **93001** | 3.8 | 0 | 50 | 31 | MB-I, MB-II |
| | 200 | 600 | 1000 | **96491** | 2.9 | 0 | 60 | 6 | **96491** | 2.9 | 0 | 60 | 6 | MB-I, MB-II |
| RUHIIRA - 2 | 30 | 500 | 750 | **144774** | 16.3 | 0 | 89 | 55 | 144860 | 13.8 | 0 | 89 | 55 | MB-I |
| | 30 | 500 | 1000 | **157328** | 9.4 | 0 | 89 | 50 | 157414 | 13.7 | 0 | 89 | 50 | MB-I |
| | 30 | 600 | 750 | 163559 | 8.8 | 0 | 87 | 62 | **163545** | 12.9 | 0 | 87 | 62 | MB-II |
| | 30 | 600 | 1000 | **176656** | 10.1 | 0 | 89 | 51 | 176714 | 13.9 | 0 | 89 | 50 | MB-I |
| | 50 | 500 | 750 | **143368** | 11.9 | 0 | 94 | 39 | **143368** | 12.6 | 0 | 94 | 39 | MB-I, MB-II |
| | 50 | 500 | 1000 | 150390 | 12.7 | 0 | 97 | 27 | **149668** | 15.3 | 0 | 98 | 25 | MB-II |
| | 50 | 600 | 750 | 163658 | 8.1 | 0 | 82 | 68 | **163590** | 12.8 | 0 | 83 | 67 | MB-II |
| | 50 | 600 | 1000 | 172251 | 9.6 | 0 | 96 | 32 | **171692** | 11.8 | 0 | 98 | 27 | MB-II |
| | 100 | 500 | 750 | **142863** | 12.9 | 0 | 97 | 32 | **142863** | 10.0 | 0 | 97 | 32 | MB-I, MB-II |
| | 100 | 500 | 1000 | 146938 | 7.6 | 0 | 102 | 12 | **146642** | 10.8 | 0 | 104 | 10 | MB-II |
| | 100 | 600 | 750 | **163105** | 7.2 | 0 | 91 | 52 | **163105** | 9.6 | 0 | 91 | 52 | MB-I, MB-II |
| | 100 | 600 | 1000 | 170073 | 8.4 | 0 | 100 | 15 | **169934** | 10.8 | 0 | 101 | 15 | MB-II |
| | 200 | 500 | 750 | **142744** | 7.8 | 0 | 99 | 28 | **142744** | 9.5 | 0 | 99 | 28 | MB-I, MB-II |
| | 200 | 500 | 1000 | **145962** | 7.8 | 0 | 110 | 4 | **145962** | 8.3 | 0 | 110 | 4 | MB-I, MB-II |
| | 200 | 600 | 750 | **163105** | 6.7 | 0 | 91 | 52 | **163105** | 8.1 | 0 | 91 | 52 | MB-I, MB-II |
| | 200 | 600 | 1000 | **169517** | 6.2 | 0 | 105 | 10 | **169517** | 8.7 | 0 | 105 | 10 | MB-I, MB-II |

| | | | | MB-I | | | | | MB-II | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F3 | F2 | Cost | Time | Gap | M | N | Cost | Time | Gap | M | N | |
| RUHIIRA - 3 | 30 | 500 | 750 | 158330 | 12.6 | 0 | 102 | 50 | **158327** | 23.6 | 0 | 103 | 50 | MB-II |
| | 30 | 500 | 1000 | 169780 | 10.5 | 0 | 102 | 46 | **169777** | 18.1 | 0 | 103 | 46 | MB-II |
| | 30 | 600 | 750 | **180541** | 12.2 | 0 | 98 | 57 | **180541** | 16.6 | 0 | 98 | 57 | MB-I, MB-II |
| | 30 | 600 | 1000 | ***192364*** | 11.5 | 0 | 102 | 47 | **192360** | 18.9 | 0 | 103 | 47 | MB-II |
| | 50 | 500 | 750 | 156855 | 12.9 | 0 | 110 | 34 | **156811** | 16.4 | 0 | 110 | 34 | MB-II |
| | 50 | 500 | 1000 | 163089 | 23.5 | 0 | 114 | 23 | **162916** | 15.7 | 0 | 114 | 22 | MB-II |
| | 50 | 600 | 750 | 180301 | 11.1 | 0 | 97 | 60 | **180282** | 15.0 | 0 | 98 | 58 | MB-II |
| | 50 | 600 | 1000 | **187816** | 10.0 | 0 | 114 | 24 | 187822 | 14.1 | 0 | 114 | 24 | MB-I |
| | 100 | 500 | 750 | **156135** | 11.4 | 0 | 114 | 25 | **156135** | 12.8 | 0 | 114 | 25 | MB-I, MB-II |
| | 100 | 500 | 1000 | 159490 | 10.1 | 0 | 118 | 10 | **159246** | 12.3 | 0 | 118 | 9 | MB-II |
| | 100 | 600 | 750 | **179896** | 9.5 | 0 | 105 | 45 | **179896** | 12.7 | 0 | 105 | 45 | MB-I, MB-II |
| | 100 | 600 | 1000 | 185721 | 10.4 | 0 | 115 | 14 | **185493** | 12.5 | 0 | 116 | 12 | MB-II |
| | 200 | 500 | 750 | **156111** | 8.2 | 0 | 115 | 24 | **156111** | 12.2 | 0 | 115 | 24 | MB-I, MB-II |
| | 200 | 500 | 1000 | **158570** | 8.5 | 0 | 121 | 4 | **158570** | 10.0 | 0 | 121 | 4 | MB-I, MB-II |
| | 200 | 600 | 750 | **179896** | 9.7 | 0 | 105 | 45 | **179896** | 10.6 | 0 | 105 | 45 | MB-I, MB-II |
| | 200 | 600 | 1000 | **185141** | 9.4 | 0 | 121 | 7 | **185141** | 9.9 | 0 | 121 | 7 | MB-I, MB-II |
| RUHIIRA - 4 | 30 | 500 | 750 | 150599 | 9.3 | 0 | 77 | 74 | **150506** | 13.1 | 0 | 77 | 73 | MB-II |
| | 30 | 500 | 1000 | 168583 | 8.1 | 0 | 77 | 72 | **168541** | 13.0 | 0 | 77 | 72 | MB-II |
| | 30 | 600 | 750 | 167442 | 8.5 | 0 | 74 | 79 | **167316** | 13.1 | 0 | 75 | 78 | MB-II |
| | 30 | 600 | 1000 | 185583 | 8.5 | 0 | 77 | 72 | **185541** | 12.8 | 0 | 77 | 72 | MB-II |
| | 50 | 500 | 750 | 148178 | 9.2 | 0 | 86 | 51 | **148151** | 13.4 | 0 | 87 | 50 | MB-II |
| | 50 | 500 | 1000 | 156962 | 11.1 | 0 | 92 | 34 | **156899** | 14.9 | 0 | 92 | 33 | MB-II |
| | 50 | 600 | 750 | **167086** | 8.0 | 0 | 75 | 79 | **167086** | 12.4 | 0 | 75 | 79 | MB-I, MB-II |
| | 50 | 600 | 1000 | 178022 | 6.7 | 0 | 92 | 38 | **178009** | 11.5 | 0 | 92 | 38 | MB-II |
| | 100 | 500 | 750 | 147603 | 8.9 | 0 | 93 | 42 | **147498** | 10.6 | 0 | 95 | 38 | MB-II |
| | 100 | 500 | 1000 | 151815 | 7.8 | 0 | 103 | 15 | **151356** | 9.6 | 0 | 104 | 14 | MB-II |
| | 100 | 600 | 750 | **166752** | 7.2 | 0 | 82 | 65 | **166752** | 12.4 | 0 | 82 | 65 | MB-I, MB-II |
| | 100 | 600 | 1000 | 174765 | 7.1 | 0 | 102 | 18 | **175779** | 10.5 | 0 | 99 | 25 | MB-I |
| | 200 | 500 | 750 | **147205** | 6.6 | 0 | 100 | 28 | **147205** | 7.7 | 0 | 100 | 28 | MB-I, MB-II |
| | 200 | 500 | 1000 | **150196** | 6.1 | 0 | 109 | 5 | **150196** | 7.5 | 0 | 109 | 5 | MB-I, MB-II |
| | 200 | 600 | 750 | **166752** | 6.9 | 0 | 82 | 65 | **166752** | 8.0 | 0 | 82 | 65 | MB-I, MB-II |
| | 200 | 600 | 1000 | **173695** | 6.3 | 0 | 107 | 9 | **173695** | 7.2 | 0 | 107 | 9 | MB-I, MB-II |

Table G.8: Results of the Clustering based Heuristics on Ruhiira (Variable Cost)

| | | | | Agglomerative (Agg) | | | | | DBSCAN - KMeans (DB-KM) | | | | DBSCAN - Agglomerative (DB-Agg) | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F3 | Cost | Type | Time | M | N | Cost | Time | M | N | Cost | Type | Time | M | N | |
| RUHIIRA - 1 | 30 | 500 | 750 | **83833** | Complete | 0.1 | 42 | 41 | 89696 | 0.1 | 24 | 77 | 89696 | GeomDiff | 0.1 | 24 | 77 | Agg. |
| | 30 | 500 | 1000 | **93586** | Ward | 0.1 | 41 | 39 | 108946 | 0.1 | 24 | 77 | 108946 | GeomDiff | 0.0 | 24 | 77 | Agg. |
| | 30 | 600 | 750 | **93333** | Complete | 0.1 | 42 | 41 | 95596 | 0.1 | 24 | 77 | 95596 | GeomDiff | 0.0 | 24 | 77 | Agg. |
| | 30 | 600 | 1000 | **103286** | Ward | 0.1 | 41 | 39 | 114846 | 0.0 | 24 | 77 | 114846 | GeomDiff | 0.0 | 24 | 77 | Agg. |
| | 50 | 500 | 750 | **82863** | Ward | 0.1 | 43 | 29 | 85359 | 0.6 | 35 | 44 | 85380 | Complete | 0.0 | 35 | 45 | Agg. |
| | 50 | 500 | 1000 | **87275** | Ward | 0.1 | 44 | 17 | 97010 | 0.1 | 33 | 45 | 96630 | Complete | 0.1 | 35 | 45 | Agg. |
| | 50 | 600 | 750 | **93261** | Complete | 0.1 | 42 | 41 | 95117 | 0.1 | 32 | 50 | 94420 | Complete | 0.0 | 35 | 46 | Agg. |
| | 50 | 600 | 1000 | **99175** | Ward | 0.1 | 44 | 17 | 105507 | 0.4 | 35 | 44 | 105730 | Complete | 0.0 | 35 | 45 | Agg. |
| | 100 | 500 | 750 | **82861** | Ward | 0.1 | 43 | 26 | 89920 | 0.6 | 29 | 28 | 86675 | GeomDiff | 0.2 | 38 | 18 | Agg. |
| | 100 | 500 | 1000 | **86894** | Ward | 0.1 | 43 | 14 | 93192 | 0.7 | 32 | 13 | 90215 | GeomDiff | 0.1 | 39 | 13 | Agg. |
| | 100 | 600 | 750 | **93261** | Complete | 0.1 | 42 | 41 | 99131 | 0.7 | 21 | 69 | 96627 | Ward | 0.0 | 32 | 59 | Agg. |
| | 100 | 600 | 1000 | **99011** | Ward | 0.1 | 44 | 17 | 105700 | 0.7 | 32 | 13 | 102515 | GeomDiff | 0.0 | 39 | 13 | Agg. |
| | 200 | 500 | 750 | **82861** | Ward | 0.1 | 43 | 26 | 101767 | 4.5 | 2 | 128 | 85617 | Ward | 0.1 | 38 | 40 | Agg. |
| | 200 | 500 | 1000 | **86894** | Ward | 0.1 | 43 | 14 | 126804 | 3.8 | 9 | 58 | 92286 | Complete | 0.1 | 40 | 18 | Agg. |
| | 200 | 600 | 750 | **93261** | Complete | 0.1 | 42 | 41 | 102000 | 3.5 | 0 | 136 | 94561 | Complete | 0.1 | 35 | 57 | Agg. |
| | 200 | 600 | 1000 | **99011** | Ward | 0.3 | 44 | 17 | 132140 | 2.8 | 9 | 70 | 104001 | Complete | 0.1 | 40 | 20 | Agg. |
| RUHIIRA - 2 | 30 | 500 | 750 | **146154** | Ward | 0.3 | 75 | 60 | 153118 | 0.1 | 55 | 105 | 152982 | GeomDiff | 0.1 | 56 | 105 | Agg. |
| | 30 | 500 | 1000 | **161154** | Ward | 0.5 | 75 | 60 | 179368 | 0.1 | 55 | 105 | 179232 | GeomDiff | 0.1 | 56 | 105 | Agg. |
| | 30 | 600 | 750 | **164254** | Complete | 0.1 | 72 | 77 | 166918 | 0.1 | 55 | 105 | 166782 | GeomDiff | 0.0 | 56 | 105 | Agg. |
| | 30 | 600 | 1000 | **179454** | Ward | 0.2 | 75 | 60 | 193168 | 0.1 | 55 | 105 | 193032 | GeomDiff | 0.1 | 56 | 105 | Agg. |
| | 50 | 500 | 750 | **145968** | Ward | 0.3 | 75 | 58 | 150581 | 0.4 | 58 | 64 | 149337 | Ward | 0.1 | 64 | 67 | Agg. |
| | 50 | 500 | 1000 | **155485** | Complete | 0.2 | 72 | 31 | 166572 | 0.4 | 58 | 64 | 165651 | Ward | 0.1 | 63 | 64 | Agg. |
| | 50 | 600 | 750 | **164177** | Ward | 0.2 | 75 | 62 | 168418 | 0.5 | 57 | 68 | 166937 | Ward | 0.0 | 64 | 67 | Agg. |
| | 50 | 600 | 1000 | **176679** | Complete | 0.3 | 72 | 32 | 184424 | 0.4 | 58 | 64 | 183551 | Ward | 0.1 | 63 | 64 | Agg. |
| | 100 | 500 | 750 | **145968** | Ward | 0.4 | 75 | 58 | 163820 | 3.9 | 45 | 36 | 148246 | Ward | 0.1 | 75 | 40 | Agg. |
| | 100 | 500 | 1000 | **153510** | Ward | 0.4 | 70 | 20 | 169689 | 3.9 | 47 | 19 | 155150 | Complete | 0.1 | 72 | 21 | Agg. |
| | 100 | 600 | 750 | **164177** | Ward | 0.4 | 75 | 62 | 178484 | 4.0 | 23 | 166 | 166854 | Complete | 0.1 | 68 | 72 | Agg. |
| | 100 | 600 | 1000 | **175810** | Ward | 0.2 | 70 | 20 | 189457 | 3.2 | 49 | 18 | 177265 | Complete | 0.1 | 73 | 22 | Agg. |
| | 200 | 500 | 750 | **145968** | Ward | 0.2 | 75 | 58 | 180182 | 4.9 | 4 | 215 | 148929 | Ward | 0.3 | 70 | 62 | Agg. |
| | 200 | 500 | 1000 | **153510** | Ward | 0.4 | 70 | 20 | 209774 | 4.6 | 26 | 12 | 156859 | Ward | 0.3 | 68 | 18 | Agg. |
| | 200 | 600 | 750 | **164177** | Ward | 0.3 | 75 | 62 | 181779 | 4.9 | 2 | 234 | 166081 | Ward | 0.3 | 66 | 86 | Agg. |
| | 200 | 600 | 1000 | **175810** | Ward | 0.3 | 70 | 20 | 228485 | 5.2 | 18 | 109 | 178999 | Ward | 0.3 | 68 | 24 | Agg. |

| | | | | Agglomerative (Agg) | | | | | DBSCAN - KMeans (DB-KM) | | | | DBSCAN - Agglomerative (DB-Agg) | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F3 | Cost | Type | Time | M | N | Cost | Time | M | N | Cost | Type | Time | M | N | |
| RUHIIRA - 3 | 30 | 500 | 750 | **161353** | Ward | 0.6 | 76 | 61 | 166616 | 0.7 | 61 | 90 | 165386 | Ward | 0.2 | 68 | 89 | Agg. |
| | 30 | 500 | 1000 | **174882** | Complete | 0.4 | 75 | 54 | 188578 | 0.4 | 62 | 89 | 187636 | Ward | 0.0 | 68 | 89 | Agg. |
| | 30 | 600 | 750 | **181697** | Ward | 0.4 | 79 | 72 | 184552 | 0.3 | 62 | 89 | 183586 | Ward | 0.1 | 68 | 89 | Agg. |
| | 30 | 600 | 1000 | **196582** | Complete | 0.5 | 75 | 54 | 206869 | 0.6 | 62 | 89 | 205836 | Ward | 0.0 | 68 | 89 | Agg. |
| | 50 | 500 | 750 | **160445** | Ward | 0.4 | 77 | 47 | 166449 | 0.8 | 58 | 54 | 163191 | GeomDiff | 0.2 | 70 | 57 | Agg. |
| | 50 | 500 | 1000 | **169547** | Ward | 0.3 | 74 | 32 | 179696 | 1.1 | 58 | 55 | 177085 | GeomDiff | 0.1 | 68 | 55 | Agg. |
| | 50 | 600 | 750 | **181697** | Ward | 0.4 | 79 | 72 | 187287 | 1.8 | 59 | 59 | 184214 | Ward | 0.1 | 72 | 65 | Agg. |
| | 50 | 600 | 1000 | **193447** | Ward | 0.6 | 74 | 32 | 201813 | 0.8 | 58 | 54 | 198685 | GeomDiff | 0.2 | 68 | 55 | Agg. |
| | 100 | 500 | 750 | **160445** | Ward | 0.3 | 77 | 47 | 182873 | 3.7 | 43 | 38 | 164354 | Ward | 0.1 | 75 | 39 | Agg. |
| | 100 | 500 | 1000 | **168426** | Ward | 0.2 | 71 | 22 | 186912 | 3.6 | 46 | 19 | 172369 | GeomDiff | 0.2 | 71 | 27 | Agg. |
| | 100 | 600 | 750 | **181697** | Ward | 0.3 | 79 | 72 | 199367 | 2.4 | 19 | 206 | 185702 | Ward | 0.2 | 69 | 93 | Agg. |
| | 100 | 600 | 1000 | **193166** | Ward | 0.4 | 74 | 32 | 212623 | 2.5 | 45 | 20 | 196590 | GeomDiff | 0.2 | 73 | 30 | Agg. |
| | 200 | 500 | 750 | **160445** | Ward | 0.3 | 77 | 47 | 201025 | 4.6 | 3 | 249 | 163359 | Ward | 0.5 | 74 | 59 | Agg. |
| | 200 | 500 | 1000 | **168426** | Ward | 0.4 | 71 | 22 | 238837 | 4.3 | 16 | 66 | 175010 | Ward | 0.4 | 68 | 32 | Agg. |
| | 200 | 600 | 750 | **181697** | Ward | 0.2 | 79 | 72 | 202852 | 4.6 | 2 | 255 | 183728 | Ward | 0.6 | 73 | 82 | Agg. |
| | 200 | 600 | 1000 | **193166** | Ward | 0.3 | 74 | 32 | 258642 | 4.7 | 13 | 132 | 198537 | Ward | 0.5 | 68 | 38 | Agg. |
| RUHIIRA - 4 | 30 | 500 | 750 | **151810** | Complete | 0.1 | 66 | 79 | 160508 | 0.1 | 42 | 138 | 160508 | GeomDiff | 0.1 | 42 | 138 | Agg. |
| | 30 | 500 | 1000 | **171560** | Complete | 0.1 | 66 | 79 | 195008 | 0.2 | 42 | 138 | 195008 | GeomDiff | 0.1 | 42 | 138 | Agg. |
| | 30 | 600 | 750 | **167949** | Ward | 0.4 | 65 | 84 | 170908 | 0.1 | 42 | 138 | 170908 | GeomDiff | 0.0 | 42 | 138 | Agg. |
| | 30 | 600 | 1000 | **187860** | Complete | 0.1 | 66 | 79 | 205408 | 0.0 | 42 | 138 | 205408 | GeomDiff | 0.1 | 42 | 138 | Agg. |
| | 50 | 500 | 750 | **149626** | Ward | 0.3 | 73 | 55 | 153893 | 0.4 | 57 | 82 | 153225 | Ward | 0.1 | 59 | 82 | Agg. |
| | 50 | 500 | 1000 | **160895** | Ward | 0.3 | 74 | 44 | 174379 | 0.3 | 57 | 82 | 173725 | Ward | 0.0 | 59 | 82 | Agg. |
| | 50 | 600 | 750 | **167862** | Ward | 0.4 | 67 | 76 | 169989 | 0.0 | 56 | 83 | 169070 | Ward | 0.2 | 59 | 86 | Agg. |
| | 50 | 600 | 1000 | **180695** | Ward | 0.4 | 74 | 44 | 190037 | 0.0 | 58 | 81 | 189725 | Ward | 0.0 | 59 | 82 | Agg. |
| | 100 | 500 | 750 | **149513** | Ward | 0.3 | 74 | 45 | 165153 | 3.5 | 44 | 82 | 153307 | Ward | 0.1 | 68 | 50 | Agg. |
| | 100 | 500 | 1000 | **157777** | Ward | 0.3 | 73 | 18 | 173394 | 3.3 | 52 | 33 | 163339 | Ward | 0.1 | 68 | 39 | Agg. |
| | 100 | 600 | 750 | **167862** | Ward | 0.3 | 67 | 76 | 178011 | 2.2 | 26 | 168 | 170400 | Ward | 0.1 | 60 | 94 | Agg. |
| | 100 | 600 | 1000 | **179434** | Complete | 0.7 | 75 | 31 | 197729 | 1.9 | 49 | 33 | 183639 | Ward | 0.1 | 68 | 39 | Agg. |
| | 200 | 500 | 750 | **149513** | Ward | 0.4 | 74 | 45 | 180971 | 9.2 | 3 | 231 | 149808 | Complete | 0.3 | 74 | 52 | Agg. |
| | 200 | 500 | 1000 | 157753 | Ward | 0.2 | 73 | 16 | 218447 | 7.5 | 23 | 75 | **157231** | Ward | 0.4 | 75 | 16 | DB-Agg. |
| | 200 | 600 | 750 | **167862** | Ward | 0.3 | 67 | 76 | 181236 | 6.3 | 1 | 239 | 168096 | Ward | 0.3 | 66 | 78 | Agg. |
| | 200 | 600 | 1000 | 179434 | Complete | 0.2 | 75 | 31 | 231718 | 7.4 | 19 | 109 | **179197** | Complete | 0.3 | 77 | 32 | DB-Agg. |

# Appendix H

# Computational Results of the Fixed and Variable Cost Problem on Real Instances

Table H.1: Results of the Model-based Heuristics on Tiby (Fixed and Variable Cost)

| | | | | | MB-I | | | | | MB-II | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | F3 | Cost | Time | Gap | M | N | Cost | Time | Gap | M | N | |
| TIBY - 1 | 30 | 1000 | 750 | 500 | 309001 | 38.5 | 0 | 31 | 186 | **308975** | 183.5 | 0 | 32 | 179 | MB-II |
| | 30 | 1000 | 750 | 600 | **318750** | 35.6 | 0 | 0 | 425 | **318750** | 142.1 | 0 | 0 | 425 | MB-I, MB-II |
| | 30 | 1000 | 1000 | 500 | 323793 | 23.1 | 0 | 67 | 19 | **323074** | 49.3 | 0 | 67 | 17 | MB-II |
| | 30 | 1000 | 1000 | 600 | 363904 | 33.1 | 0 | 59 | 43 | **363494** | 86.3 | 0 | 60 | 38 | MB-II |
| | 30 | 2000 | 750 | 500 | **318750** | 41 | 0 | 0 | 425 | **318750** | 85.8 | 0 | 0 | 425 | MB-I, MB-II |
| | 30 | 2000 | 750 | 600 | **318750** | 37 | 0 | 0 | 425 | **318750** | 80.5 | 0 | 0 | 425 | MB-I, MB-II |
| | 30 | 2000 | 1000 | 500 | 380916 | 63.5 | 0 | 45 | 101 | **380167** | 317.8 | 0 | 48 | 85 | MB-II |
| | 30 | 2000 | 1000 | 600 | 409667 | 89.2 | 0 | 28 | 199 | **409655** | 317.7 | 0 | 28 | 199 | MB-II |
| | 50 | 1000 | 750 | 500 | **299833** | 8213.1 | 0 | 30 | 73 | 300062 | 10831.4 | 0.55 | 30 | 78 | MB-I |
| | 50 | 1000 | 750 | 600 | **318750** | 69.7 | 0 | 0 | 425 | **318750** | 80.6 | 0 | 0 | 425 | MB-I, MB-II |
| | 50 | 1000 | 1000 | 500 | 305592 | 3742.1 | 0 | 44 | 5 | **305536** | 4311.7 | 0 | 41 | 5 | MB-II |
| | 50 | 1000 | 1000 | 600 | 347028 | 10794.2 | 0 | 39 | 21 | **346878** | 10828.8 | 0.53 | 40 | 14 | MB-II |
| | 50 | 2000 | 750 | 500 | **316511** | 1563.4 | 0 | 6 | 317 | **316511** | 1824.9 | 0 | 6 | 317 | MB-I, MB-II |
| | 50 | 2000 | 750 | 600 | **318750** | 51.8 | 0 | 0 | 425 | **318750** | 45.8 | 0 | 0 | 425 | MB-I, MB-II |
| | 50 | 2000 | 1000 | 500 | 341195 | 10823.1 | 0.98 | 33 | 17 | **341145** | 10827 | 1.46 | 33 | 17 | MB-II |
| | 50 | 2000 | 1000 | 600 | 380943 | 10827.4 | 1.84 | 27 | 61 | **380791** | 10828.5 | 1.78 | 28 | 52 | MB-II |
| | 100 | 1000 | 750 | 500 | **299295** | 10828.0 | 0.95 | 29 | 65 | 299763 | 10832.2 | 1.99 | 31 | 50 | MB-I |
| | 100 | 1000 | 750 | 600 | **318750** | 608.3 | 0 | 0 | 425 | **318750** | 635.2 | 0 | 0 | 425 | MB-I, MB-II |
| | 100 | 1000 | 1000 | 500 | **302118** | 6612.0 | 0 | 34 | 3 | **302118** | 7622.4 | 0 | 34 | 3 | MB-I, MB-II |
| | 100 | 1000 | 1000 | 600 | 344393 | 10823.7 | 0.78 | 35 | 6 | **344191** | 10830.6 | 0.54 | 35 | 6 | MB-II |
| | 100 | 2000 | 750 | 500 | **316302** | 10838.4 | 7.26 | 8 | 253 | 317560 | 10844.4 | 9.11 | 10 | 234 | MB-I |
| | 100 | 2000 | 750 | 600 | **318750** | 321.7 | 0 | 0 | 425 | **318750** | 361.2 | 0 | 0 | 425 | MB-I, MB-II |
| | 100 | 2000 | 1000 | 500 | **330067** | 10823.9 | 9.20 | 24 | 6 | 330596 | 10831.1 | 8.94 | 23 | 6 | MB-I |
| | 100 | 2000 | 1000 | 600 | 371464 | 10823.5 | 7.86 | 22 | 11 | **371161** | 10831.1 | 10 | 22 | 11 | MB-II |
| | 200 | 1000 | 750 | 500 | 300009 | 10908.8 | 2.04 | 32 | 55 | **299930** | 10919.8 | 2.62 | 31 | 52 | MB-II |
| | 200 | 1000 | 750 | 600 | **318750** | 2076.2 | 0 | 0 | 425 | **318750** | 1572.9 | 0 | 0 | 425 | MB-I, MB-II |
| | 200 | 1000 | 1000 | 500 | 302953 | 10910.4 | 1.65 | 39 | 4 | **302892** | 10920.8 | 2.26 | 38 | 4 | MB-II |
| | 200 | 1000 | 1000 | 600 | 345509 | 10911.6 | 2.52 | 40 | 6 | **344802** | 10923.7 | 2.59 | 37 | 6 | MB-II |
| | 200 | 2000 | 750 | 500 | **316354** | 10928.7 | 8.72 | 6 | 288 | 316759 | 10933.8 | 10.18 | 8 | 246 | MB-I |
| | 200 | 2000 | 750 | 600 | **318750** | 1246.3 | 0 | 0 | 425 | **318750** | 1345.1 | 0 | 0 | 425 | MB-I, MB-II |
| | 200 | 2000 | 1000 | 500 | 331574 | 10905.4 | 10.57 | 26 | 6 | **329739** | 10921.0 | 11.50 | 24 | 4 | MB-II |
| | 200 | 2000 | 1000 | 600 | **372130** | 10912.7 | 7.69 | 21 | 19 | 372167 | 10921.8 | 8.41 | 24 | 10 | MB-I |

| | | | | | MB-I | | | | | MB-II | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | F3 | Cost | Time | Gap | M | N | Cost | Time | Gap | M | N | |
| TIBY - 2 | 30 | 1000 | 750 | 500 | **283456** | 241.4 | 0 | 27 | 155 | 283464 | 538.8 | 0 | 28 | 149 | MB-I |
| | 30 | 1000 | 750 | 600 | **297596** | 44.6 | 0 | 1 | 383 | **297596** | 79.4 | 0 | 1 | 383 | MB-I, MB-II |
| | 30 | 1000 | 1000 | 500 | 295104 | 69.9 | 0 | 59 | 15 | **294551** | 61.8 | 0 | 58 | 13 | MB-II |
| | 30 | 1000 | 1000 | 600 | 332907 | 146.5 | 0 | 53 | 33 | **332473** | 271 | 0 | 53 | 29 | MB-II |
| | 30 | 2000 | 750 | 500 | **296831** | 42.6 | 0 | 3 | 358 | **296831** | 63.3 | 0 | 3 | 358 | MB-I, MB-II |
| | 30 | 2000 | 750 | 600 | **297750** | 31.3 | 0 | 0 | 397 | **297750** | 44.5 | 0 | 0 | 397 | MB-I, MB-II |
| | 30 | 2000 | 1000 | 500 | 344778 | 447.9 | 0 | 40 | 80 | **344543** | 1940 | 0 | 41 | 75 | MB-II |
| | 30 | 2000 | 1000 | 600 | 373067 | 359 | 0 | 27 | 151 | **372987** | 945.4 | 0 | 26 | 157 | MB-II |
| | 50 | 1000 | 750 | 500 | 275661 | 10819.5 | 0.75 | 25 | 62 | **275648** | 10822.6 | 1.01 | 27 | 54 | MB-II |
| | 50 | 1000 | 750 | 600 | **297530** | 358.4 | 0 | 1 | 378 | **297530** | 472.1 | 0 | 1 | 378 | MB-I, MB-II |
| | 50 | 1000 | 1000 | 500 | **278931** | 1444.4 | 0 | 34 | 5 | 278933 | 2623.7 | 0 | 34 | 5 | MB-I |
| | 50 | 1000 | 1000 | 600 | **318134** | 9482.1 | 0 | 34 | 10 | 318141 | 10821.4 | 0.54 | 34 | 11 | MB-I |
| | 50 | 2000 | 750 | 500 | **291638** | 10829.3 | 0.23 | 10 | 193 | **291638** | 10841.6 | 0.53 | 10 | 193 | MB-I, MB-II |
| | 50 | 2000 | 750 | 600 | **297750** | 48.9 | 0 | 0 | 397 | **297750** | 74.8 | 0 | 0 | 397 | MB-I, MB-II |
| | 50 | 2000 | 1000 | 500 | **309375** | 10817 | 2.17 | 28 | 13 | 309574 | 10821.1 | 3.15 | 28 | 15 | MB-I |
| | 50 | 2000 | 1000 | 600 | **347682** | 10817.5 | 3.40 | 26 | 30 | 347970 | 10823.3 | 4.52 | 25 | 40 | MB-I |
| | 100 | 1000 | 750 | 500 | 275276 | 10824.3 | 1.59 | 27 | 40 | **275199** | 10827.0 | 1.22 | 27 | 39 | MB-II |
| | 100 | 1000 | 750 | 600 | **297530** | 2126.9 | 0 | 1 | 378 | **297530** | 1858.6 | 0 | 1 | 378 | MB-I, MB-II |
| | 100 | 1000 | 1000 | 500 | **276644** | 8439.1 | 0 | 30 | 2 | **276644** | 9636.6 | 0 | 30 | 2 | MB-I, MB-II |
| | 100 | 1000 | 1000 | 600 | 316236 | 10821.8 | 0.73 | 31 | 4 | **316202** | 10824.7 | 0.64 | 31 | 4 | MB-II |
| | 100 | 2000 | 750 | 500 | **291944** | 10833.4 | 9.52 | 9 | 186 | 292327 | 10837.7 | 10.09 | 11 | 145 | MB-I |
| | 100 | 2000 | 750 | 600 | **297750** | 849.5 | 0 | 0 | 397 | **297750** | 1068.1 | 0 | 0 | 397 | MB-I, MB-II |
| | 100 | 2000 | 1000 | 500 | **302135** | 10821.0 | 9.58 | 21 | 6 | 302216 | 10824.0 | 10.38 | 24 | 3 | MB-I |
| | 100 | 2000 | 1000 | 600 | **339618** | 10825.0 | 10.89 | 19 | 5 | 340338 | 10824.7 | 9.85 | 21 | 7 | MB-I |
| | 200 | 1000 | 750 | 500 | 277582 | 10899.8 | 5.01 | 34 | 30 | **275735** | 10960.6 | 5.92 | 28 | 41 | MB-II |
| | 200 | 1000 | 750 | 600 | **297530** | 5463.2 | 0 | 1 | 378 | 297812 | 10980.4 | 3.25 | 2 | 371 | MB-I |
| | 200 | 1000 | 1000 | 500 | **276782** | 10897.3 | 1.10 | 30 | 1 | 276919 | 10965.9 | 2.63 | 32 | 1 | MB-I |
| | 200 | 1000 | 1000 | 600 | **316774** | 10893.3 | 2.80 | 33 | 4 | 317067 | 10954.4 | 4.65 | 34 | 4 | MB-I |
| | 200 | 2000 | 750 | 500 | **293034** | 10908.9 | 12.03 | 10 | 174 | 294054 | 10963.9 | 19.95 | 8 | 222 | MB-I |
| | 200 | 2000 | 750 | 600 | **297750** | 4117.0 | 0 | 0 | 397 | **297750** | 10999.2 | 1.50 | 0 | 397 | MB-I, MB-II |
| | 200 | 2000 | 1000 | 500 | 303101 | 10898.4 | 13.56 | 23 | 5 | **301370** | 10953.2 | 15.83 | 22 | 3 | MB-II |
| | 200 | 2000 | 1000 | 600 | **340595** | 10898.5 | 10.10 | 19 | 17 | 340738 | 10953.5 | 18.16 | 22 | 5 | MB-I |

| | | | | | MB-I | | | | | MB-II | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | F3 | Cost | Time | Gap | M | N | Cost | Time | Gap | M | N | |
| TIBY - 3 | 30 | 1000 | 750 | 500 | 300254 | 61.3 | 0 | 17 | 270 | **300218** | 250.3 | 0 | 17 | 269 | MB-II |
| | 30 | 1000 | 750 | 600 | **306750** | 36.6 | 0 | 0 | 409 | **306750** | 195.6 | 0 | 0 | 409 | MB-I, MB-II |
| | 30 | 1000 | 1000 | 500 | 323296 | 26.6 | 0 | 70 | 35 | **323289** | 82 | 0 | 69 | 37 | MB-II |
| | 30 | 1000 | 1000 | 600 | 359832 | 25.5 | 0 | 60 | 64 | **359826** | 185.2 | 0 | 60 | 64 | MB-II |
| | 30 | 2000 | 750 | 500 | **306750** | 37.5 | 0 | 0 | 409 | **306750** | 213.2 | 0 | 0 | 409 | MB-I, MB-II |
| | 30 | 2000 | 750 | 600 | **306750** | 37.6 | 0 | 0 | 409 | **306750** | 189.5 | 0 | 0 | 409 | MB-I, MB-II |
| | 30 | 2000 | 1000 | 500 | 378743 | 64.9 | 0 | 39 | 149 | **378667** | 293.2 | 0 | 40 | 144 | MB-II |
| | 30 | 2000 | 1000 | 600 | **398286** | 61.8 | 0 | 14 | 287 | **398286** | 230.8 | 0 | 14 | 287 | MB-I, MB-II |
| | 50 | 1000 | 750 | 500 | 292777 | 775.6 | 0 | 25 | 131 | **292701** | 1219.6 | 0 | 25 | 129 | MB-II |
| | 50 | 1000 | 750 | 600 | **306750** | 35.2 | 0 | 0 | 409 | **306750** | 142.6 | 0 | 0 | 409 | MB-I, MB-II |
| | 50 | 1000 | 1000 | 500 | 303183 | 189.1 | 0 | 46 | 11 | **302955** | 663.5 | 0 | 46 | 8 | MB-II |
| | 50 | 1000 | 1000 | 600 | 342591 | 872.8 | 0 | 41 | 29 | **342312** | 1585.9 | 0 | 42 | 23 | MB-II |
| | 50 | 2000 | 750 | 500 | 305336 | 100.2 | 0 | 5 | 324 | **305291** | 261.6 | 0 | 5 | 323 | MB-II |
| | 50 | 2000 | 750 | 600 | **306750** | 29 | 0 | 0 | 409 | **306750** | 63.3 | 0 | 0 | 409 | MB-I, MB-II |
| | 50 | 2000 | 1000 | 500 | 342140 | 7989.8 | 0 | 32 | 59 | **342073** | 10822.4 | 0.76 | 32 | 58 | MB-II |
| | 50 | 2000 | 1000 | 600 | 375720 | 6407.7 | 0 | 22 | 126 | **375503** | 9658.6 | 0 | 23 | 116 | MB-II |
| | 100 | 1000 | 750 | 500 | **291818** | 3506.2 | 0 | 25 | 93 | **291818** | 3725.0 | 0 | 25 | 93 | MB-I, MB-II |
| | 100 | 1000 | 750 | 600 | **306750** | 300.5 | 0 | 0 | 409 | **306750** | 307.2 | 0 | 0 | 409 | MB-I, MB-II |
| | 100 | 1000 | 1000 | 500 | **297107** | 992.1 | 0 | 37 | 3 | **297107** | 392.9 | 0 | 37 | 3 | MB-I, MB-II |
| | 100 | 1000 | 1000 | 600 | **337596** | 3757.8 | 0 | 37 | 4 | **337596** | 4089.8 | 0 | 37 | 4 | MB-I, MB-II |
| | 100 | 2000 | 750 | 500 | **304922** | 10835.2 | 1.22 | 6 | 288 | 304934 | 10852.6 | 1.74 | 5 | 305 | MB-I |
| | 100 | 2000 | 750 | 600 | **306750** | 149.0 | 0 | 0 | 409 | **306750** | 130.4 | 0 | 0 | 409 | MB-I, MB-II |
| | 100 | 2000 | 1000 | 500 | **326917** | 10815.4 | 2.22 | 25 | 18 | 327177 | 10822.0 | 3.68 | 25 | 20 | MB-I |
| | 100 | 2000 | 1000 | 600 | 366104 | 10816.7 | 3.63 | 21 | 36 | **365096** | 10822.4 | 3.03 | 23 | 34 | MB-II |
| | 200 | 1000 | 750 | 500 | 291867 | 10841.1 | 0.17 | 25 | 93 | **291833** | 10847.2 | 0.15 | 26 | 91 | MB-II |
| | 200 | 1000 | 750 | 600 | **306750** | 899.7 | 0 | 0 | 409 | **306750** | 741.1 | 0 | 0 | 409 | MB-I, MB-II |
| | 200 | 1000 | 1000 | 500 | **296782** | 5430.8 | 0 | 37 | 0 | **296782** | 5817.6 | 0 | 37 | 0 | MB-I, MB-II |
| | 200 | 1000 | 1000 | 600 | **337596** | 8926.7 | 0 | 37 | 4 | **337596** | 7597.6 | 0 | 37 | 4 | MB-I, MB-II |
| | 200 | 2000 | 750 | 500 | 306277 | 10858.5 | 4.76 | 6 | 314 | **305140** | 10874.5 | 4.32 | 6 | 289 | MB-II |
| | 200 | 2000 | 750 | 600 | **306750** | 484.5 | 0 | 0 | 409 | **306750** | 965.9 | 0 | 0 | 409 | MB-I, MB-II |
| | 200 | 2000 | 1000 | 500 | **326618** | 10838.2 | 7.87 | 23 | 16 | 327315 | 10848.2 | 7.48 | 24 | 16 | MB-I |
| | 200 | 2000 | 1000 | 600 | 365978 | 10840.0 | 5.10 | 21 | 35 | **365287** | 10848.4 | 7.12 | 20 | 40 | MB-II |

| | DLim | F1 | F2 | F3 | MB-I Cost | MB-I Time | MB-I Gap | MB-I M | MB-I N | MB-II Cost | MB-II Time | MB-II Gap | MB-II M | MB-II N | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| TIBY - 4 | 30 | 1000 | 750 | 500 | 158311 | 25.5 | 0 | 12 | 117 | **158296** | 82.7 | 0 | 13 | 110 | MB-II |
| | 30 | 1000 | 750 | 600 | **163500** | 6.4 | 0 | 0 | 218 | **163500** | 37.3 | 0 | 0 | 218 | MB-I, MB-II |
| | 30 | 1000 | 1000 | 500 | **166140** | 24 | 0 | 36 | 8 | 166152 | 61.8 | 0 | 36 | 8 | MB-I |
| | 30 | 1000 | 1000 | 600 | 186988 | 31.7 | 0 | 30 | 25 | **186924** | 107.1 | 0 | 30 | 25 | MB-II |
| | 30 | 2000 | 750 | 500 | **163500** | 6.9 | 0 | 0 | 218 | **163500** | 46.4 | 0 | 0 | 218 | MB-I, MB-II |
| | 30 | 2000 | 750 | 600 | **163500** | 7.1 | 0 | 0 | 218 | **163500** | 39.8 | 0 | 0 | 218 | MB-I, MB-II |
| | 30 | 2000 | 1000 | 500 | 195230 | 48.6 | 0 | 22 | 56 | **195129** | 211.4 | 0 | 22 | 56 | MB-II |
| | 30 | 2000 | 1000 | 600 | 209221 | 14.1 | 0 | 13 | 107 | **209197** | 63.4 | 0 | 13 | 107 | MB-II |
| | 50 | 1000 | 750 | 500 | 153886 | 3049.3 | 0 | 17 | 31 | **153883** | 8092.3 | 0 | 17 | 31 | MB-II |
| | 50 | 1000 | 750 | 600 | **163500** | 21.2 | 0 | 0 | 218 | **163500** | 82.8 | 0 | 0 | 218 | MB-I, MB-II |
| | 50 | 1000 | 1000 | 500 | 156434 | 80.2 | 0 | 22 | 4 | **156301** | 404.7 | 0 | 21 | 4 | MB-II |
| | 50 | 1000 | 1000 | 600 | 177796 | 303.5 | 0 | 20 | 11 | **177614** | 681 | 0 | 20 | 7 | MB-II |
| | 50 | 2000 | 750 | 500 | **162078** | 335.8 | 0 | 4 | 142 | **162078** | 546.4 | 0 | 4 | 142 | MB-I, MB-II |
| | 50 | 2000 | 750 | 600 | **163500** | 5.9 | 0 | 0 | 218 | **163500** | 35.5 | 0 | 0 | 218 | MB-I, MB-II |
| | 50 | 2000 | 1000 | 500 | 174567 | 4692.4 | 0 | 16 | 15 | **174142** | 10805.9 | 1.32 | 16 | 14 | MB-II |
| | 50 | 2000 | 1000 | 600 | **194830** | 10803.6 | 0.29 | 15 | 22 | 194959 | 10806.5 | 2.05 | 15 | 20 | MB-I |
| | 100 | 1000 | 750 | 500 | **153390** | 6743.7 | 0 | 15 | 20 | **153390** | 10408.5 | 0 | 15 | 20 | MB-I, MB-II |
| | 100 | 1000 | 750 | 600 | **163500** | 249.8 | 0 | 0 | 218 | **163500** | 287.8 | 0 | 0 | 218 | MB-I, MB-II |
| | 100 | 1000 | 1000 | 500 | **155353** | 1241.5 | 0 | 18 | 3 | **155353** | 1131.7 | 0 | 18 | 3 | MB-I, MB-II |
| | 100 | 1000 | 1000 | 600 | **176767** | 2043.9 | 0 | 17 | 6 | **176767** | 3108.4 | 0 | 17 | 6 | MB-I, MB-II |
| | 100 | 2000 | 750 | 500 | 161786 | 10809.9 | 2.67 | 4 | 128 | **161753** | 10811.7 | 2.81 | 4 | 126 | MB-II |
| | 100 | 2000 | 750 | 600 | **163500** | 88.0 | 0 | 0 | 218 | **163500** | 64.7 | 0 | 0 | 218 | MB-I, MB-II |
| | 100 | 2000 | 1000 | 500 | **167943** | 10805.8 | 2.07 | 10 | 9 | 167947 | 10807.2 | 2.32 | 10 | 9 | MB-I |
| | 100 | 2000 | 1000 | 600 | 188878 | 10805.9 | 1.71 | 10 | 11 | **188845** | 10806.8 | 2.78 | 10 | 9 | MB-II |
| | 200 | 1000 | 750 | 500 | 153496 | 10818.6 | 0.55 | 16 | 20 | **153407** | 10821.0 | 0.96 | 15 | 21 | MB-II |
| | 200 | 1000 | 750 | 600 | **163500** | 948.2 | 0 | 0 | 218 | **163500** | 928.9 | 0 | 0 | 218 | MB-I, MB-II |
| | 200 | 1000 | 1000 | 500 | 155415 | 2793.1 | 0 | 19 | 2 | **155318** | 3756.0 | 0 | 18 | 2 | MB-II |
| | 200 | 1000 | 1000 | 600 | **176767** | 7974.5 | 0 | 17 | 6 | 176823 | 10819.1 | 0..36 | 17 | 6 | MB-I |
| | 200 | 2000 | 750 | 500 | 162219 | 10821.8 | 6.08 | 4 | 131 | **161993** | 10820.7 | 5.77 | 3 | 145 | MB-II |
| | 200 | 2000 | 750 | 600 | **163500** | 549.9 | 0 | 0 | 218 | **163500** | 388.4 | 0 | 0 | 218 | MB-I, MB-II |
| | 200 | 2000 | 1000 | 500 | **168450** | 10817.8 | 3.14 | 11 | 7 | 168995 | 10819.1 | 6.66 | 12 | 7 | MB-I |
| | 200 | 2000 | 1000 | 600 | **188885** | 10819.2 | 2.31 | 10 | 11 | 190297 | 10819.2 | 7.96 | 12 | 12 | MB-I |

Table H.2: Results of the Clustering-based Heuristics on Tiby (Fixed and Variable Cost)

| | | | | | Agglomerative (Agg) | | | | | DBSCAN - KMeans (DB-KM) | | | | DBSCAN - Agglomerative (DB-Agg) | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | F3 | Cost | Type | Time | M | N | Cost | Time | M | N | Cost | Type | Time | M | N | |
| TIBY - 1 | 30 | 1000 | 750 | 500 | 318750 | GeomDiff | 1.4 | 0 | 425 | **312116** | 19.5 | 23 | 257 | 318750 | GeomDiff | 0.5 | 0 | 425 | DB-KM |
| | 30 | 1000 | 750 | 600 | **318750** | GeomDiff | 1.5 | 0 | 425 | **318750** | 16.9 | 0 | 425 | **318750** | GeomDiff | 0.7 | 0 | 425 | Agg., DB-KM, DB-Agg. |
| | 30 | 1000 | 1000 | 500 | **338047** | Comp | 0.6 | 79 | 42 | 341844 | 19.2 | 75 | 61 | 339543 | Comp | 0.3 | 74 | 58 | Agg. |
| | 30 | 1000 | 1000 | 600 | **375810** | Comp | 1 | 75 | 53 | 379522 | 19.1 | 78 | 59 | 376195 | Comp | 0.4 | 72 | 64 | Agg. |
| | 30 | 2000 | 750 | 500 | **318750** | GeomDiff | 0.8 | 0 | 425 | **318750** | 17.9 | 0 | 425 | **318750** | GeomDiff | 0.6 | 0 | 425 | Agg., DB-KM, DB-Agg. |
| | 30 | 2000 | 750 | 600 | **318750** | GeomDiff | 0.6 | 0 | 425 | **318750** | 18.7 | 0 | 425 | **318750** | GeomDiff | 1 | 0 | 425 | Agg., DB-KM, DB-Agg. |
| | 30 | 2000 | 1000 | 500 | 425000 | GeomDiff | 0.7 | 0 | 425 | 398006 | 19.6 | 34 | 202 | **396773** | Comp | 0.2 | 40 | 172 | DB-Agg. |
| | 30 | 2000 | 1000 | 600 | 425000 | GeomDiff | 0.6 | 0 | 425 | **415923** | 18.8 | 14 | 312 | 425000 | GeomDiff | 0.6 | 0 | 425 | DB-KM |
| | 50 | 1000 | 750 | 500 | **302958** | Comp | 0.7 | 32 | 74 | 304680 | 18.2 | 29 | 113 | **302958** | Comp | 0.8 | 32 | 74 | Agg., DB-Agg. |
| | 50 | 1000 | 750 | 600 | **318750** | GeomDiff | 0.8 | 0 | 425 | **318750** | 17.4 | 0 | 425 | **318750** | GeomDiff | 1.2 | 0 | 425 | Agg., DB-KM, DB-Agg. |
| | 50 | 1000 | 1000 | 500 | **310282** | Comp | 1 | 49 | 6 | 312950 | 16.4 | 53 | 10 | 310387 | Comp | 1 | 48 | 9 | Agg. |
| | 50 | 1000 | 1000 | 600 | **351492** | Comp | 0.4 | 47 | 10 | 354132 | 16.7 | 52 | 12 | **351492** | Comp | 0.9 | 47 | 10 | Agg., DB-Agg. |
| | 50 | 2000 | 750 | 500 | 318750 | GeomDiff | 1.3 | 0 | 425 | **318602** | 17.2 | 1 | 408 | 318750 | GeomDiff | 1 | 0 | 425 | DB-KM |
| | 50 | 2000 | 750 | 600 | **318750** | GeomDiff | 0.8 | 0 | 425 | **318750** | 15.8 | 0 | 425 | **318750** | GeomDiff | 0.8 | 0 | 425 | Agg., DB-KM, DB-Agg. |
| | 50 | 2000 | 1000 | 500 | **353231** | Comp | 0.7 | 41 | 31 | 360011 | 18.7 | 41 | 48 | **353231** | Comp | 0.7 | 41 | 31 | Agg., DB-Agg. |
| | 50 | 2000 | 1000 | 600 | **389049** | Comp | 0.9 | 32 | 75 | 392489 | 16.6 | 30 | 102 | **389049** | Comp | 1 | 32 | 75 | Agg., DB-Agg. |
| | 100 | 1000 | 750 | 500 | **302008** | Comp | 0.8 | 31 | 56 | 313596 | 7.8 | 11 | 156 | **302008** | Comp | 1.4 | 31 | 56 | Agg., DB-Agg. |
| | 100 | 1000 | 750 | 600 | **318750** | GeomDiff | 2.0 | 0 | 425 | **318750** | 7.6 | 0 | 425 | **318750** | GeomDiff | 2.7 | 0 | 425 | Agg., DB-KM, DB-Agg. |
| | 100 | 1000 | 1000 | 500 | **304932** | GeomDiff | 3.0 | 38 | 3 | 320490 | 7.7 | 19 | 3 | **304932** | GeomDiff | 3.1 | 38 | 3 | Agg., DB-Agg. |
| | 100 | 1000 | 1000 | 600 | **346934** | GeomDiff | 2.4 | 37 | 5 | 361759 | 7.9 | 19 | 5 | **346934** | GeomDiff | 2.3 | 37 | 5 | Agg., DB-Agg. |
| | 100 | 2000 | 750 | 500 | **318750** | GeomDiff | 1.9 | 0 | 425 | **318750** | 8.7 | 0 | 425 | **318750** | GeomDiff | 2.4 | 0 | 425 | Agg., DB-KM, DB-Agg. |
| | 100 | 2000 | 750 | 600 | **318750** | GeomDiff | 2.2 | 0 | 425 | **318750** | 9 | 0 | 425 | **318750** | GeomDiff | 2.2 | 0 | 425 | Agg., DB-KM, DB-Agg. |
| | 100 | 2000 | 1000 | 500 | 334294 | Ward | 0.8 | 25 | 10 | 339141 | 9.6 | 22 | 5 | **332860** | Ward | 1.1 | 23 | 6 | DB-Agg. |
| | 100 | 2000 | 1000 | 600 | 375402 | Ward | 1.0 | 24 | 16 | 380076 | 9.6 | 20 | 11 | **374368** | Ward | 1.6 | 22 | 12 | DB-Agg. |
| | 200 | 1000 | 750 | 500 | **302008** | Comp | 1.4 | 31 | 56 | 318750 | 2.5 | 0 | 425 | **302008** | Comp | 2.2 | 31 | 56 | Agg., DB-Agg. |
| | 200 | 1000 | 750 | 600 | **318750** | GeomDiff | 4.7 | 0 | 425 | **318750** | 3.2 | 0 | 425 | **318750** | GeomDiff | 5.6 | 0 | 425 | Agg., DB-KM, DB-Agg. |
| | 200 | 1000 | 1000 | 500 | **304944** | GeomDiff | 5.6 | 36 | 2 | 380332 | 3 | 6 | 1 | **304944** | GeomDiff | 5.5 | 36 | 2 | Agg., DB-Agg. |
| | 200 | 1000 | 1000 | 600 | **347244** | GeomDiff | 5.0 | 36 | 2 | 412544 | 2.9 | 3 | 221 | **347244** | GeomDiff | 5.2 | 36 | 2 | Agg., DB-Agg. |
| | 200 | 2000 | 750 | 500 | **318750** | GeomDiff | 4.7 | 0 | 425 | **318750** | 2.7 | 0 | 425 | **318750** | GeomDiff | 5.3 | 0 | 425 | Agg., DB-KM, DB-Agg. |
| | 200 | 2000 | 750 | 600 | **318750** | GeomDiff | 5.5 | 0 | 425 | **318750** | 2.9 | 0 | 425 | **318750** | GeomDiff | 5.5 | 0 | 425 | Agg., DB-KM, DB-Agg. |
| | 200 | 2000 | 1000 | 500 | **333580** | Ward | 1.9 | 21 | 1 | 386332 | 2.8 | 6 | 1 | **333580** | Ward | 2.2 | 21 | 1 | Agg., DB-Agg. |
| | 200 | 2000 | 1000 | 600 | **374990** | Ward | 1.7 | 19 | 11 | 415544 | 2.8 | 3 | 221 | **374990** | Ward | 2.5 | 19 | 11 | Agg., DB-Agg. |

| | | | | | Agglomerative (Agg) | | | | | DBSCAN - KMeans (DB-KM) | | | | DBSCAN - Agglomerative (DB-Agg) | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | F3 | Cost | Type | Time | M | N | Cost | Time | M | N | Cost | Type | Time | M | N | |
| TIBY - 2 | 30 | 1000 | 750 | 500 | 297750 | GeomDiff | 1.1 | 0 | 397 | **287375** | 17.8 | 22 | 215 | 289123 | Ward | 0.6 | 23 | 223 | DB-KM |
| | 30 | 1000 | 750 | 600 | **297750** | GeomDiff | 1.6 | 0 | 397 | **297750** | 16.8 | 0 | 397 | **297750** | GeomDiff | 0.8 | 0 | 397 | Agg., DB-KM, DB-Agg. |
| | 30 | 1000 | 1000 | 500 | 310731 | Ward | 0.4 | 74 | 33 | 311578 | 17.4 | 67 | 46 | **308113** | Ward | 1.3 | 66 | 42 | DB-Agg. |
| | 30 | 1000 | 1000 | 600 | 346992 | Ward | 0.4 | 71 | 42 | 346109 | 17.2 | 68 | 42 | **343743** | Ward | 0.6 | 64 | 48 | DB-Agg. |
| | 30 | 2000 | 750 | 500 | **297750** | GeomDiff | 0.8 | 0 | 397 | **297750** | 17 | 0 | 397 | **297750** | GeomDiff | 0.8 | 0 | 397 | Agg., DB-KM, DB-Agg. |
| | 30 | 2000 | 750 | 600 | **297750** | GeomDiff | 0.8 | 0 | 397 | **297750** | 15.4 | 0 | 397 | **297750** | GeomDiff | 0.7 | 0 | 397 | Agg., DB-KM, DB-Agg. |
| | 30 | 2000 | 1000 | 500 | 397000 | GeomDiff | 1 | 0 | 397 | **361208** | 16.9 | 35 | 150 | 361800 | Comp | 0.6 | 38 | 137 | DB-KM |
| | 30 | 2000 | 1000 | 600 | 397000 | GeomDiff | 0.9 | 0 | 397 | **381327** | 16.4 | 19 | 233 | 397000 | GeomDiff | 0.7 | 0 | 397 | DB-KM |
| | 50 | 1000 | 750 | 500 | **279162** | GeomDiff | 1 | 31 | 78 | 280191 | 12.8 | 31 | 64 | **279162** | GeomDiff | 1.3 | 31 | 78 | Agg., DB-Agg. |
| | 50 | 1000 | 750 | 600 | 297750 | GeomDiff | 0.9 | 0 | 397 | **297634** | 13.5 | 1 | 378 | 297750 | GeomDiff | 1.3 | 0 | 397 | DB-KM |
| | 50 | 1000 | 1000 | 500 | **283584** | Comp | 0.5 | 41 | 4 | 284977 | 14 | 44 | 6 | 283852 | Comp | 1 | 41 | 5 | Agg. |
| | 50 | 1000 | 1000 | 600 | **322545** | Comp | 0.9 | 40 | 6 | 323766 | 14.5 | 43 | 8 | 322695 | Comp | 1.1 | 39 | 10 | Agg. |
| | 50 | 2000 | 750 | 500 | 297750 | GeomDiff | 0.9 | 0 | 397 | **293930** | 13.8 | 3 | 322 | 297750 | GeomDiff | 1.1 | 0 | 397 | DB-KM |
| | 50 | 2000 | 750 | 600 | **297750** | GeomDiff | 1 | 0 | 397 | **297750** | 15.3 | 0 | 397 | **297750** | GeomDiff | 1.1 | 0 | 397 | Agg., DB-KM, DB-Agg. |
| | 50 | 2000 | 1000 | 500 | **321775** | Comp | 0.9 | 36 | 21 | 327556 | 14.4 | 42 | 12 | **321775** | Comp | 1.2 | 36 | 21 | Agg., DB-Agg. |
| | 50 | 2000 | 1000 | 600 | **357191** | Comp | 0.7 | 27 | 73 | 360177 | 14.7 | 32 | 54 | **357191** | Comp | 0.8 | 27 | 73 | Agg., DB-Agg. |
| | 100 | 1000 | 750 | 500 | **276737** | GeomDiff | 1.8 | 26 | 41 | 286543 | 7.1 | 13 | 66 | **276737** | GeomDiff | 2.2 | 26 | 41 | Agg., DB-Agg. |
| | 100 | 1000 | 750 | 600 | **297750** | GeomDiff | 1.7 | 0 | 397 | **297750** | 7 | 0 | 397 | **297750** | GeomDiff | 1.9 | 0 | 397 | Agg., DB-KM, DB-Agg. |
| | 100 | 1000 | 1000 | 500 | **278329** | GeomDiff | 1.5 | 31 | 0 | 287875 | 6.5 | 18 | 0 | **278329** | GeomDiff | 2.4 | 31 | 0 | Agg., DB-Agg. |
| | 100 | 1000 | 1000 | 600 | **317674** | GeomDiff | 1.7 | 30 | 3 | 328073 | 7 | 18 | 0 | **317674** | GeomDiff | 2.0 | 30 | 3 | Agg., DB-Agg. |
| | 100 | 2000 | 750 | 500 | 297750 | GeomDiff | 1.9 | 0 | 397 | **294902** | 6.4 | 6 | 210 | 297750 | GeomDiff | 2.1 | 0 | 397 | DB-KM |
| | 100 | 2000 | 750 | 600 | **297750** | GeomDiff | 1.7 | 0 | 397 | **297750** | 7.3 | 0 | 397 | **297750** | GeomDiff | 1.7 | 0 | 397 | Agg., DB-KM, DB-Agg. |
| | 100 | 2000 | 1000 | 500 | **302713** | Ward | 0.8 | 20 | 0 | 306373 | 6.6 | 18 | 0 | **302713** | Ward | 1.3 | 20 | 0 | Agg., DB-Agg. |
| | 100 | 2000 | 1000 | 600 | **341119** | Ward | 1.3 | 17 | 15 | 345366 | 7.2 | 17 | 4 | **341119** | Ward | 1.5 | 17 | 15 | Agg., DB-Agg. |
| | 200 | 1000 | 750 | 500 | **276933** | GeomDiff | 4.2 | 25 | 48 | 297750 | 2 | 0 | 397 | **276933** | GeomDiff | 4.4 | 25 | 48 | Agg., DB-Agg. |
| | 200 | 1000 | 750 | 600 | **297750** | GeomDiff | 4.2 | 0 | 397 | **297750** | 1.6 | 0 | 397 | **297750** | GeomDiff | 4.2 | 0 | 397 | Agg., DB-KM, DB-Agg. |
| | 200 | 1000 | 1000 | 500 | **278149** | GeomDiff | 4.1 | 30 | 0 | 342595 | 1.6 | 5 | 0 | **278149** | GeomDiff | 5.2 | 30 | 0 | Agg., DB-Agg. |
| | 200 | 1000 | 1000 | 600 | **317849** | GeomDiff | 4.2 | 30 | 0 | 381601 | 1.9 | 4 | 76 | **317849** | GeomDiff | 4.6 | 30 | 0 | Agg., DB-Agg. |
| | 200 | 2000 | 750 | 500 | **297750** | GeomDiff | 4.6 | 0 | 397 | **297750** | 1.8 | 0 | 397 | **297750** | GeomDiff | 4.5 | 0 | 397 | Agg., DB-KM, DB-Agg. |
| | 200 | 2000 | 750 | 600 | **297750** | GeomDiff | 3.8 | 0 | 397 | **297750** | 1.9 | 0 | 397 | **297750** | GeomDiff | 4.9 | 0 | 397 | Agg., DB-KM, DB-Agg. |
| | 200 | 2000 | 1000 | 500 | **302525** | Ward | 1.6 | 20 | 0 | 347301 | 1.9 | 5 | 0 | **302525** | Ward | 2.0 | 20 | 0 | Agg., DB-Agg. |
| | 200 | 2000 | 1000 | 600 | **341052** | Ward | 1.8 | 17 | 15 | 384149 | 1.8 | 3 | 199 | **341052** | Ward | 1.8 | 17 | 15 | Agg., DB-Agg. |

| | | | | | Agglomerative (Agg) | | | | | DBSCAN - KMeans (DB-KM) | | | | DBSCAN - Agglomerative (DB-Agg) | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | F3 | Cost | Type | Time | M | N | Cost | Time | M | N | Cost | Type | Time | M | N | |
| TIBY - 3 | 30 | 1000 | 750 | 500 | 306750 | GeomDiff | 1.4 | 0 | 409 | **303338** | 13.6 | 14 | 313 | 306064 | Ward | 0.4 | 6 | 370 | DB-KM |
| | 30 | 1000 | 750 | 600 | **306750** | GeomDiff | 1.5 | 0 | 409 | **306750** | 13.1 | 0 | 409 | **306750** | GeomDiff | 0.6 | 0 | 409 | Agg., DB-KM, DB-Agg. |
| | 30 | 1000 | 1000 | 500 | **334504** | Comp | 0.8 | 79 | 55 | 339285 | 13.2 | 70 | 89 | 337756 | Comp | 0.1 | 69 | 87 | Agg. |
| | 30 | 1000 | 1000 | 600 | **369754** | Comp | 0.7 | 74 | 70 | 370880 | 12.5 | 67 | 96 | 369956 | Comp | 0.1 | 69 | 87 | Agg. |
| | 30 | 2000 | 750 | 500 | **306750** | GeomDiff | 1.4 | 0 | 409 | **306750** | 13.5 | 0 | 409 | **306750** | GeomDiff | 0.6 | 0 | 409 | Agg., DB-KM, DB-Agg. |
| | 30 | 2000 | 750 | 600 | **306750** | GeomDiff | 1.1 | 0 | 409 | **306750** | 13.6 | 0 | 409 | **306750** | GeomDiff | 0.5 | 0 | 409 | Agg., DB-KM, DB-Agg. |
| | 30 | 2000 | 1000 | 500 | 409000 | GeomDiff | 0.7 | 0 | 409 | 391218 | 13.2 | 31 | 224 | **389645** | Comp | 0.4 | 26 | 243 | DB-Agg. |
| | 30 | 2000 | 1000 | 600 | 409000 | GeomDiff | 0.8 | 0 | 409 | **404530** | 13.1 | 10 | 335 | 409000 | GeomDiff | 0.4 | 0 | 409 | DB-KM |
| | 50 | 1000 | 750 | 500 | 306750 | GeomDiff | 0.8 | 0 | 409 | **296317** | 15.4 | 29 | 148 | 303909 | GeomDiff | 1.2 | 7 | 343 | DB-KM |
| | 50 | 1000 | 750 | 600 | **306750** | GeomDiff | 0.8 | 0 | 409 | **306750** | 15.3 | 0 | 409 | **306750** | GeomDiff | 1.2 | 0 | 409 | Agg., DB-KM, DB-Agg. |
| | 50 | 1000 | 1000 | 500 | **308839** | Comp | 0.7 | 60 | 12 | 311631 | 15.8 | 58 | 20 | 309516 | Comp | 0.6 | 59 | 17 | Agg. |
| | 50 | 1000 | 1000 | 600 | **348282** | Comp | 0.7 | 56 | 24 | 348988 | 16 | 54 | 29 | 348347 | Comp | 0.4 | 55 | 28 | Agg. |
| | 50 | 2000 | 750 | 500 | 306750 | GeomDiff | 1.3 | 0 | 409 | **306357** | 14.8 | 2 | 379 | 306529 | GeomDiff | 0.5 | 1 | 394 | DB-KM |
| | 50 | 2000 | 750 | 600 | **306750** | GeomDiff | 0.9 | 0 | 409 | **306750** | 15.9 | 0 | 409 | **306750** | GeomDiff | 0.7 | 0 | 409 | Agg., DB-KM, DB-Agg. |
| | 50 | 2000 | 1000 | 500 | 358261 | Comp | 0.6 | 42 | 72 | **357826** | 15.3 | 41 | 74 | 358261 | Comp | 0.4 | 42 | 72 | DB-KM |
| | 50 | 2000 | 1000 | 600 | 409000 | GeomDiff | 0.9 | 0 | 409 | **387058** | 17.5 | 28 | 145 | 402932 | GeomDiff | 0.7 | 5 | 354 | DB-KM |
| | 100 | 1000 | 750 | 500 | **293726** | Ward | 1.1 | 24 | 105 | 299991 | 9.3 | 9 | 208 | **293726** | Ward | 0.7 | 24 | 105 | Agg., DB-Agg. |
| | 100 | 1000 | 750 | 600 | **306750** | GeomDiff | 1.0 | 0 | 409 | **306750** | 9.9 | 0 | 409 | **306750** | GeomDiff | 1.2 | 0 | 409 | Agg., DB-KM, DB-Agg. |
| | 100 | 1000 | 1000 | 500 | **298790** | GeomDiff | 1.3 | 40 | 0 | 309276 | 8.7 | 27 | 2 | **298790** | GeomDiff | 1.4 | 40 | 0 | Agg., DB-Agg. |
| | 100 | 1000 | 1000 | 600 | **339382** | GeomDiff | 1.1 | 39 | 2 | 349609 | 9.4 | 26 | 4 | **339382** | GeomDiff | 1.0 | 39 | 2 | Agg., DB-Agg. |
| | 100 | 2000 | 750 | 500 | 306750 | GeomDiff | 1.1 | 0 | 409 | **306151** | 8.6 | 3 | 346 | 306750 | GeomDiff | 1.2 | 0 | 409 | DB-KM |
| | 100 | 2000 | 750 | 600 | **306750** | GeomDiff | 1.3 | 0 | 409 | **306750** | 9.4 | 0 | 409 | **306750** | GeomDiff | 1.4 | 0 | 409 | Agg., DB-KM, DB-Agg. |
| | 100 | 2000 | 1000 | 500 | **329678** | Ward | 0.9 | 26 | 15 | 332360 | 9 | 22 | 17 | **329678** | Ward | 1.1 | 26 | 15 | Agg., DB-Agg. |
| | 100 | 2000 | 1000 | 600 | **367432** | Ward | 0.9 | 22 | 41 | 370046 | 8.2 | 16 | 58 | **367432** | Ward | 0.8 | 22 | 41 | Agg., DB-Agg. |
| | 200 | 1000 | 750 | 500 | **293801** | Ward | 1.3 | 23 | 105 | 306750 | 3.3 | 0 | 409 | 295340 | Ward | 1.4 | 19 | 150 | Agg. |
| | 200 | 1000 | 750 | 600 | **306750** | GeomDiff | 2.9 | 0 | 409 | **306750** | 3.8 | 0 | 409 | **306750** | GeomDiff | 3.2 | 0 | 409 | Agg., DB-KM, DB-Agg. |
| | 200 | 1000 | 1000 | 500 | **298690** | GeomDiff | 2.6 | 39 | 0 | 348342 | 3.5 | 10 | 0 | 301790 | GeomDiff | 3.5 | 36 | 0 | Agg. |
| | 200 | 1000 | 1000 | 600 | **339590** | GeomDiff | 2.5 | 39 | 0 | 386799 | 3.8 | 7 | 78 | 342690 | GeomDiff | 3.1 | 36 | 0 | Agg. |
| | 200 | 2000 | 750 | 500 | **306750** | GeomDiff | 2.8 | 0 | 409 | **306750** | 3.5 | 0 | 409 | **306750** | GeomDiff | 3.0 | 0 | 409 | Agg., DB-KM, DB-Agg. |
| | 200 | 2000 | 750 | 600 | **306750** | GeomDiff | 3.0 | 0 | 409 | **306750** | 3.3 | 0 | 409 | **306750** | GeomDiff | 3.0 | 0 | 409 | Agg., DB-KM, DB-Agg. |
| | 200 | 2000 | 1000 | 500 | **328427** | GeomDiff | 2.8 | 22 | 10 | 358185 | 3.7 | 9 | 9 | 329397 | GeomDiff | 3.1 | 21 | 10 | Agg. |
| | 200 | 2000 | 1000 | 600 | **367932** | GeomDiff | 3.0 | 20 | 31 | 394054 | 3.2 | 7 | 78 | 368902 | GeomDiff | 3.1 | 19 | 31 | Agg. |

| | DLim | F1 | F2 | F3 | Agglomerative (Agg) Cost | Type | Time | M | N | DBSCAN - KMeans (DB-KM) Cost | Time | M | N | DBSCAN - Agglomerative (DB-Agg) Cost | Type | Time | M | N | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| TIBY - 4 | 30 | 1000 | 750 | 500 | 163500 | GeomDiff | 0.4 | 0 | 218 | **161288** | 11.1 | 10 | 148 | 163500 | GeomDiff | 0.5 | 0 | 218 | DB-KM |
| | 30 | 1000 | 750 | 600 | **163500** | GeomDiff | 0.4 | 0 | 218 | **163500** | 10.3 | 0 | 218 | **163500** | GeomDiff | 0.3 | 0 | 218 | Agg., DB-KM, DB-Agg. |
| | 30 | 1000 | 1000 | 500 | **171227** | Comp | 0.1 | 42 | 11 | 174749 | 9.5 | 39 | 27 | 172985 | Comp | 0.2 | 38 | 26 | Agg. |
| | 30 | 1000 | 1000 | 600 | **191755** | Comp | 0.2 | 39 | 20 | 194539 | 9.8 | 40 | 27 | 192185 | Comp | 0.2 | 38 | 26 | Agg. |
| | 30 | 2000 | 750 | 500 | **163500** | GeomDiff | 0.4 | 0 | 218 | **163500** | 10.1 | 0 | 218 | **163500** | GeomDiff | 0.5 | 0 | 218 | Agg., DB-KM, DB-Agg. |
| | 30 | 2000 | 750 | 600 | **163500** | GeomDiff | 0.3 | 0 | 218 | **163500** | 9 | 0 | 218 | **163500** | GeomDiff | 0.3 | 0 | 218 | Agg., DB-KM, DB-Agg. |
| | 30 | 2000 | 1000 | 500 | 218000 | GeomDiff | 0.3 | 0 | 218 | 205311 | 10.2 | 19 | 99 | **203447** | Comp | 0.1 | 18 | 99 | DB-Agg. |
| | 30 | 2000 | 1000 | 600 | 218000 | GeomDiff | 0.4 | 0 | 218 | **214865** | 9.6 | 8 | 159 | 218000 | GeomDiff | 0.2 | 0 | 218 | DB-KM |
| | 50 | 1000 | 750 | 500 | **155377** | Comp | 0.1 | 19 | 32 | 156144 | 8.3 | 19 | 36 | **155377** | Comp | 0.2 | 19 | 32 | Agg., DB-Agg. |
| | 50 | 1000 | 750 | 600 | **163500** | GeomDiff | 0.6 | 0 | 218 | **163500** | 6.9 | 0 | 218 | **163500** | GeomDiff | 0.2 | 0 | 218 | Agg., DB-KM, DB-Agg. |
| | 50 | 1000 | 1000 | 500 | **158059** | Comp | 0.1 | 25 | 3 | 160396 | 7.8 | 28 | 5 | 158213 | Comp | 0.2 | 25 | 4 | Agg. |
| | 50 | 1000 | 1000 | 600 | **178969** | Comp | 0.2 | 23 | 7 | 181610 | 7.9 | 27 | 8 | 179024 | Comp | 0.2 | 23 | 8 | Agg. |
| | 50 | 2000 | 750 | 500 | 163500 | GeomDiff | 0.5 | 0 | 218 | **163072** | 7.5 | 1 | 198 | 163500 | GeomDiff | 0.2 | 0 | 218 | DB-KM |
| | 50 | 2000 | 750 | 600 | **163500** | GeomDiff | 0.4 | 0 | 218 | **163500** | 7.8 | 0 | 218 | **163500** | GeomDiff | 0.2 | 0 | 218 | Agg., DB-KM, DB-Agg. |
| | 50 | 2000 | 1000 | 500 | **180178** | Comp | 0.1 | 22 | 10 | 182809 | 7.6 | 23 | 13 | 180333 | Comp | 0.2 | 22 | 11 | Agg. |
| | 50 | 2000 | 1000 | 600 | **200501** | Comp | 0.1 | 20 | 21 | 202043 | 7.7 | 18 | 41 | 200502 | Comp | 0.2 | 19 | 29 | Agg. |
| | 100 | 1000 | 750 | 500 | **154736** | Ward | 0.3 | 17 | 18 | 161273 | 3.5 | 7 | 52 | **154736** | Ward | 0.4 | 17 | 18 | Agg., DB-Agg. |
| | 100 | 1000 | 750 | 600 | **163500** | GeomDiff | 0.6 | 0 | 218 | **163500** | 3.4 | 0 | 218 | **163500** | GeomDiff | 0.7 | 0 | 218 | Agg., DB-KM, DB-Agg. |
| | 100 | 1000 | 1000 | 500 | **156488** | Ward | 0.3 | 20 | 3 | 164000 | 3.2 | 10 | 3 | **156488** | Ward | 0.4 | 20 | 3 | Agg., DB-Agg. |
| | 100 | 1000 | 1000 | 600 | **177902** | Ward | 0.3 | 19 | 6 | 185413 | 3.8 | 9 | 6 | **177902** | Ward | 0.4 | 19 | 6 | Agg., DB-Agg. |
| | 100 | 2000 | 750 | 500 | **163500** | GeomDiff | 0.5 | 0 | 218 | **163500** | 3.1 | 0 | 218 | **163500** | GeomDiff | 0.8 | 0 | 218 | Agg., DB-KM, DB-Agg. |
| | 100 | 2000 | 750 | 600 | **163500** | GeomDiff | 0.6 | 0 | 218 | **163500** | 3.4 | 0 | 218 | **163500** | GeomDiff | 1.0 | 0 | 218 | Agg., DB-KM, DB-Agg. |
| | 100 | 2000 | 1000 | 500 | **169903** | GeomDiff | 0.5 | 10 | 9 | 172626 | 3.3 | 8 | 9 | **169903** | GeomDiff | 0.6 | 10 | 9 | Agg., DB-Agg. |
| | 100 | 2000 | 1000 | 600 | **190803** | GeomDiff | 0.7 | 10 | 9 | 193526 | 3.2 | 8 | 9 | **190803** | GeomDiff | 0.7 | 10 | 9 | Agg., DB-Agg. |
| | 200 | 1000 | 750 | 500 | **154736** | Ward | 0.4 | 17 | 18 | 163500 | 1.5 | 0 | 218 | **154736** | Ward | 0.6 | 17 | 18 | Agg., DB-Agg. |
| | 200 | 1000 | 750 | 600 | **163500** | GeomDiff | 1.2 | 0 | 218 | **163500** | 1.8 | 0 | 218 | **163500** | GeomDiff | 1.5 | 0 | 218 | Agg., DB-KM, DB-Agg. |
| | 200 | 1000 | 1000 | 500 | **156462** | Ward | 0.7 | 20 | 2 | 187516 | 1.6 | 4 | 18 | **156462** | Ward | 0.6 | 20 | 2 | Agg., DB-Agg. |
| | 200 | 1000 | 1000 | 600 | **177902** | Ward | 0.4 | 19 | 6 | 201325 | 2 | 3 | 69 | **177902** | Ward | 0.7 | 19 | 6 | Agg., DB-Agg. |
| | 200 | 2000 | 750 | 500 | **163500** | GeomDiff | 1.3 | 0 | 218 | **163500** | 1.6 | 0 | 218 | **163500** | GeomDiff | 2.0 | 0 | 218 | Agg., DB-KM, DB-Agg. |
| | 200 | 2000 | 750 | 600 | **163500** | GeomDiff | 1.2 | 0 | 218 | **163500** | 1.8 | 0 | 218 | **163500** | GeomDiff | 1.5 | 0 | 218 | Agg., DB-KM, DB-Agg. |
| | 200 | 2000 | 1000 | 500 | **170399** | GeomDiff | 1.2 | 10 | 3 | 191516 | 1.7 | 4 | 18 | **170399** | GeomDiff | 1.6 | 10 | 3 | Agg., DB-Agg. |
| | 200 | 2000 | 1000 | 600 | **191692** | Comp | 0.3 | 9 | 6 | 204325 | 1.7 | 3 | 69 | **191692** | Comp | 0.4 | 9 | 6 | Agg., DB-Agg. |

Table H.3: Results of the Model-based Heuristics on Mbola (Fixed and Variable Cost)

| | | | | | MB-I | | | | | MB-II | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | F3 | Cost | Time | Gap | M | N | Cost | Time | Gap | M | N | |
| MBOLA - 1 | 30 | 1000 | 750 | 500 | **108581** | 5.5 | 0 | 1 | 139 | **108581** | 5.9 | 0 | 1 | 139 | MB-I, MB-II |
| | 30 | 1000 | 750 | 600 | **108750** | 2.7 | 0 | 0 | 145 | **108750** | 8.6 | 0 | 0 | 145 | MB-I, MB-II |
| | 30 | 1000 | 1000 | 500 | **132331** | 3.6 | 0 | 21 | 66 | **132331** | 2.3 | 0 | 21 | 66 | MB-I, MB-II |
| | 30 | 1000 | 1000 | 600 | **140016** | 2.5 | 0 | 18 | 74 | **140016** | 4.7 | 0 | 18 | 74 | MB-I, MB-II |
| | 30 | 2000 | 750 | 500 | **108750** | 4 | 0 | 0 | 145 | **108750** | 8.6 | 0 | 0 | 145 | MB-I, MB-II |
| | 30 | 2000 | 750 | 600 | **108750** | 11.1 | 0 | 0 | 145 | **108750** | 9.7 | 0 | 0 | 145 | MB-I, MB-II |
| | 30 | 2000 | 1000 | 500 | **144250** | 13.4 | 0 | 2 | 134 | **144250** | 7.1 | 0 | 2 | 134 | MB-I, MB-II |
| | 30 | 2000 | 1000 | 600 | **144931** | 3.6 | 0 | 1 | 139 | **144931** | 7.8 | 0 | 1 | 139 | MB-I, MB-II |
| | 50 | 1000 | 750 | 500 | **108520** | 3.2 | 0 | 2 | 131 | **108520** | 4.1 | 0 | 2 | 131 | MB-I, MB-II |
| | 50 | 1000 | 750 | 600 | **108750** | 3 | 0 | 0 | 145 | **108750** | 5.9 | 0 | 0 | 145 | MB-I, MB-II |
| | 50 | 1000 | 1000 | 500 | 127678 | 2.2 | 0 | 21 | 47 | **127247** | 2.3 | 0 | 23 | 40 | MB-II |
| | 50 | 1000 | 1000 | 600 | 137499 | 2.5 | 0 | 17 | 64 | **136969** | 3.7 | 0 | 18 | 57 | MB-II |
| | 50 | 2000 | 750 | 500 | **108750** | 3.2 | 0 | 0 | 145 | **108750** | 7.6 | 0 | 0 | 145 | MB-I, MB-II |
| | 50 | 2000 | 750 | 600 | **108750** | 3.1 | 0 | 0 | 145 | **108750** | 10 | 0 | 0 | 145 | MB-I, MB-II |
| | 50 | 2000 | 1000 | 500 | 142257 | 32.9 | 0 | 5 | 112 | **142050** | 5.1 | 0 | 6 | 106 | MB-II |
| | 50 | 2000 | 1000 | 600 | **144537** | 10.6 | 0 | 2 | 130 | **144537** | 5.2 | 0 | 2 | 130 | MB-I, MB-II |
| | 100 | 1000 | 750 | 500 | **108511** | 5.4 | 0 | 2 | 130 | **108511** | 11.1 | 0 | 2 | 130 | MB-I, MB-II |
| | 100 | 1000 | 750 | 600 | **108750** | 2.0 | 0 | 0 | 145 | **108750** | 3.4 | 0 | 0 | 145 | MB-I, MB-II |
| | 100 | 1000 | 1000 | 500 | **124047** | 6.3 | 0 | 23 | 21 | 124309 | 10.2 | 0 | 22 | 21 | MB-I |
| | 100 | 1000 | 1000 | 600 | **135419** | 6.2 | 0 | 17 | 44 | **135419** | 14.4 | 0 | 17 | 44 | MB-I, MB-II |
| | 100 | 2000 | 750 | 500 | **108750** | 2.3 | 0 | 0 | 145 | **108750** | 3.6 | 0 | 0 | 145 | MB-I, MB-II |
| | 100 | 2000 | 750 | 600 | **108750** | 2.2 | 0 | 0 | 145 | **108750** | 3.0 | 0 | 0 | 145 | MB-I, MB-II |
| | 100 | 2000 | 1000 | 500 | 138225 | 9.0 | 0 | 8 | 71 | **138105** | 17.5 | 0 | 8 | 69 | MB-II |
| | 100 | 2000 | 1000 | 600 | **144057** | 7.5 | 0 | 3 | 115 | **144057** | 14.9 | 0 | 3 | 115 | MB-I, MB-II |
| | 200 | 1000 | 750 | 500 | **108511** | 5.5 | 0 | 2 | 130 | **108511** | 6.3 | 0 | 2 | 130 | MB-I, MB-II |
| | 200 | 1000 | 750 | 600 | **108750** | 3.1 | 0 | 0 | 145 | **108750** | 3.9 | 0 | 0 | 145 | MB-I, MB-II |
| | 200 | 1000 | 1000 | 500 | 123829 | 11.7 | 0 | 21 | 18 | **123818** | 17.8 | 0 | 21 | 17 | MB-II |
| | 200 | 1000 | 1000 | 600 | **135419** | 10.3 | 0 | 17 | 44 | **135419** | 13.6 | 0 | 17 | 44 | MB-I, MB-II |
| | 200 | 2000 | 750 | 500 | **108750** | 5.2 | 0 | 0 | 145 | **108750** | 7.1 | 0 | 0 | 145 | MB-I, MB-II |
| | 200 | 2000 | 750 | 600 | **108750** | 1.9 | 0 | 0 | 145 | **108750** | 2.8 | 0 | 0 | 145 | MB-I, MB-II |
| | 200 | 2000 | 1000 | 500 | **137603** | 88.2 | 0 | 8 | 54 | **137603** | 174.0 | 0 | 8 | 54 | MB-I, MB-II |
| | 200 | 2000 | 1000 | 600 | **144057** | 32.2 | 0 | 3 | 115 | **144057** | 37.9 | 0 | 3 | 115 | MB-I, MB-II |

| | | | | | MB-I | | | | | MB-II | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | F3 | Cost | Time | Gap | M | N | Cost | Time | Gap | M | N | |
| MBOLA - 2 | 30 | 1000 | 750 | 500 | **57642** | 8.2 | 0 | 1 | 71 | **57642** | 9 | 0 | 1 | 71 | MB-I, MB-II |
| | 30 | 1000 | 750 | 600 | **57750** | 1.7 | 0 | 0 | 77 | **57750** | 3.9 | 0 | 0 | 77 | MB-I, MB-II |
| | 30 | 1000 | 1000 | 500 | 71737 | 0.7 | 0 | 6 | 51 | **71628** | 0.8 | 0 | 6 | 51 | MB-II |
| | 30 | 1000 | 1000 | 600 | 74337 | 1.3 | 0 | 6 | 51 | **74228** | 3.2 | 0 | 6 | 51 | MB-II |
| | 30 | 2000 | 750 | 500 | **57750** | 2.2 | 0 | 0 | 77 | **57750** | 3.3 | 0 | 0 | 77 | MB-I, MB-II |
| | 30 | 2000 | 750 | 600 | **57750** | 4.5 | 0 | 0 | 77 | **57750** | 3.8 | 0 | 0 | 77 | MB-I, MB-II |
| | 30 | 2000 | 1000 | 500 | 76195 | 2 | 0 | 3 | 61 | **76086** | 3.4 | 0 | 3 | 61 | MB-II |
| | 30 | 2000 | 1000 | 600 | **77000** | 2.8 | 0 | 0 | 77 | **77000** | 3 | 0 | 0 | 77 | MB-I, MB-II |
| | 50 | 1000 | 750 | 500 | **57624** | 1.6 | 0 | 1 | 71 | **57624** | 3 | 0 | 1 | 71 | MB-I, MB-II |
| | 50 | 1000 | 750 | 600 | **57750** | 1.5 | 0 | 0 | 77 | **57750** | 3 | 0 | 0 | 77 | MB-I, MB-II |
| | 50 | 1000 | 1000 | 500 | **70303** | 0.6 | 0 | 9 | 39 | **70303** | 0.6 | 0 | 9 | 39 | MB-I, MB-II |
| | 50 | 1000 | 1000 | 600 | 74014 | 1.1 | 0 | 6 | 50 | **73908** | 1.7 | 0 | 7 | 46 | MB-II |
| | 50 | 2000 | 750 | 500 | **57750** | 2.5 | 0 | 0 | 77 | **57750** | 5 | 0 | 0 | 77 | MB-I, MB-II |
| | 50 | 2000 | 750 | 600 | **57750** | 1.4 | 0 | 0 | 77 | **57750** | 6.2 | 0 | 0 | 77 | MB-I, MB-II |
| | 50 | 2000 | 1000 | 500 | **75772** | 1.8 | 0 | 3 | 60 | **75772** | 3.4 | 0 | 3 | 60 | MB-I, MB-II |
| | 50 | 2000 | 1000 | 600 | **76974** | 1.7 | 0 | 1 | 71 | **76974** | 6.4 | 0 | 1 | 71 | MB-I, MB-II |
| | 100 | 1000 | 750 | 500 | **57624** | 1.2 | 0 | 1 | 71 | **57624** | 2.5 | 0 | 1 | 71 | MB-I, MB-II |
| | 100 | 1000 | 750 | 600 | **57750** | 1.7 | 0 | 0 | 77 | **57750** | 3.3 | 0 | 0 | 77 | MB-I, MB-II |
| | 100 | 1000 | 1000 | 500 | **69848** | 0.8 | 0 | 12 | 29 | **69848** | 0.9 | 0 | 12 | 29 | MB-I, MB-II |
| | 100 | 1000 | 1000 | 600 | **73891** | 1.2 | 0 | 7 | 46 | **73891** | 1.9 | 0 | 7 | 46 | MB-I, MB-II |
| | 100 | 2000 | 750 | 500 | **57750** | 2.4 | 0 | 0 | 77 | **57750** | 4.5 | 0 | 0 | 77 | MB-I, MB-II |
| | 100 | 2000 | 750 | 600 | **57750** | 1.0 | 0 | 0 | 77 | **57750** | 31.0 | 0 | 0 | 77 | MB-I, MB-II |
| | 100 | 2000 | 1000 | 500 | **75772** | 2.0 | 0 | 3 | 60 | **75772** | 1.7 | 0 | 3 | 60 | MB-I, MB-II |
| | 100 | 2000 | 1000 | 600 | **76974** | 1.9 | 0 | 1 | 71 | **76974** | 2.3 | 0 | 1 | 71 | MB-I, MB-II |
| | 200 | 1000 | 750 | 500 | **57624** | 1.7 | 0 | 1 | 71 | **57624** | 2.0 | 0 | 1 | 71 | MB-I, MB-II |
| | 200 | 1000 | 750 | 600 | **57750** | 1.0 | 0 | 0 | 77 | **57750** | 1.4 | 0 | 0 | 77 | MB-I, MB-II |
| | 200 | 1000 | 1000 | 500 | **69701** | 1.5 | 0 | 12 | 26 | **69701** | 2.0 | 0 | 12 | 26 | MB-I, MB-II |
| | 200 | 1000 | 1000 | 600 | **73891** | 1.8 | 0 | 7 | 46 | **73891** | 2.1 | 0 | 7 | 46 | MB-I, MB-II |
| | 200 | 2000 | 750 | 500 | **57750** | 0.8 | 0 | 0 | 77 | **57750** | 1.0 | 0 | 0 | 77 | MB-I, MB-II |
| | 200 | 2000 | 750 | 600 | **57750** | 1.2 | 0 | 0 | 77 | **57750** | 1.8 | 0 | 0 | 77 | MB-I, MB-II |
| | 200 | 2000 | 1000 | 500 | **75772** | 2.1 | 0 | 3 | 60 | **75772** | 2.4 | 0 | 3 | 60 | MB-I, MB-II |
| | 200 | 2000 | 1000 | 600 | **76974** | 2.3 | 0 | 1 | 71 | **76974** | 2.7 | 0 | 1 | 71 | MB-I, MB-II |

| | | | | | MB-I | | | | | MB-II | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | F3 | Cost | Time | Gap | M | N | Cost | Time | Gap | M | N | |
| MBOLA - 3 | 30 | 1000 | 750 | 500 | **35250** | 4.4 | 0 | 0 | 47 | **35250** | 2.6 | 0 | 0 | 47 | MB-I, MB-II |
| | 30 | 1000 | 750 | 600 | **35250** | 1.7 | 0 | 0 | 47 | **35250** | 4.3 | 0 | 0 | 47 | MB-I, MB-II |
| | 30 | 1000 | 1000 | 500 | **44131** | 0.4 | 0 | 5 | 29 | **44131** | 0.5 | 0 | 5 | 29 | MB-I, MB-II |
| | 30 | 1000 | 1000 | 600 | **45931** | 0.7 | 0 | 5 | 29 | **45931** | 1.4 | 0 | 5 | 29 | MB-I, MB-II |
| | 30 | 2000 | 750 | 500 | **35250** | 1.5 | 0 | 0 | 47 | **35250** | 2.4 | 0 | 0 | 47 | MB-I, MB-II |
| | 30 | 2000 | 750 | 600 | **35250** | 1.3 | 0 | 0 | 47 | **35250** | 1.7 | 0 | 0 | 47 | MB-I, MB-II |
| | 30 | 2000 | 1000 | 500 | 47000 | 2.3 | 0 | 0 | 47 | **46967** | 2.4 | 0 | 1 | 42 | MB-II |
| | 30 | 2000 | 1000 | 600 | **47000** | 0.8 | 0 | 0 | 47 | **47000** | 2.5 | 0 | 0 | 47 | MB-I, MB-II |
| | 50 | 1000 | 750 | 500 | **35250** | 1.2 | 0 | 0 | 47 | **35250** | 2 | 0 | 0 | 47 | MB-I, MB-II |
| | 50 | 1000 | 750 | 600 | **35250** | 1 | 0 | 0 | 47 | **35250** | 6 | 0 | 0 | 47 | MB-I, MB-II |
| | 50 | 1000 | 1000 | 500 | **43783** | 0.3 | 0 | 5 | 28 | **43783** | 0.5 | 0 | 5 | 28 | MB-I, MB-II |
| | 50 | 1000 | 1000 | 600 | **45683** | 0.6 | 0 | 5 | 28 | **45683** | 1.2 | 0 | 5 | 28 | MB-I, MB-II |
| | 50 | 2000 | 750 | 500 | **35250** | 1.7 | 0 | 0 | 47 | **35250** | 2.8 | 0 | 0 | 47 | MB-I, MB-II |
| | 50 | 2000 | 750 | 600 | **35250** | 1 | 0 | 0 | 47 | **35250** | 3.1 | 0 | 0 | 47 | MB-I, MB-II |
| | 50 | 2000 | 1000 | 500 | **46619** | 9.2 | 0 | 1 | 41 | **46619** | 2.2 | 0 | 1 | 41 | MB-I, MB-II |
| | 50 | 2000 | 1000 | 600 | **47000** | 6.4 | 0 | 0 | 47 | **47000** | 3.3 | 0 | 0 | 47 | MB-I, MB-II |
| | 100 | 1000 | 750 | 500 | **35250** | 1.0 | 0 | 0 | 47 | **35250** | 2.5 | 0 | 0 | 47 | MB-I, MB-II |
| | 100 | 1000 | 750 | 600 | **35250** | 1.2 | 0 | 0 | 47 | **35250** | 2.1 | 0 | 0 | 47 | MB-I, MB-II |
| | 100 | 1000 | 1000 | 500 | **42943** | 0.5 | 0 | 9 | 13 | **42943** | 0.6 | 0 | 9 | 13 | MB-I, MB-II |
| | 100 | 1000 | 1000 | 600 | **45618** | 1.4 | 0 | 5 | 27 | **45618** | 1.2 | 0 | 5 | 27 | MB-I, MB-II |
| | 100 | 2000 | 750 | 500 | **35250** | 1.2 | 0 | 0 | 47 | **35250** | 2.3 | 0 | 0 | 47 | MB-I, MB-II |
| | 100 | 2000 | 750 | 600 | **35250** | 1.3 | 0 | 0 | 47 | **35250** | 2.3 | 0 | 0 | 47 | MB-I, MB-II |
| | 100 | 2000 | 1000 | 500 | **46619** | 15.0 | 0 | 1 | 41 | **46619** | 15.1 | 0 | 1 | 41 | MB-I, MB-II |
| | 100 | 2000 | 1000 | 600 | **47000** | 1.5 | 0 | 0 | 47 | **47000** | 2.2 | 0 | 0 | 47 | MB-I, MB-II |
| | 200 | 1000 | 750 | 500 | **35250** | 1.1 | 0 | 0 | 47 | **35250** | 1.3 | 0 | 0 | 47 | MB-I, MB-II |
| | 200 | 1000 | 750 | 600 | **35250** | 0.6 | 0 | 0 | 47 | **35250** | 1.0 | 0 | 0 | 47 | MB-I, MB-II |
| | 200 | 1000 | 1000 | 500 | **42943** | 1.0 | 0 | 9 | 13 | **42943** | 1.3 | 0 | 9 | 13 | MB-I, MB-II |
| | 200 | 1000 | 1000 | 600 | **45618** | 1.1 | 0 | 5 | 27 | **45618** | 2.1 | 0 | 5 | 27 | MB-I, MB-II |
| | 200 | 2000 | 750 | 500 | **35250** | 0.9 | 0 | 0 | 47 | **35250** | 1.1 | 0 | 0 | 47 | MB-I, MB-II |
| | 200 | 2000 | 750 | 600 | **35250** | 0.7 | 0 | 0 | 47 | **35250** | 2.5 | 0 | 0 | 47 | MB-I, MB-II |
| | 200 | 2000 | 1000 | 500 | **46619** | 1.1 | 0 | 1 | 41 | **46619** | 1.6 | 0 | 1 | 41 | MB-I, MB-II |
| | 200 | 2000 | 1000 | 600 | **47000** | 1.0 | 0 | 0 | 47 | **47000** | 1.5 | 0 | 0 | 47 | MB-I, MB-II |

| | | | | | MB-I | | | | | MB-II | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | F3 | Cost | Time | Gap | M | N | Cost | Time | Gap | M | N | |
| MBOLA - 4 | 30 | 1000 | 750 | 500 | **46500** | 2 | 0 | 0 | 62 | **46500** | 1.5 | 0 | 0 | 62 | MB-I, MB-II |
| | 30 | 1000 | 750 | 600 | **46500** | 1.3 | 0 | 0 | 62 | **46500** | 3.5 | 0 | 0 | 62 | MB-I, MB-II |
| | 30 | 1000 | 1000 | 500 | **57955** | 0.5 | 0 | 10 | 29 | **57955** | 0.6 | 0 | 10 | 29 | MB-I, MB-II |
| | 30 | 1000 | 1000 | 600 | **61050** | 13.5 | 0 | 6 | 41 | **61050** | 1.5 | 0 | 6 | 41 | MB-I, MB-II |
| | 30 | 2000 | 750 | 500 | **46500** | 1.4 | 0 | 0 | 62 | **46500** | 2.5 | 0 | 0 | 62 | MB-I, MB-II |
| | 30 | 2000 | 750 | 600 | **46500** | 1.6 | 0 | 0 | 62 | **46500** | 2.9 | 0 | 0 | 62 | MB-I, MB-II |
| | 30 | 2000 | 1000 | 500 | **61927** | 2.1 | 0 | 1 | 57 | **61927** | 2.7 | 0 | 1 | 57 | MB-I, MB-II |
| | 30 | 2000 | 1000 | 600 | **62000** | 0.9 | 0 | 0 | 62 | **62000** | 3 | 0 | 0 | 62 | MB-I, MB-II |
| | 50 | 1000 | 750 | 500 | **46500** | 0.8 | 0 | 0 | 62 | **46500** | 2.2 | 0 | 0 | 62 | MB-I, MB-II |
| | 50 | 1000 | 750 | 600 | **46500** | 2.7 | 0 | 0 | 62 | **46500** | 1.9 | 0 | 0 | 62 | MB-I, MB-II |
| | 50 | 1000 | 1000 | 500 | 55497 | 0.6 | 0 | 10 | 19 | **55268** | 0.7 | 0 | 11 | 15 | MB-II |
| | 50 | 1000 | 1000 | 600 | 59727 | 1.1 | 0 | 5 | 36 | **59527** | 0.9 | 0 | 7 | 28 | MB-II |
| | 50 | 2000 | 750 | 500 | **46500** | 1.9 | 0 | 0 | 62 | **46500** | 3.1 | 0 | 0 | 62 | MB-I, MB-II |
| | 50 | 2000 | 750 | 600 | **46500** | 1.2 | 0 | 0 | 62 | **46500** | 3.9 | 0 | 0 | 62 | MB-I, MB-II |
| | 50 | 2000 | 1000 | 500 | **60822** | 1.3 | 0 | 2 | 48 | **60822** | 1.6 | 0 | 2 | 48 | MB-I, MB-II |
| | 50 | 2000 | 1000 | 600 | **62000** | 1.4 | 0 | 0 | 62 | **62000** | 2.2 | 0 | 0 | 62 | MB-I, MB-II |
| | 100 | 1000 | 750 | 500 | **46500** | 1.7 | 0 | 0 | 62 | **46500** | 2.0 | 0 | 0 | 62 | MB-I, MB-II |
| | 100 | 1000 | 750 | 600 | **46500** | 0.7 | 0 | 0 | 62 | **46500** | 1.8 | 0 | 0 | 62 | MB-I, MB-II |
| | 100 | 1000 | 1000 | 500 | **54424** | 2.1 | 0 | 9 | 14 | **54424** | 1.9 | 0 | 9 | 14 | MB-I, MB-II |
| | 100 | 1000 | 1000 | 600 | **58968** | 1.5 | 0 | 7 | 21 | **58968** | 2.9 | 0 | 7 | 21 | MB-I, MB-II |
| | 100 | 2000 | 750 | 500 | **46500** | 1.2 | 0 | 0 | 62 | **46500** | 4.2 | 0 | 0 | 62 | MB-I, MB-II |
| | 100 | 2000 | 750 | 600 | **46500** | 0.9 | 0 | 0 | 62 | **46500** | 6.6 | 0 | 0 | 62 | MB-I, MB-II |
| | 100 | 2000 | 1000 | 500 | **60194** | 2.2 | 0 | 3 | 38 | **60194** | 2.4 | 0 | 3 | 38 | MB-I, MB-II |
| | 100 | 2000 | 1000 | 600 | **61934** | 2.3 | 0 | 1 | 54 | **61934** | 2.8 | 0 | 1 | 54 | MB-I, MB-II |
| | 200 | 1000 | 750 | 500 | **46500** | 4.9 | 0 | 0 | 62 | **46500** | 7.1 | 0 | 0 | 62 | MB-I, MB-II |
| | 200 | 1000 | 750 | 600 | **46500** | 1.0 | 0 | 0 | 62 | **46500** | 0.8 | 0 | 0 | 62 | MB-I, MB-II |
| | 200 | 1000 | 1000 | 500 | **54307** | 2.8 | 0 | 8 | 12 | **54307** | 2.9 | 0 | 8 | 12 | MB-I, MB-II |
| | 200 | 1000 | 1000 | 600 | **58968** | 3.6 | 0 | 7 | 21 | **58968** | 4.0 | 0 | 7 | 21 | MB-I, MB-II |
| | 200 | 2000 | 750 | 500 | **46500** | 1.0 | 0 | 0 | 62 | **46500** | 1.2 | 0 | 0 | 62 | MB-I, MB-II |
| | 200 | 2000 | 750 | 600 | **46500** | 0.7 | 0 | 0 | 62 | **46500** | 4.3 | 0 | 0 | 62 | MB-I, MB-II |
| | 200 | 2000 | 1000 | 500 | **60100** | 4.3 | 0 | 3 | 36 | **60100** | 5.8 | 0 | 3 | 36 | MB-I, MB-II |
| | 200 | 2000 | 1000 | 600 | **61934** | 3.5 | 0 | 1 | 54 | **61934** | 18.7 | 0 | 1 | 54 | MB-I, MB-II |

Table H.4: Results of the Clustering-based Heuristics on Mbola (Fixed and Variable Cost)

| | | | | | Agglomerative (Agg) | | | | | DBSCAN - KMeans (DB-KM) | | | | DBSCAN - Agglomerative (DB-Agg) | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | F3 | Cost | Type | Time | M | N | Cost | Time | M | N | Cost | Type | Time | M | N | |
| MBOLA - 1 | 30 | 1000 | 750 | 500 | 108750 | GeomDiff | 0.3 | 0 | 145 | **108581** | 0.7 | 1 | 139 | **108581** | GeomDiff | 0.1 | 1 | 139 | DB-KM, DB-Agg. |
| | 30 | 1000 | 750 | 600 | **108750** | GeomDiff | 0 | 0 | 145 | **108750** | 0.1 | 0 | 145 | **108750** | GeomDiff | 0.1 | 0 | 145 | Agg., DB-KM, DB-Agg. |
| | 30 | 1000 | 1000 | 500 | **133528** | Comp | 0.1 | 21 | 71 | 134853 | 0 | 19 | 80 | 134853 | GeomDiff | 0 | 19 | 80 | Agg. |
| | 30 | 1000 | 1000 | 600 | 145000 | GeomDiff | 0 | 0 | 145 | 141643 | 0 | 20 | 78 | **141353** | GeomDiff | 0 | 19 | 80 | DB-Agg. |
| | 30 | 2000 | 750 | 500 | **108750** | GeomDiff | 0 | 0 | 145 | **108750** | 0.1 | 0 | 145 | **108750** | GeomDiff | 0.1 | 0 | 145 | Agg., DB-KM, DB-Agg. |
| | 30 | 2000 | 750 | 600 | **108750** | GeomDiff | 0 | 0 | 145 | **108750** | 0 | 0 | 145 | **108750** | GeomDiff | 0 | 0 | 145 | Agg., DB-KM, DB-Agg. |
| | 30 | 2000 | 1000 | 500 | 145000 | GeomDiff | 0 | 0 | 145 | **144331** | 0 | 1 | 139 | **144331** | GeomDiff | 0.2 | 1 | 139 | DB-KM, DB-Agg. |
| | 30 | 2000 | 1000 | 600 | 145000 | GeomDiff | 0 | 0 | 145 | **144931** | 0 | 1 | 139 | **144931** | GeomDiff | 0 | 1 | 139 | DB-KM, DB-Agg. |
| | 50 | 1000 | 750 | 500 | 108750 | GeomDiff | 0.1 | 0 | 145 | **108581** | 0.5 | 1 | 139 | 108750 | GeomDiff | 0.1 | 0 | 145 | DB-KM |
| | 50 | 1000 | 750 | 600 | **108750** | GeomDiff | 0.1 | 0 | 145 | **108750** | 0.1 | 0 | 145 | **108750** | GeomDiff | 0.1 | 0 | 145 | Agg., DB-KM, DB-Agg. |
| | 50 | 1000 | 1000 | 500 | **127748** | Comp | 0 | 24 | 40 | 128732 | 0.4 | 20 | 56 | 128732 | GeomDiff | 0.1 | 20 | 56 | Agg. |
| | 50 | 1000 | 1000 | 600 | **137160** | Comp | 0 | 18 | 58 | 137876 | 0.5 | 19 | 60 | 137409 | GeomDiff | 0.1 | 18 | 62 | Agg. |
| | 50 | 2000 | 750 | 500 | **108750** | GeomDiff | 0.1 | 0 | 145 | **108750** | 0.5 | 0 | 145 | **108750** | GeomDiff | 0 | 0 | 145 | Agg., DB-KM, DB-Agg. |
| | 50 | 2000 | 750 | 600 | **108750** | GeomDiff | 0.1 | 0 | 145 | **108750** | 0.3 | 0 | 145 | **108750** | GeomDiff | 0 | 0 | 145 | Agg., DB-KM, DB-Agg. |
| | 50 | 2000 | 1000 | 500 | 145000 | GeomDiff | 0 | 0 | 145 | **142827** | 0.3 | 7 | 104 | 144013 | GeomDiff | 0 | 4 | 121 | DB-KM |
| | 50 | 2000 | 1000 | 600 | 145000 | GeomDiff | 0 | 0 | 145 | **144931** | 0.5 | 1 | 139 | 145000 | GeomDiff | 0 | 0 | 145 | DB-KM |
| | 100 | 1000 | 750 | 500 | **108750** | GeomDiff | 0.1 | 0 | 145 | **108750** | 4.6 | 0 | 145 | **108750** | GeomDiff | 0.1 | 0 | 145 | Agg., DB-KM, DB-Agg. |
| | 100 | 1000 | 750 | 600 | **108750** | GeomDiff | 0.1 | 0 | 145 | **108750** | 5.2 | 0 | 145 | **108750** | GeomDiff | 0.1 | 0 | 145 | Agg., DB-KM, DB-Agg. |
| | 100 | 1000 | 1000 | 500 | **124537** | GeomDiff | 0.3 | 24 | 24 | 126019 | 3.6 | 21 | 19 | 124553 | GeomDiff | 0.2 | 25 | 19 | Agg. |
| | 100 | 1000 | 1000 | 600 | **135592** | GeomDiff | 0.2 | 18 | 42 | 137263 | 3.4 | 15 | 40 | 135953 | GeomDiff | 0.2 | 18 | 41 | Agg. |
| | 100 | 2000 | 750 | 500 | **108750** | GeomDiff | 0.1 | 0 | 145 | **108750** | 3.3 | 0 | 145 | **108750** | GeomDiff | 0.2 | 0 | 145 | Agg., DB-KM, DB-Agg. |
| | 100 | 2000 | 750 | 600 | **108750** | GeomDiff | 0.1 | 0 | 145 | **108750** | 3.4 | 0 | 145 | **108750** | GeomDiff | 0.2 | 0 | 145 | Agg., DB-KM, DB-Agg. |
| | 100 | 2000 | 1000 | 500 | 145000 | GeomDiff | 0.2 | 0 | 145 | **139886** | 3.1 | 9 | 67 | 142830 | GeomDiff | 0.1 | 3 | 121 | DB-KM |
| | 100 | 2000 | 1000 | 600 | 145000 | GeomDiff | 0.2 | 0 | 145 | **144842** | 3.6 | 1 | 135 | 145000 | GeomDiff | 0.1 | 0 | 145 | DB-KM |
| | 200 | 1000 | 750 | 500 | **108750** | GeomDiff | 0.6 | 0 | 145 | **108750** | 2.5 | 0 | 145 | **108750** | GeomDiff | 0.6 | 0 | 145 | Agg., DB-KM, DB-Agg. |
| | 200 | 1000 | 750 | 600 | **108750** | GeomDiff | 0.5 | 0 | 145 | **108750** | 2.6 | 0 | 145 | **108750** | GeomDiff | 0.6 | 0 | 145 | Agg., DB-KM, DB-Agg. |
| | 200 | 1000 | 1000 | 500 | **124381** | Ward | 0.2 | 24 | 14 | 134946 | 2.3 | 9 | 55 | **124381** | Ward | 0.3 | 24 | 14 | Agg., DB-Agg. |
| | 200 | 1000 | 1000 | 600 | **135851** | Ward | 0.2 | 18 | 37 | 142870 | 2.5 | 5 | 98 | **135851** | Ward | 0.3 | 18 | 37 | Agg., DB-Agg. |
| | 200 | 2000 | 750 | 500 | **108750** | GeomDiff | 0.5 | 0 | 145 | **108750** | 2.3 | 0 | 145 | **108750** | GeomDiff | 0.2 | 0 | 145 | Agg., DB-KM, DB-Agg. |
| | 200 | 2000 | 750 | 600 | **108750** | GeomDiff | 0.5 | 0 | 145 | **108750** | 1.7 | 0 | 145 | **108750** | GeomDiff | 0.5 | 0 | 145 | Agg., DB-KM, DB-Agg. |
| | 200 | 2000 | 1000 | 500 | 145000 | GeomDiff | 0.6 | 0 | 145 | 141557 | 2.7 | 4 | 93 | **139907** | Comp | 0.3 | 7 | 59 | DB-Agg. |
| | 200 | 2000 | 1000 | 600 | **145000** | GeomDiff | 0.5 | 0 | 145 | **145000** | 2 | 0 | 145 | **145000** | GeomDiff | 0.3 | 0 | 145 | Agg., DB-KM, DB-Agg. |

| | | | | | | Agglomerative (Agg) | | | | DBSCAN - KMeans (DB-KM) | | | | DBSCAN - Agglomerative (DB-Agg) | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | F3 | Cost | Type | Time | M | N | Cost | Time | M | N | Cost | Type | Time | M | N | |
| MBOLA - 2 | 30 | 1000 | 750 | 500 | 57750 | GeomDiff | 0.1 | 0 | 77 | **57642** | 0.1 | 1 | 71 | **57642** | GeomDiff | 0 | 1 | 71 | DB-KM, DB-Agg. |
| | 30 | 1000 | 750 | 600 | **57750** | GeomDiff | 0 | 0 | 77 | **57750** | 0 | 0 | 77 | **57750** | GeomDiff | 0 | 0 | 77 | Agg., DB-KM, DB-Agg. |
| | 30 | 1000 | 1000 | 500 | **71628** | Comp | 0 | 6 | 51 | 72091 | 0 | 7 | 50 | **71628** | Comp | 0 | 6 | 51 | Agg., DB-Agg. |
| | 30 | 1000 | 1000 | 600 | 77000 | GeomDiff | 0 | 0 | 77 | **74228** | 0 | 6 | 51 | **74228** | Comp | 0 | 6 | 51 | DB-KM, DB-Agg. |
| | 30 | 2000 | 750 | 500 | **57750** | GeomDiff | 0 | 0 | 77 | **57750** | 0.1 | 0 | 77 | **57750** | GeomDiff | 0 | 0 | 77 | Agg., DB-KM, DB-Agg. |
| | 30 | 2000 | 750 | 600 | **57750** | GeomDiff | 0.1 | 0 | 77 | **57750** | 0 | 0 | 77 | **57750** | GeomDiff | 0 | 0 | 77 | Agg., DB-KM, DB-Agg. |
| | 30 | 2000 | 1000 | 500 | 77000 | GeomDiff | 0 | 0 | 77 | 76236 | 0 | 2 | 66 | **76086** | Comp | 0 | 3 | 61 | DB-Agg. |
| | 30 | 2000 | 1000 | 600 | 77000 | GeomDiff | 0 | 0 | 77 | **76992** | 0 | 1 | 71 | **76992** | GeomDiff | 0 | 1 | 71 | DB-KM, DB-Agg. |
| | 50 | 1000 | 750 | 500 | 57750 | GeomDiff | 0.1 | 0 | 77 | **57624** | 0 | 1 | 71 | **57624** | GeomDiff | 0 | 1 | 71 | DB-KM, DB-Agg. |
| | 50 | 1000 | 750 | 600 | **57750** | GeomDiff | 0 | 0 | 77 | **57750** | 0 | 0 | 77 | **57750** | GeomDiff | 0 | 0 | 77 | Agg., DB-KM, DB-Agg. |
| | 50 | 1000 | 1000 | 500 | **70217** | Ward | 0 | 10 | 36 | 70823 | 0 | 8 | 44 | 70823 | GeomDiff | 0 | 8 | 44 | Agg. |
| | 50 | 1000 | 1000 | 600 | 77000 | GeomDiff | 0 | 0 | 77 | **74014** | 0 | 6 | 50 | **74014** | GeomDiff | 0 | 6 | 50 | DB-KM, DB-Agg. |
| | 50 | 2000 | 750 | 500 | **57750** | GeomDiff | 0 | 0 | 77 | **57750** | 0 | 0 | 77 | **57750** | GeomDiff | 0 | 0 | 77 | Agg., DB-KM, DB-Agg. |
| | 50 | 2000 | 750 | 600 | **57750** | GeomDiff | 0 | 0 | 77 | **57750** | 0 | 0 | 77 | **57750** | GeomDiff | 0 | 0 | 77 | Agg., DB-KM, DB-Agg. |
| | 50 | 2000 | 1000 | 500 | 77000 | GeomDiff | 0 | 0 | 77 | **75772** | 0 | 3 | 60 | **75772** | GeomDiff | 0 | 3 | 60 | DB-KM, DB-Agg. |
| | 50 | 2000 | 1000 | 600 | 77000 | GeomDiff | 0 | 0 | 77 | **76974** | 0 | 1 | 71 | **76974** | GeomDiff | 0 | 1 | 71 | DB-KM, DB-Agg. |
| | 100 | 1000 | 750 | 500 | 57750 | GeomDiff | 0.0 | 0 | 77 | **57624** | 0.2 | 1 | 71 | **57624** | GeomDiff | 0.0 | 1 | 71 | DB-KM, DB-Agg. |
| | 100 | 1000 | 750 | 600 | **57750** | GeomDiff | 0.0 | 0 | 77 | **57750** | 0 | 0 | 77 | **57750** | GeomDiff | 0.0 | 0 | 77 | Agg., DB-KM, DB-Agg. |
| | 100 | 1000 | 1000 | 500 | **69835** | GeomDiff | 0.0 | 12 | 28 | 69848 | 0 | 12 | 29 | 69848 | GeomDiff | 0.0 | 12 | 29 | Agg. |
| | 100 | 1000 | 1000 | 600 | 77000 | GeomDiff | 0.0 | 0 | 77 | **73891** | 0 | 7 | 46 | **73891** | GeomDiff | 0.0 | 7 | 46 | DB-KM, DB-Agg. |
| | 100 | 2000 | 750 | 500 | **57750** | GeomDiff | 0.0 | 0 | 77 | **57750** | 0 | 0 | 77 | **57750** | GeomDiff | 0.0 | 0 | 77 | Agg., DB-KM, DB-Agg. |
| | 100 | 2000 | 750 | 600 | **57750** | GeomDiff | 0.0 | 0 | 77 | **57750** | 0 | 0 | 77 | **57750** | GeomDiff | 0.0 | 0 | 77 | Agg., DB-KM, DB-Agg. |
| | 100 | 2000 | 1000 | 500 | 77000 | GeomDiff | 0.0 | 0 | 77 | **75772** | 0 | 3 | 60 | **75772** | GeomDiff | 0.0 | 3 | 60 | DB-KM, DB-Agg. |
| | 100 | 2000 | 1000 | 600 | 77000 | GeomDiff | 0.0 | 0 | 77 | **76974** | 0 | 1 | 71 | **76974** | GeomDiff | 0.0 | 1 | 71 | DB-KM, DB-Agg. |
| | 200 | 1000 | 750 | 500 | 57750 | GeomDiff | 0.1 | 0 | 77 | **57624** | 0 | 1 | 71 | **57624** | GeomDiff | 0.0 | 1 | 71 | DB-KM, DB-Agg. |
| | 200 | 1000 | 750 | 600 | **57750** | GeomDiff | 0.1 | 0 | 77 | **57750** | 0 | 0 | 77 | **57750** | GeomDiff | 0.0 | 0 | 77 | Agg., DB-KM, DB-Agg. |
| | 200 | 1000 | 1000 | 500 | **69731** | Comp | 0.0 | 12 | 26 | 72324 | 0 | 8 | 40 | 72324 | GeomDiff | 0.0 | 8 | 40 | Agg. |
| | 200 | 1000 | 1000 | 600 | 77000 | GeomDiff | 0.1 | 0 | 77 | **75277** | 0 | 3 | 63 | **75277** | GeomDiff | 0.0 | 3 | 63 | DB-KM, DB-Agg. |
| | 200 | 2000 | 750 | 500 | **57750** | GeomDiff | 0.1 | 0 | 77 | **57750** | 0 | 0 | 77 | **57750** | GeomDiff | 0.0 | 0 | 77 | Agg., DB-KM, DB-Agg. |
| | 200 | 2000 | 750 | 600 | **57750** | GeomDiff | 0.1 | 0 | 77 | **57750** | 0 | 0 | 77 | **57750** | GeomDiff | 0.0 | 0 | 77 | Agg., DB-KM, DB-Agg. |
| | 200 | 2000 | 1000 | 500 | 77000 | GeomDiff | 0.0 | 0 | 77 | **76219** | 0 | 2 | 66 | **76219** | GeomDiff | 0.0 | 2 | 66 | DB-KM, DB-Agg. |
| | 200 | 2000 | 1000 | 600 | 77000 | GeomDiff | 0.1 | 0 | 77 | **76974** | 0 | 1 | 71 | **76974** | GeomDiff | 0.0 | 1 | 71 | DB-KM, DB-Agg. |

| | | | | | Agglomerative (Agg) | | | | | DBSCAN - KMeans (DB-KM) | | | | DBSCAN - Agglomerative (DB-Agg) | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | F3 | Cost | Type | Time | M | N | Cost | Time | M | N | Cost | Type | Time | M | N | |
| MBOLA - 3 | 30 | 1000 | 750 | 500 | **35250** | GeomDiff | 0.1 | 0 | 47 | **35250** | 0 | 0 | 47 | **35250** | GeomDiff | 0 | 0 | 47 | Agg., DB-KM, DB-Agg. |
| | 30 | 1000 | 750 | 600 | **35250** | GeomDiff | 0 | 0 | 47 | **35250** | 0 | 0 | 47 | **35250** | GeomDiff | 0 | 0 | 47 | Agg., DB-KM, DB-Agg. |
| | 30 | 1000 | 1000 | 500 | **44377** | GeomDiff | 0 | 6 | 28 | **44377** | 0 | 6 | 28 | **44377** | GeomDiff | 0 | 6 | 28 | Agg., DB-KM, DB-Agg. |
| | 30 | 1000 | 1000 | 600 | 47000 | GeomDiff | 0 | 0 | 47 | **46277** | 0 | 6 | 28 | **46277** | GeomDiff | 0 | 6 | 28 | DB-KM, DB-Agg. |
| | 30 | 2000 | 750 | 500 | **35250** | GeomDiff | 0 | 0 | 47 | **35250** | 0 | 0 | 47 | **35250** | GeomDiff | 0 | 0 | 47 | Agg., DB-KM, DB-Agg. |
| | 30 | 2000 | 750 | 600 | **35250** | GeomDiff | 0 | 0 | 47 | **35250** | 0 | 0 | 47 | **35250** | GeomDiff | 0 | 0 | 47 | Agg., DB-KM, DB-Agg. |
| | 30 | 2000 | 1000 | 500 | **47000** | GeomDiff | 0 | 0 | 47 | **47000** | 0 | 0 | 47 | **47000** | GeomDiff | 0 | 0 | 47 | Agg., DB-KM, DB-Agg. |
| | 30 | 2000 | 1000 | 600 | **47000** | GeomDiff | 0 | 0 | 47 | **47000** | 0 | 0 | 47 | **47000** | GeomDiff | 0 | 0 | 47 | Agg., DB-KM, DB-Agg. |
| | 50 | 1000 | 750 | 500 | **35250** | GeomDiff | 0 | 0 | 47 | **35250** | 0 | 0 | 47 | **35250** | GeomDiff | 0 | 0 | 47 | Agg., DB-KM, DB-Agg. |
| | 50 | 1000 | 750 | 600 | **35250** | GeomDiff | 0 | 0 | 47 | **35250** | 0 | 0 | 47 | **35250** | GeomDiff | 0 | 0 | 47 | Agg., DB-KM, DB-Agg. |
| | 50 | 1000 | 1000 | 500 | **43592** | GeomDiff | 0 | 7 | 22 | 43783 | 0 | 5 | 28 | 43783 | GeomDiff | 0 | 5 | 28 | Agg. |
| | 50 | 1000 | 1000 | 600 | 47000 | GeomDiff | 0 | 0 | 47 | **45683** | 0 | 5 | 28 | **45683** | GeomDiff | 0 | 5 | 28 | DB-KM, DB-Agg. |
| | 50 | 2000 | 750 | 500 | **35250** | GeomDiff | 0 | 0 | 47 | **35250** | 0 | 0 | 47 | **35250** | GeomDiff | 0 | 0 | 47 | Agg., DB-KM, DB-Agg. |
| | 50 | 2000 | 750 | 600 | **35250** | GeomDiff | 0 | 0 | 47 | **35250** | 0 | 0 | 47 | **35250** | GeomDiff | 0 | 0 | 47 | Agg., DB-KM, DB-Agg. |
| | 50 | 2000 | 1000 | 500 | 47000 | GeomDiff | 0 | 0 | 47 | **46619** | 0 | 1 | 41 | **46619** | GeomDiff | 0 | 1 | 41 | DB-KM, DB-Agg. |
| | 50 | 2000 | 1000 | 600 | **47000** | GeomDiff | 0 | 0 | 47 | **47000** | 0 | 0 | 47 | **47000** | GeomDiff | 0 | 0 | 47 | Agg., DB-KM, DB-Agg. |
| | 100 | 1000 | 750 | 500 | **35250** | GeomDiff | 0.0 | 0 | 47 | **35250** | 0 | 0 | 47 | **35250** | GeomDiff | 0.0 | 0 | 47 | Agg., DB-KM, DB-Agg. |
| | 100 | 1000 | 750 | 600 | **35250** | GeomDiff | 0.0 | 0 | 47 | **35250** | 0 | 0 | 47 | **35250** | GeomDiff | 0.0 | 0 | 47 | Agg., DB-KM, DB-Agg. |
| | 100 | 1000 | 1000 | 500 | **42943** | GeomDiff | 0.0 | 9 | 13 | **42943** | 0 | 9 | 13 | **42943** | GeomDiff | 0.0 | 9 | 13 | Agg., DB-KM, DB-Agg. |
| | 100 | 1000 | 1000 | 600 | 47000 | GeomDiff | 0.0 | 0 | 47 | **45618** | 0 | 5 | 27 | **45618** | GeomDiff | 0.0 | 5 | 27 | DB-KM, DB-Agg. |
| | 100 | 2000 | 750 | 500 | **35250** | GeomDiff | 0.0 | 0 | 47 | **35250** | 0.1 | 0 | 47 | **35250** | GeomDiff | 0.0 | 0 | 47 | Agg., DB-KM, DB-Agg. |
| | 100 | 2000 | 750 | 600 | **35250** | GeomDiff | 0.0 | 0 | 47 | **35250** | 0 | 0 | 47 | **35250** | GeomDiff | 0.0 | 0 | 47 | Agg., DB-KM, DB-Agg. |
| | 100 | 2000 | 1000 | 500 | 47000 | GeomDiff | 0.0 | 0 | 47 | **46619** | 0 | 1 | 41 | **46619** | GeomDiff | 0.0 | 1 | 41 | DB-KM, DB-Agg. |
| | 100 | 2000 | 1000 | 600 | **47000** | GeomDiff | 0.0 | 0 | 47 | **47000** | 0 | 0 | 47 | **47000** | GeomDiff | 0.0 | 0 | 47 | Agg., DB-KM, DB-Agg. |
| | 200 | 1000 | 750 | 500 | **35250** | GeomDiff | 0.0 | 0 | 47 | **35250** | 0 | 0 | 47 | **35250** | GeomDiff | 0.0 | 0 | 47 | Agg., DB-KM, DB-Agg. |
| | 200 | 1000 | 750 | 600 | **35250** | GeomDiff | 0.0 | 0 | 47 | **35250** | 0 | 0 | 47 | **35250** | GeomDiff | 0.0 | 0 | 47 | Agg., DB-KM, DB-Agg. |
| | 200 | 1000 | 1000 | 500 | **42943** | GeomDiff | 0.0 | 9 | 13 | 43572 | 0 | 8 | 12 | **42943** | GeomDiff | 0.0 | 9 | 13 | Agg., DB-Agg. |
| | 200 | 1000 | 1000 | 600 | 47000 | GeomDiff | 0.0 | 0 | 47 | 45792 | 0 | 3 | 34 | **45618** | GeomDiff | 0.0 | 5 | 27 | DB-Agg. |
| | 200 | 2000 | 750 | 500 | **35250** | GeomDiff | 0.0 | 0 | 47 | **35250** | 0 | 0 | 47 | **35250** | GeomDiff | 0.0 | 0 | 47 | Agg., DB-KM, DB-Agg. |
| | 200 | 2000 | 750 | 600 | **35250** | GeomDiff | 0.0 | 0 | 47 | **35250** | 0 | 0 | 47 | **35250** | GeomDiff | 0.0 | 0 | 47 | Agg., DB-KM, DB-Agg. |
| | 200 | 2000 | 1000 | 500 | 47000 | GeomDiff | 0.0 | 0 | 47 | **46619** | 0 | 1 | 41 | **46619** | GeomDiff | 0.0 | 1 | 41 | DB-KM, DB-Agg. |
| | 200 | 2000 | 1000 | 600 | **47000** | GeomDiff | 0.0 | 0 | 47 | **47000** | 0 | 0 | 47 | **47000** | GeomDiff | 0.0 | 0 | 47 | Agg., DB-KM, DB-Agg. |

| | | | | | Agglomerative (Agg) | | | | | DBSCAN - KMeans (DB-KM) | | | | DBSCAN - Agglomerative (DB-Agg) | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | F3 | Cost | Type | Time | M | N | Cost | Time | M | N | Cost | Type | Time | M | N | |
| MBOLA - 4 | 30 | 1000 | 750 | 500 | **46500** | GeomDiff | 0 | 0 | 62 | **46500** | 0 | 0 | 62 | **46500** | GeomDiff | 0 | 0 | 62 | Agg., DB-KM, DB-Agg. |
| | 30 | 1000 | 750 | 600 | **46500** | GeomDiff | 0.1 | 0 | 62 | **46500** | 0 | 0 | 62 | **46500** | GeomDiff | 0 | 0 | 62 | Agg., DB-KM, DB-Agg. |
| | 30 | 1000 | 1000 | 500 | **58434** | Ward | 0 | 8 | 35 | 60335 | 0 | 5 | 47 | 60335 | GeomDiff | 0 | 5 | 47 | Agg. |
| | 30 | 1000 | 1000 | 600 | 62000 | GeomDiff | 0 | 0 | 62 | **61835** | 0 | 5 | 47 | **61835** | GeomDiff | 0 | 5 | 47 | DB-KM, DB-Agg. |
| | 30 | 2000 | 750 | 500 | **46500** | GeomDiff | 0 | 0 | 62 | **46500** | 0 | 0 | 62 | **46500** | GeomDiff | 0 | 0 | 62 | Agg., DB-KM, DB-Agg. |
| | 30 | 2000 | 750 | 600 | **46500** | GeomDiff | 0 | 0 | 62 | **46500** | 0 | 0 | 62 | **46500** | GeomDiff | 0 | 0 | 62 | Agg., DB-KM, DB-Agg. |
| | 30 | 2000 | 1000 | 500 | **62000** | GeomDiff | 0 | 0 | 62 | **62000** | 0 | 0 | 62 | **62000** | GeomDiff | 0 | 0 | 62 | Agg., DB-KM, DB-Agg. |
| | 30 | 2000 | 1000 | 600 | **62000** | GeomDiff | 0 | 0 | 62 | **62000** | 0 | 0 | 62 | **62000** | GeomDiff | 0 | 0 | 62 | Agg., DB-KM, DB-Agg. |
| | 50 | 1000 | 750 | 500 | **46500** | GeomDiff | 0 | 0 | 62 | **46500** | 0 | 0 | 62 | **46500** | GeomDiff | 0 | 0 | 62 | Agg., DB-KM, DB-Agg. |
| | 50 | 1000 | 750 | 600 | **46500** | GeomDiff | 0 | 0 | 62 | **46500** | 0 | 0 | 62 | **46500** | GeomDiff | 0 | 0 | 62 | Agg., DB-KM, DB-Agg. |
| | 50 | 1000 | 1000 | 500 | **55575** | Ward | 0 | 12 | 14 | 56088 | 0 | 10 | 22 | 56344 | GeomDiff | 0 | 10 | 23 | Agg. |
| | 50 | 1000 | 1000 | 600 | **59848** | Ward | 0 | 8 | 27 | 59930 | 0 | 7 | 31 | 60086 | GeomDiff | 0 | 7 | 32 | Agg. |
| | 50 | 2000 | 750 | 500 | **46500** | GeomDiff | 0 | 0 | 62 | **46500** | 0 | 0 | 62 | **46500** | GeomDiff | 0 | 0 | 62 | Agg., DB-KM, DB-Agg. |
| | 50 | 2000 | 750 | 600 | **46500** | GeomDiff | 0.1 | 0 | 62 | **46500** | 0 | 0 | 62 | **46500** | GeomDiff | 0 | 0 | 62 | Agg., DB-KM, DB-Agg. |
| | 50 | 2000 | 1000 | 500 | 62000 | GeomDiff | 0 | 0 | 62 | **61626** | 0 | 2 | 51 | 62000 | GeomDiff | 0 | 0 | 62 | DB-KM |
| | 50 | 2000 | 1000 | 600 | **62000** | GeomDiff | 0.1 | 0 | 62 | **62000** | 0 | 0 | 62 | **62000** | GeomDiff | 0 | 0 | 62 | Agg., DB-KM, DB-Agg. |
| | 100 | 1000 | 750 | 500 | **46500** | GeomDiff | 0.0 | 0 | 62 | **46500** | 0.7 | 0 | 62 | **46500** | GeomDiff | 0.0 | 0 | 62 | Agg., DB-KM, DB-Agg. |
| | 100 | 1000 | 750 | 600 | **46500** | GeomDiff | 0.0 | 0 | 62 | **46500** | 0.9 | 0 | 62 | **46500** | GeomDiff | 0.0 | 0 | 62 | Agg., DB-KM, DB-Agg. |
| | 100 | 1000 | 1000 | 500 | **54525** | GeomDiff | 0.0 | 9 | 13 | **54525** | 0.9 | 9 | 13 | **54525** | GeomDiff | 0.0 | 9 | 13 | Agg., DB-KM, DB-Agg. |
| | 100 | 1000 | 1000 | 600 | **59100** | Ward | 0.0 | 7 | 21 | 59107 | 0.8 | 7 | 19 | 59107 | GeomDiff | 0.0 | 7 | 19 | Agg. |
| | 100 | 2000 | 750 | 500 | **46500** | GeomDiff | 0.0 | 0 | 62 | **46500** | 0.6 | 0 | 62 | **46500** | GeomDiff | 0.0 | 0 | 62 | Agg., DB-KM, DB-Agg. |
| | 100 | 2000 | 750 | 600 | **46500** | GeomDiff | 0.0 | 0 | 62 | **46500** | 0.7 | 0 | 62 | **46500** | GeomDiff | 0.0 | 0 | 62 | Agg., DB-KM, DB-Agg. |
| | 100 | 2000 | 1000 | 500 | 62000 | GeomDiff | 0.0 | 0 | 62 | **60246** | 0.8 | 2 | 44 | 61112 | GeomDiff | 0.0 | 1 | 52 | DB-KM |
| | 100 | 2000 | 1000 | 600 | 62000 | GeomDiff | 0.0 | 0 | 62 | **61934** | 0.8 | 1 | 54 | 62000 | GeomDiff | 0.0 | 0 | 62 | DB-KM |
| | 200 | 1000 | 750 | 500 | **46500** | GeomDiff | 0.1 | 0 | 62 | **46500** | 0.6 | 0 | 62 | **46500** | GeomDiff | 0.1 | 0 | 62 | Agg., DB-KM, DB-Agg. |
| | 200 | 1000 | 750 | 600 | **46500** | GeomDiff | 0.1 | 0 | 62 | **46500** | 0.9 | 0 | 62 | **46500** | GeomDiff | 0.1 | 0 | 62 | Agg., DB-KM, DB-Agg. |
| | 200 | 1000 | 1000 | 500 | 54432 | Comp | 0.0 | 9 | 12 | 58459 | 0.6 | 4 | 26 | **54397** | Ward | 0.0 | 8 | 10 | DB-Agg. |
| | 200 | 1000 | 1000 | 600 | **59058** | Comp | 0.0 | 7 | 19 | 61094 | 0.6 | 1 | 52 | 59176 | GeomDiff | 0.1 | 6 | 23 | Agg. |
| | 200 | 2000 | 750 | 500 | **46500** | GeomDiff | 0.1 | 0 | 62 | **46500** | 0.5 | 0 | 62 | **46500** | GeomDiff | 0.1 | 0 | 62 | Agg., DB-KM, DB-Agg. |
| | 200 | 2000 | 750 | 600 | **46500** | GeomDiff | 0.1 | 0 | 62 | **46500** | 0.9 | 0 | 62 | **46500** | GeomDiff | 0.1 | 0 | 62 | Agg., DB-KM, DB-Agg. |
| | 200 | 2000 | 1000 | 500 | 62000 | GeomDiff | 0.1 | 0 | 62 | **61094** | 0.5 | 1 | 52 | **61094** | GeomDiff | 0.1 | 1 | 52 | DB-KM, DB-Agg. |
| | 200 | 2000 | 1000 | 600 | **62000** | GeomDiff | 0.1 | 0 | 62 | **62000** | 0.4 | 0 | 62 | **62000** | GeomDiff | 0.1 | 0 | 62 | Agg., DB-KM, DB-Agg. |

Table H.5: Results of the Model-based Heuristics on Potou (Fixed and Variable Cost)

| | | | | | MB-I | | | | | MB-II | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | F3 | Cost | Time | Gap | M | N | Cost | Time | Gap | M | N | |
| POTOU - 1 | 30 | 1000 | 750 | 500 | **285107** | 7256.4 | 0 | 25 | 120 | 285146 | 10829 | 0.83 | 25 | 112 | MB-I |
| | 30 | 1000 | 750 | 600 | **310238** | 1420.7 | 0 | 9 | 248 | **310238** | 2559.7 | 0 | 9 | 248 | MB-I, MB-II |
| | 30 | 1000 | 1000 | 500 | 298118 | 175.1 | 0 | 47 | 25 | **297618** | 1261.9 | 0 | 45 | 23 | MB-II |
| | 30 | 1000 | 1000 | 600 | 337296 | 824.5 | 0 | 44 | 37 | **337048** | 8370.5 | 0 | 41 | 35 | MB-II |
| | 30 | 2000 | 750 | 500 | 301382 | 10826.9 | 0.69 | 12 | 206 | **301323** | 10840.1 | 1.21 | 12 | 203 | MB-II |
| | 30 | 2000 | 750 | 600 | **315000** | 62.1 | 0 | 0 | 420 | **315000** | 105.1 | 0 | 0 | 420 | MB-I, MB-II |
| | 30 | 2000 | 1000 | 500 | 336179 | 10820.7 | 0.47 | 30 | 80 | **335013** | 10826.3 | 1.1 | 31 | 72 | MB-II |
| | 30 | 2000 | 1000 | 600 | 368604 | 10838.6 | 1.16 | 23 | 121 | **368005** | 10841.4 | 1.68 | 24 | 111 | MB-II |
| | 50 | 1000 | 750 | 500 | **281825** | 10818.2 | 2.34 | 24 | 64 | 281944 | 10830.5 | 2.48 | 26 | 65 | MB-I |
| | 50 | 1000 | 750 | 600 | **309978** | 10826.5 | 1.22 | 10 | 215 | 310074 | 10837.9 | 1.71 | 11 | 207 | MB-I |
| | 50 | 1000 | 1000 | 500 | **288498** | 2282.8 | 0 | 32 | 17 | 288519 | 2083 | 0 | 32 | 14 | MB-I |
| | 50 | 1000 | 1000 | 600 | **328615** | 8019.6 | 0 | 30 | 22 | 328700 | 8607.7 | 0 | 29 | 22 | MB-I |
| | 50 | 2000 | 750 | 500 | 295892 | 10825.3 | 5.92 | 10 | 159 | **295477** | 10845.1 | 6.01 | 11 | 150 | MB-II |
| | 50 | 2000 | 750 | 600 | **315000** | 10842.7 | 1.51 | 0 | 420 | **315000** | 10844.5 | 2.27 | 0 | 420 | MB-I, MB-II |
| | 50 | 2000 | 1000 | 500 | 316686 | 10815.8 | 3.41 | 25 | 35 | **316334** | 10830 | 4.07 | 24 | 37 | MB-II |
| | 50 | 2000 | 1000 | 600 | 355101 | 10817.2 | 5.81 | 23 | 52 | **354073** | 10830.6 | 5.22 | 20 | 56 | MB-II |
| | 100 | 1000 | 750 | 500 | 282723 | 10833.6 | 4.58 | 27 | 66 | **282070** | 10841.6 | 5.41 | 27 | 63 | MB-II |
| | 100 | 1000 | 750 | 600 | **310429** | 10840.0 | 3.68 | 13 | 184 | 310453 | 10849.3 | 3.94 | 13 | 194 | MB-I |
| | 100 | 1000 | 1000 | 500 | **286015** | 8522.4 | 0 | 30 | 7 | 286045 | 10837.1 | 0.76 | 30 | 7 | MB-I |
| | 100 | 1000 | 1000 | 600 | **326942** | 10828.7 | 0.89 | 28 | 16 | 327025 | 10837.2 | 1.1 | 29 | 16 | MB-I |
| | 100 | 2000 | 750 | 500 | 296748 | 10838.6 | 14.15 | 14 | 124 | **295529** | 10853.5 | 13.05 | 10 | 150 | MB-II |
| | 100 | 2000 | 750 | 600 | **316454** | 10850.9 | 9.48 | 3 | 350 | 316566 | 10853.8 | 9.77 | 5 | 287 | MB-I |
| | 100 | 2000 | 1000 | 500 | **310561** | 10828.4 | 9.53 | 21 | 24 | 311068 | 10838.5 | 11.7 | 22 | 23 | MB-I |
| | 100 | 2000 | 1000 | 600 | **350448** | 10830.1 | 11.64 | 21 | 32 | 351910 | 10838.7 | 12.58 | 21 | 35 | MB-I |
| | 200 | 1000 | 750 | 500 | 282260 | 10874.7 | 4.62 | 27 | 62 | **281916** | 10886.2 | 4.59 | 27 | 63 | MB-II |
| | 200 | 1000 | 750 | 600 | 310622 | 10886.1 | 6.13 | 11 | 217 | **310485** | 10897.8 | 6.69 | 10 | 223 | MB-II |
| | 200 | 1000 | 1000 | 500 | **286108** | 10873.5 | 0.73 | 31 | 7 | 286766 | 10881.4 | 2.41 | 34 | 7 | MB-I |
| | 200 | 1000 | 1000 | 600 | **327074** | 10872.4 | 2.01 | 30 | 16 | 327417 | 10883.2 | 2.88 | 33 | 16 | MB-I |
| | 200 | 2000 | 750 | 500 | 294872 | 10886.2 | 11.46 | 8 | 149 | **294686** | 10898.0 | 12.87 | 9 | 143 | MB-II |
| | 200 | 2000 | 750 | 600 | 316399 | 10892.7 | 13.33 | 3 | 339 | **315264** | 10910.0 | 11.43 | 1 | 387 | MB-II |
| | 200 | 2000 | 1000 | 500 | 313351 | 10872.3 | 14.75 | 24 | 21 | **312066** | 10883.0 | 12.78 | 23 | 21 | MB-II |
| | 200 | 2000 | 1000 | 600 | **348588** | 10873.2 | 11.01 | 18 | 33 | 351334 | 10883.7 | 13.63 | 21 | 36 | MB-I |

| | | | | | MB-I | | | | | MB-II | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | F3 | Cost | Time | Gap | M | N | Cost | Time | Gap | M | N | |
| POTOU - 2 | 30 | 1000 | 750 | 500 | **77092** | 4.2 | 0 | 3 | 86 | 77143 | 12 | 0 | 3 | 86 | MB-I |
| | 30 | 1000 | 750 | 600 | **77250** | 1.8 | 0 | 0 | 103 | **77250** | 8.4 | 0 | 0 | 103 | MB-I, MB-II |
| | 30 | 1000 | 1000 | 500 | **90536** | 0.7 | 0 | 16 | 37 | **90536** | 1.1 | 0 | 16 | 37 | MB-I, MB-II |
| | 30 | 1000 | 1000 | 600 | **96846** | 1.8 | 0 | 14 | 42 | 96898 | 2.3 | 0 | 14 | 42 | MB-I |
| | 30 | 2000 | 750 | 500 | **77250** | 2.8 | 0 | 0 | 103 | **77250** | 5.8 | 0 | 0 | 103 | MB-I, MB-II |
| | 30 | 2000 | 750 | 600 | **77250** | 2.5 | 0 | 0 | 103 | **77250** | 7.6 | 0 | 0 | 103 | MB-I, MB-II |
| | 30 | 2000 | 1000 | 500 | **101333** | 1.8 | 0 | 5 | 76 | 101384 | 7.4 | 0 | 5 | 76 | MB-I |
| | 30 | 2000 | 1000 | 600 | **103000** | 2.3 | 0 | 0 | 103 | **103000** | 10.4 | 0 | 0 | 103 | MB-I, MB-II |
| | 50 | 1000 | 750 | 500 | **76927** | 2 | 0 | 3 | 84 | **76927** | 3.5 | 0 | 3 | 84 | MB-I, MB-II |
| | 50 | 1000 | 750 | 600 | **77250** | 1.3 | 0 | 0 | 103 | **77250** | 4.4 | 0 | 0 | 103 | MB-I, MB-II |
| | 50 | 1000 | 1000 | 500 | 87799 | 1.1 | 0 | 14 | 30 | **87738** | 1.5 | 0 | 14 | 28 | MB-II |
| | 50 | 1000 | 1000 | 600 | **94990** | 1.7 | 0 | 13 | 34 | **94990** | 2.5 | 0 | 13 | 34 | MB-I, MB-II |
| | 50 | 2000 | 750 | 500 | **77250** | 1.9 | 0 | 0 | 103 | **77250** | 8 | 0 | 0 | 103 | MB-I, MB-II |
| | 50 | 2000 | 750 | 600 | **77250** | 2.2 | 0 | 0 | 103 | **77250** | 6.9 | 0 | 0 | 103 | MB-I, MB-II |
| | 50 | 2000 | 1000 | 500 | 98953 | 1.9 | 0 | 8 | 52 | **98892** | 2.5 | 0 | 8 | 50 | MB-II |
| | 50 | 2000 | 1000 | 600 | **102402** | 1.7 | 0 | 2 | 86 | **102402** | 4.1 | 0 | 2 | 86 | MB-I, MB-II |
| | 100 | 1000 | 750 | 500 | **76927** | 3.3 | 0 | 3 | 84 | **76927** | 7.3 | 0 | 3 | 84 | MB-I, MB-II |
| | 100 | 1000 | 750 | 600 | **77250** | 1.5 | 0 | 0 | 103 | **77250** | 2.6 | 0 | 0 | 103 | MB-I, MB-II |
| | 100 | 1000 | 1000 | 500 | **85895** | 2.5 | 0 | 16 | 15 | **85895** | 2.3 | 0 | 16 | 15 | MB-I, MB-II |
| | 100 | 1000 | 1000 | 600 | **94382** | 3.3 | 0 | 14 | 25 | **94382** | 3.3 | 0 | 14 | 25 | MB-I, MB-II |
| | 100 | 2000 | 750 | 500 | **77250** | 3.8 | 0 | 0 | 103 | **77250** | 3.2 | 0 | 0 | 103 | MB-I, MB-II |
| | 100 | 2000 | 750 | 600 | **77250** | 1.5 | 0 | 0 | 103 | **77250** | 4.4 | 0 | 0 | 103 | MB-I, MB-II |
| | 100 | 2000 | 1000 | 500 | **97617** | 5.5 | 0 | 7 | 45 | **97617** | 5.4 | 0 | 7 | 45 | MB-I, MB-II |
| | 100 | 2000 | 1000 | 600 | **101911** | 5.0 | 0 | 2 | 83 | **101911** | 8.2 | 0 | 2 | 83 | MB-I, MB-II |
| | 200 | 1000 | 750 | 500 | **76927** | 7.6 | 0 | 3 | 84 | **76927** | 8.1 | 0 | 3 | 84 | MB-I, MB-II |
| | 200 | 1000 | 750 | 600 | **77250** | 4.2 | 0 | 0 | 103 | **77250** | 4.5 | 0 | 0 | 103 | MB-I, MB-II |
| | 200 | 1000 | 1000 | 500 | **85727** | 6.9 | 0 | 17 | 9 | **85727** | 9.6 | 0 | 17 | 9 | MB-I, MB-II |
| | 200 | 1000 | 1000 | 600 | **94382** | 10.2 | 0 | 14 | 25 | **94382** | 13.0 | 0 | 14 | 25 | MB-I, MB-II |
| | 200 | 2000 | 750 | 500 | **77250** | 6.5 | 0 | 0 | 103 | **77250** | 4.1 | 0 | 0 | 103 | MB-I, MB-II |
| | 200 | 2000 | 750 | 600 | **77250** | 1.3 | 0 | 0 | 103 | **77250** | 1.2 | 0 | 0 | 103 | MB-I, MB-II |
| | 200 | 2000 | 1000 | 500 | **97469** | 15.1 | 0 | 7 | 43 | **97469** | 12.5 | 0 | 7 | 43 | MB-I, MB-II |
| | 200 | 2000 | 1000 | 600 | **101911** | 10.2 | 0 | 2 | 83 | **101911** | 10.2 | 0 | 2 | 83 | MB-I, MB-II |

| | | | | | MB-I | | | | | MB-II | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | F3 | Cost | Time | Gap | M | N | Cost | Time | Gap | M | N | |
| POTOU - 3 | 30 | 1000 | 750 | 500 | 48813 | 3.9 | 0 | 3 | 45 | **48701** | 2.5 | 0 | 4 | 39 | MB-II |
| | 30 | 1000 | 750 | 600 | **49500** | 1.6 | 0 | 0 | 66 | **49500** | 3.3 | 0 | 0 | 66 | MB-I, MB-II |
| | 30 | 1000 | 1000 | 500 | 53542 | 1 | 0 | 10 | 13 | **53475** | 1.1 | 0 | 10 | 13 | MB-II |
| | 30 | 1000 | 1000 | 600 | 58842 | 1 | 0 | 10 | 13 | **58775** | 2.2 | 0 | 10 | 13 | MB-II |
| | 30 | 2000 | 750 | 500 | **49500** | 2.2 | 0 | 0 | 66 | **49500** | 7.1 | 0 | 0 | 66 | MB-I, MB-II |
| | 30 | 2000 | 750 | 600 | **49500** | 1.6 | 0 | 0 | 66 | **49500** | 7.5 | 0 | 0 | 66 | MB-I, MB-II |
| | 30 | 2000 | 1000 | 500 | 61894 | 2 | 0 | 6 | 28 | **61857** | 2.4 | 0 | 6 | 28 | MB-II |
| | 30 | 2000 | 1000 | 600 | 65089 | 1.5 | 0 | 1 | 57 | **65052** | 3 | 0 | 1 | 57 | MB-II |
| | 50 | 1000 | 750 | 500 | 48177 | 1.9 | 0 | 5 | 28 | **48139** | 2 | 0 | 5 | 27 | MB-II |
| | 50 | 1000 | 750 | 600 | **49500** | 1.1 | 0 | 0 | 66 | **49500** | 2.6 | 0 | 0 | 66 | MB-I, MB-II |
| | 50 | 1000 | 1000 | 500 | **50747** | 0.5 | 0 | 9 | 5 | **50747** | 0.7 | 0 | 9 | 5 | MB-I, MB-II |
| | 50 | 1000 | 1000 | 600 | 56981 | 0.9 | 0 | 9 | 7 | **56847** | 0.8 | 0 | 9 | 5 | MB-II |
| | 50 | 2000 | 750 | 500 | **49500** | 1.7 | 0 | 0 | 66 | **49500** | 8.2 | 0 | 0 | 66 | MB-I, MB-II |
| | 50 | 2000 | 750 | 600 | **49500** | 1.1 | 0 | 0 | 66 | **49500** | 7 | 0 | 0 | 66 | MB-I, MB-II |
| | 50 | 2000 | 1000 | 500 | **59237** | 0.8 | 0 | 7 | 14 | **59237** | 1.5 | 0 | 7 | 14 | MB-I, MB-II |
| | 50 | 2000 | 1000 | 600 | **63712** | 0.9 | 0 | 3 | 39 | **63712** | 2 | 0 | 3 | 39 | MB-I, MB-II |
| | 100 | 1000 | 750 | 500 | **48136** | 2.9 | 0 | 5 | 27 | **48136** | 7.2 | 0 | 5 | 27 | MB-I, MB-II |
| | 100 | 1000 | 750 | 600 | **49500** | 1.2 | 0 | 0 | 66 | **49500** | 2.4 | 0 | 0 | 66 | MB-I, MB-II |
| | 100 | 1000 | 1000 | 500 | **49864** | 0.9 | 0 | 9 | 2 | **49864** | 0.9 | 0 | 9 | 2 | MB-I, MB-II |
| | 100 | 1000 | 1000 | 600 | **56264** | 2.1 | 0 | 9 | 2 | **56264** | 2.7 | 0 | 9 | 2 | MB-I, MB-II |
| | 100 | 2000 | 750 | 500 | **49500** | 2.0 | 0 | 0 | 66 | **49500** | 3.8 | 0 | 0 | 66 | MB-I, MB-II |
| | 100 | 2000 | 750 | 600 | **49500** | 1.0 | 0 | 0 | 66 | **49500** | 6.5 | 0 | 0 | 66 | MB-I, MB-II |
| | 100 | 2000 | 1000 | 500 | **58241** | 2.4 | 0 | 7 | 8 | **58241** | 3.2 | 0 | 7 | 8 | MB-I, MB-II |
| | 100 | 2000 | 1000 | 600 | **63232** | 3.4 | 0 | 5 | 21 | **63232** | 8.2 | 0 | 5 | 21 | MB-I, MB-II |
| | 200 | 1000 | 750 | 500 | **48136** | 4.0 | 0 | 5 | 27 | **48136** | 14.7 | 0 | 5 | 27 | MB-I, MB-II |
| | 200 | 1000 | 750 | 600 | **49500** | 1.5 | 0 | 0 | 66 | **49500** | 1.5 | 0 | 0 | 66 | MB-I, MB-II |
| | 200 | 1000 | 1000 | 500 | **49787** | 2.1 | 0 | 9 | 0 | **49787** | 2.2 | 0 | 9 | 0 | MB-I, MB-II |
| | 200 | 1000 | 1000 | 600 | **56264** | 3.1 | 0 | 9 | 2 | **56264** | 5.0 | 0 | 9 | 2 | MB-I, MB-II |
| | 200 | 2000 | 750 | 500 | **49500** | 2.3 | 0 | 0 | 66 | **49500** | 2.1 | 0 | 0 | 66 | MB-I, MB-II |
| | 200 | 2000 | 750 | 600 | **49500** | 0.7 | 0 | 0 | 66 | **49500** | 4.7 | 0 | 0 | 66 | MB-I, MB-II |
| | 200 | 2000 | 1000 | 500 | **58105** | 3.6 | 0 | 7 | 5 | **58105** | 8.9 | 0 | 7 | 5 | MB-I, MB-II |
| | 200 | 2000 | 1000 | 600 | **63232** | 5.4 | 0 | 5 | 21 | **63232** | 16.3 | 0 | 5 | 21 | MB-I, MB-II |

| | | | | | MB-I | | | | | MB-II | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | F3 | Cost | Time | Gap | M | N | Cost | Time | Gap | M | N | |
| POTOU - 4 | 30 | 1000 | 750 | 500 | **91674** | 11.7 | 0 | 7 | 63 | **91674** | 16.1 | 0 | 7 | 63 | MB-I, MB-II |
| | 30 | 1000 | 750 | 600 | **95792** | 3.2 | 0 | 1 | 112 | **95792** | 7 | 0 | 1 | 112 | MB-I, MB-II |
| | 30 | 1000 | 1000 | 500 | 98404 | 3 | 0 | 18 | 16 | **98395** | 5.3 | 0 | 18 | 16 | MB-II |
| | 30 | 1000 | 1000 | 600 | 109618 | 4.8 | 0 | 17 | 19 | **109595** | 11.3 | 0 | 18 | 16 | MB-II |
| | 30 | 2000 | 750 | 500 | **95192** | 4.5 | 0 | 1 | 112 | **95192** | 9.7 | 0 | 1 | 112 | MB-I, MB-II |
| | 30 | 2000 | 750 | 600 | **96000** | 4.7 | 0 | 0 | 128 | **96000** | 8.6 | 0 | 0 | 128 | MB-I, MB-II |
| | 30 | 2000 | 1000 | 500 | **113717** | 14 | 0 | 10 | 47 | **113717** | 78.4 | 0 | 10 | 47 | MB-I, MB-II |
| | 30 | 2000 | 1000 | 600 | **120785** | 11.5 | 0 | 6 | 68 | **120785** | 41.3 | 0 | 6 | 68 | MB-I, MB-II |
| | 50 | 1000 | 750 | 500 | 89770 | 34 | 0 | 8 | 32 | **89754** | 45.9 | 0 | 8 | 32 | MB-II |
| | 50 | 1000 | 750 | 600 | **95776** | 38.5 | 0 | 1 | 111 | **95776** | 44 | 0 | 1 | 111 | MB-I, MB-II |
| | 50 | 1000 | 1000 | 500 | **93345** | 5.5 | 0 | 14 | 7 | **93345** | 21.7 | 0 | 14 | 7 | MB-I, MB-II |
| | 50 | 1000 | 1000 | 600 | **105345** | 19 | 0 | 12 | 12 | 105470 | 32.2 | 0 | 11 | 14 | MB-I |
| | 50 | 2000 | 750 | 500 | **93726** | 23.7 | 0 | 2 | 81 | **93726** | 23.6 | 0 | 2 | 81 | MB-I, MB-II |
| | 50 | 2000 | 750 | 600 | **96000** | 8.1 | 0 | 0 | 128 | **96000** | 18.4 | 0 | 0 | 128 | MB-I, MB-II |
| | 50 | 2000 | 1000 | 500 | **104289** | 49.6 | 0 | 10 | 16 | **104289** | 152.7 | 0 | 10 | 16 | MB-I, MB-II |
| | 50 | 2000 | 1000 | 600 | **115008** | 97.7 | 0 | 6 | 42 | **115008** | 117.4 | 0 | 6 | 42 | MB-I, MB-II |
| | 100 | 1000 | 750 | 500 | **89609** | 61.5 | 0 | 7 | 25 | **89609** | 139.2 | 0 | 7 | 25 | MB-I, MB-II |
| | 100 | 1000 | 750 | 600 | **95776** | 66.3 | 0 | 1 | 111 | **95776** | 112.9 | 0 | 1 | 111 | MB-I, MB-II |
| | 100 | 1000 | 1000 | 500 | 90953 | 16.1 | 0 | 10 | 1 | **90940** | 29.5 | 0 | 10 | 1 | MB-II |
| | 100 | 1000 | 1000 | 600 | **103584** | 32.3 | 0 | 10 | 3 | **103584** | 36.6 | 0 | 10 | 3 | MB-I, MB-II |
| | 100 | 2000 | 750 | 500 | **93543** | 227.0 | 0 | 2 | 74 | **93543** | 273.6 | 0 | 2 | 74 | MB-I, MB-II |
| | 100 | 2000 | 750 | 600 | **96000** | 6.3 | 0 | 0 | 128 | **96000** | 17.3 | 0 | 0 | 128 | MB-I, MB-II |
| | 100 | 2000 | 1000 | 500 | **99018** | 33.8 | 0 | 7 | 4 | **99018** | 73.1 | 0 | 7 | 4 | MB-I, MB-II |
| | 100 | 2000 | 1000 | 600 | **111455** | 55.2 | 0 | 6 | 10 | 111471 | 206.7 | 0 | 6 | 11 | MB-I |
| | 200 | 1000 | 750 | 500 | **89609** | 84.2 | 0 | 7 | 25 | **89609** | 122.9 | 0 | 7 | 25 | MB-I, MB-II |
| | 200 | 1000 | 750 | 600 | **95776** | 132.0 | 0 | 1 | 111 | **95776** | 258.5 | 0 | 1 | 111 | MB-I, MB-II |
| | 200 | 1000 | 1000 | 500 | **90905** | 18.1 | 0 | 10 | 1 | **90905** | 40.4 | 0 | 10 | 1 | MB-I, MB-II |
| | 200 | 1000 | 1000 | 600 | **103584** | 33.7 | 0 | 10 | 3 | **103584** | 83.4 | 0 | 10 | 3 | MB-I, MB-II |
| | 200 | 2000 | 750 | 500 | **93543** | 189.9 | 0 | 2 | 74 | **93543** | 302.8 | 0 | 2 | 74 | MB-I, MB-II |
| | 200 | 2000 | 750 | 600 | **96000** | 35.4 | 0 | 0 | 128 | **96000** | 26.0 | 0 | 0 | 128 | MB-I, MB-II |
| | 200 | 2000 | 1000 | 500 | **98973** | 63.3 | 0 | 7 | 2 | **98973** | 189.7 | 0 | 7 | 2 | MB-I, MB-II |
| | 200 | 2000 | 1000 | 600 | **111455** | 171.8 | 0 | 6 | 10 | **111455** | 325.7 | 0 | 6 | 10 | MB-I, MB-II |

Table H.6: Results of the Clustering-based Heuristics on Potou (Fixed and Variable Cost)

| | | | | | Agglomerative (Agg) | | | | | DBSCAN - KMeans (DB-KM) | | | | DBSCAN - Agglomerative (DB-Agg) | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | F3 | Cost | Type | Time | M | N | Cost | Time | M | N | Cost | Type | Time | M | N | |
| POTOU - 1 | 30 | 1000 | 750 | 500 | **288293** | Comp | 0.7 | 25 | 140 | 291100 | 13.2 | 29 | 137 | **288293** | Comp | 0.9 | 25 | 140 | Agg., DB-Agg. |
| | 30 | 1000 | 750 | 600 | 315000 | GeomDiff | 2.5 | 0 | 420 | **311257** | 12.3 | 8 | 274 | 315000 | GeomDiff | 1.5 | 0 | 420 | DB-KM |
| | 30 | 1000 | 1000 | 500 | **306318** | Comp | 0.5 | 55 | 33 | 308525 | 12.8 | 52 | 45 | 307806 | Comp | 0.5 | 53 | 42 | Agg. |
| | 30 | 1000 | 1000 | 600 | **344848** | Comp | 0.4 | 52 | 42 | 351375 | 14.5 | 60 | 45 | 345641 | Comp | 0.5 | 52 | 45 | Agg. |
| | 30 | 2000 | 750 | 500 | 315000 | GeomDiff | 1.6 | 0 | 420 | **304657** | 11.7 | 8 | 274 | 315000 | GeomDiff | 1.1 | 0 | 420 | DB-KM |
| | 30 | 2000 | 750 | 600 | **315000** | GeomDiff | 1.1 | 0 | 420 | **315000** | 14.3 | 0 | 420 | **315000** | GeomDiff | 1 | 0 | 420 | Agg., DB-KM, DB-Agg. |
| | 30 | 2000 | 1000 | 500 | **348267** | Comp | 0.8 | 34 | 98 | 350994 | 12.6 | 37 | 91 | 348478 | Comp | 0.4 | 32 | 108 | Agg. |
| | 30 | 2000 | 1000 | 600 | **376045** | Comp | 0.6 | 24 | 145 | 385474 | 14.5 | 29 | 149 | **376045** | Comp | 0.8 | 24 | 145 | Agg., DB-Agg. |
| | 50 | 1000 | 750 | 500 | 283162 | Ward | 0.8 | 24 | 72 | 283487 | 9.1 | 20 | 80 | **283058** | Ward | 0.9 | 23 | 69 | DB-Agg. |
| | 50 | 1000 | 750 | 600 | 315000 | GeomDiff | 1.1 | 0 | 420 | **312301** | 8.6 | 5 | 270 | 315000 | GeomDiff | 1.5 | 0 | 420 | DB-KM |
| | 50 | 1000 | 1000 | 500 | 289987 | Ward | 1 | 38 | 10 | 291425 | 8.4 | 35 | 14 | **289787** | Ward | 1.5 | 35 | 14 | DB-Agg. |
| | 50 | 1000 | 1000 | 600 | 330677 | Ward | 0.6 | 34 | 22 | 333690 | 8.5 | 33 | 24 | **330186** | Ward | 1.5 | 32 | 23 | DB-Agg. |
| | 50 | 2000 | 750 | 500 | 315000 | GeomDiff | 1.1 | 0 | 420 | 297969 | 8.7 | 10 | 161 | **297611** | Ward | 0.8 | 12 | 152 | DB-Agg. |
| | 50 | 2000 | 750 | 600 | **315000** | GeomDiff | 1.1 | 0 | 420 | **315000** | 9 | 0 | 420 | **315000** | GeomDiff | 1.1 | 0 | 420 | Agg., DB-KM, DB-Agg. |
| | 50 | 2000 | 1000 | 500 | 322004 | Comp | 0.7 | 26 | 36 | 325050 | 9.3 | 28 | 43 | **321505** | Ward | 1.1 | 27 | 43 | DB-Agg. |
| | 50 | 2000 | 1000 | 600 | 358260 | Comp | 0.4 | 19 | 74 | **357487** | 8.5 | 20 | 80 | 357498 | Ward | 1.1 | 22 | 69 | DB-KM |
| | 100 | 1000 | 750 | 500 | **282601** | Ward | 0.8 | 23 | 67 | 295861 | 3.6 | 7 | 94 | 282927 | Ward | 1.4 | 21 | 77 | Agg. |
| | 100 | 1000 | 750 | 600 | **315000** | GeomDiff | 3.0 | 0 | 420 | **315000** | 3.5 | 0 | 420 | **315000** | GeomDiff | 2.6 | 0 | 420 | Agg., DB-KM, DB-Agg. |
| | 100 | 1000 | 1000 | 500 | **287824** | Ward | 1.2 | 34 | 9 | 303698 | 3.6 | 16 | 7 | 290353 | Ward | 1.7 | 30 | 9 | Agg. |
| | 100 | 1000 | 1000 | 600 | **328676** | GeomDiff | 2.9 | 31 | 15 | 344601 | 3.2 | 13 | 15 | 331230 | Ward | 1.4 | 28 | 15 | Agg. |
| | 100 | 2000 | 750 | 500 | 315000 | GeomDiff | 3.0 | 0 | 420 | 301153 | 3.4 | 5 | 131 | **297089** | Ward | 1.6 | 8 | 133 | DB-Agg. |
| | 100 | 2000 | 750 | 600 | **315000** | GeomDiff | 3.1 | 0 | 420 | **315000** | 3.5 | 0 | 420 | **315000** | GeomDiff | 2.8 | 0 | 420 | Agg., DB-KM, DB-Agg. |
| | 100 | 2000 | 1000 | 500 | 313982 | Ward | 1.0 | 21 | 22 | 317014 | 4 | 13 | 15 | **313424** | Ward | 1.3 | 16 | 22 | DB-Agg. |
| | 100 | 2000 | 1000 | 600 | **352127** | Ward | 1.0 | 18 | 36 | 357024 | 3.8 | 11 | 37 | 352307 | Ward | 1.2 | 14 | 42 | Agg. |
| | 200 | 1000 | 750 | 500 | **282601** | Ward | 1.5 | 23 | 67 | 315000 | 2.1 | 0 | 420 | 282690 | Ward | 2.2 | 22 | 67 | Agg. |
| | 200 | 1000 | 750 | 600 | **315000** | GeomDiff | 3.8 | 0 | 420 | **315000** | 1.1 | 0 | 420 | **315000** | GeomDiff | 4.0 | 0 | 420 | Agg., DB-KM, DB-Agg. |
| | 200 | 1000 | 1000 | 500 | 287824 | Ward | 1.4 | 34 | 8 | 345818 | 1.4 | 8 | 3 | **287705** | Ward | 2.5 | 32 | 7 | DB-Agg. |
| | 200 | 1000 | 1000 | 600 | 328702 | Ward | 1.4 | 32 | 15 | 385714 | 1.2 | 4 | 95 | **328614** | Ward | 2.1 | 30 | 15 | DB-Agg. |
| | 200 | 2000 | 750 | 500 | 315000 | GeomDiff | 3.8 | 0 | 420 | 315000 | 1.2 | 0 | 420 | **296202** | Ward | 1.9 | 8 | 138 | DB-Agg. |
| | 200 | 2000 | 750 | 600 | **315000** | GeomDiff | 3.7 | 0 | 420 | **315000** | 1.4 | 0 | 420 | **315000** | GeomDiff | 4.5 | 0 | 420 | Agg., DB-KM, DB-Agg. |
| | 200 | 2000 | 1000 | 500 | **312222** | Ward | 1.5 | 17 | 16 | 352985 | 1.4 | 6 | 26 | **312222** | Ward | 2.3 | 17 | 16 | Agg., DB-Agg. |
| | 200 | 2000 | 1000 | 600 | **351077** | Ward | 1.3 | 15 | 28 | 388903 | 1.3 | 3 | 104 | 351567 | Ward | 1.9 | 14 | 38 | Agg. |

| | | | | | Agglomerative (Agg) | | | | | DBSCAN - KMeans (DB-KM) | | | | DBSCAN - Agglomerative (DB-Agg) | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | F3 | Cost | Type | Time | M | N | Cost | Time | M | N | Cost | Type | Time | M | N | |
| POTOU - 2 | 30 | 1000 | 750 | 500 | 77250 | GeomDiff | 0 | 0 | 103 | **77159** | 0 | 2 | 92 | **77159** | GeomDiff | 0 | 2 | 92 | DB-KM, DB-Agg. |
| | 30 | 1000 | 750 | 600 | **77250** | GeomDiff | 0 | 0 | 103 | **77250** | 0 | 0 | 103 | **77250** | GeomDiff | 0 | 0 | 103 | Agg., DB-KM, DB-Agg. |
| | 30 | 1000 | 1000 | 500 | **91111** | GeomDiff | 0.1 | 16 | 39 | 92068 | 0 | 15 | 44 | 92046 | GeomDiff | 0 | 15 | 44 | Agg. |
| | 30 | 1000 | 1000 | 600 | **97511** | GeomDiff | 0.1 | 16 | 39 | 97968 | 0 | 15 | 44 | 97946 | GeomDiff | 0 | 15 | 44 | Agg. |
| | 30 | 2000 | 750 | 500 | **77250** | GeomDiff | 0.1 | 0 | 103 | **77250** | 0 | 0 | 103 | **77250** | GeomDiff | 0 | 0 | 103 | Agg., DB-KM, DB-Agg. |
| | 30 | 2000 | 750 | 600 | **77250** | GeomDiff | 0.1 | 0 | 103 | **77250** | 0 | 0 | 103 | **77250** | GeomDiff | 0 | 0 | 103 | Agg., DB-KM, DB-Agg. |
| | 30 | 2000 | 1000 | 500 | 103000 | GeomDiff | 0.1 | 0 | 103 | **101767** | 0 | 5 | 77 | 101900 | GeomDiff | 0 | 4 | 82 | DB-KM |
| | 30 | 2000 | 1000 | 600 | **103000** | GeomDiff | 0 | 0 | 103 | **103000** | 0 | 0 | 103 | **103000** | GeomDiff | 0 | 0 | 103 | Agg., DB-KM, DB-Agg. |
| | 50 | 1000 | 750 | 500 | 77250 | GeomDiff | 0 | 0 | 103 | **76927** | 0.6 | 3 | 84 | **76927** | GeomDiff | 0 | 3 | 84 | DB-KM, DB-Agg. |
| | 50 | 1000 | 750 | 600 | **77250** | GeomDiff | 0 | 0 | 103 | **77250** | 0 | 0 | 103 | **77250** | GeomDiff | 0 | 0 | 103 | Agg., DB-KM, DB-Agg. |
| | 50 | 1000 | 1000 | 500 | **87636** | Comp | 0 | 16 | 24 | 88885 | 0.5 | 16 | 32 | 88344 | Ward | 0 | 15 | 32 | Agg. |
| | 50 | 1000 | 1000 | 600 | **95314** | Comp | 0 | 14 | 31 | 95362 | 0 | 14 | 35 | 95378 | Ward | 0 | 14 | 35 | Agg. |
| | 50 | 2000 | 750 | 500 | **77250** | GeomDiff | 0 | 0 | 103 | **77250** | 0 | 0 | 103 | **77250** | GeomDiff | 0 | 0 | 103 | Agg., DB-KM, DB-Agg. |
| | 50 | 2000 | 750 | 600 | **77250** | GeomDiff | 0 | 0 | 103 | **77250** | 0.4 | 0 | 103 | **77250** | GeomDiff | 0 | 0 | 103 | Agg., DB-KM, DB-Agg. |
| | 50 | 2000 | 1000 | 500 | 103000 | GeomDiff | 0 | 0 | 103 | 100131 | 0.5 | 6 | 67 | **99886** | GeomDiff | 0 | 6 | 66 | DB-Agg. |
| | 50 | 2000 | 1000 | 600 | 103000 | GeomDiff | 0 | 0 | 103 | **102568** | 0.4 | 1 | 95 | **102568** | GeomDiff | 0 | 1 | 95 | DB-KM, DB-Agg. |
| | 100 | 1000 | 750 | 500 | 77250 | GeomDiff | 0.1 | 0 | 103 | **77171** | 0.2 | 1 | 97 | **77171** | GeomDiff | 0.1 | 1 | 97 | DB-KM, DB-Agg. |
| | 100 | 1000 | 750 | 600 | **77250** | GeomDiff | 0.1 | 0 | 103 | **77250** | 0 | 0 | 103 | **77250** | GeomDiff | 0.0 | 0 | 103 | Agg., DB-KM, DB-Agg. |
| | 100 | 1000 | 1000 | 500 | **85885** | Ward | 0.0 | 17 | 10 | 87210 | 0 | 14 | 14 | 86624 | Ward | 0.0 | 15 | 14 | Agg. |
| | 100 | 1000 | 1000 | 600 | **94482** | Ward | 0.0 | 13 | 25 | 95282 | 0 | 12 | 25 | 95296 | GeomDiff | 0.0 | 12 | 27 | Agg. |
| | 100 | 2000 | 750 | 500 | **77250** | GeomDiff | 0.1 | 0 | 103 | **77250** | 0 | 0 | 103 | **77250** | GeomDiff | 0.0 | 0 | 103 | Agg., DB-KM, DB-Agg. |
| | 100 | 2000 | 750 | 600 | **77250** | GeomDiff | 0.1 | 0 | 103 | **77250** | 0 | 0 | 103 | **77250** | GeomDiff | 0.1 | 0 | 103 | Agg., DB-KM, DB-Agg. |
| | 100 | 2000 | 1000 | 500 | 103000 | GeomDiff | 0.1 | 0 | 103 | 97991 | 0 | 7 | 44 | **97677** | GeomDiff | 0.0 | 7 | 46 | DB-Agg. |
| | 100 | 2000 | 1000 | 600 | 103000 | GeomDiff | 0.0 | 0 | 103 | **102630** | 0 | 1 | 86 | **102630** | GeomDiff | 0.0 | 1 | 86 | DB-KM, DB-Agg. |
| | 200 | 1000 | 750 | 500 | **77250** | GeomDiff | 0.3 | 0 | 103 | **77250** | 1.5 | 0 | 103 | **77250** | GeomDiff | 0.3 | 0 | 103 | Agg., DB-KM, DB-Agg. |
| | 200 | 1000 | 750 | 600 | **77250** | GeomDiff | 0.2 | 0 | 103 | **77250** | 1.2 | 0 | 103 | **77250** | GeomDiff | 0.3 | 0 | 103 | Agg., DB-KM, DB-Agg. |
| | 200 | 1000 | 1000 | 500 | **85751** | Ward | 0.1 | 17 | 8 | 96982 | 1.4 | 6 | 59 | **85751** | Ward | 0.2 | 17 | 8 | Agg., DB-Agg. |
| | 200 | 1000 | 1000 | 600 | **94482** | Ward | 0.1 | 13 | 25 | 100571 | 1 | 4 | 75 | 94581 | Ward | 0.1 | 12 | 30 | Agg. |
| | 200 | 2000 | 750 | 500 | **77250** | GeomDiff | 0.2 | 0 | 103 | **77250** | 0.9 | 0 | 103 | **77250** | GeomDiff | 0.3 | 0 | 103 | Agg., DB-KM, DB-Agg. |
| | 200 | 2000 | 750 | 600 | **77250** | GeomDiff | 0.2 | 0 | 103 | **77250** | 1.2 | 0 | 103 | **77250** | GeomDiff | 0.3 | 0 | 103 | Agg., DB-KM, DB-Agg. |
| | 200 | 2000 | 1000 | 500 | 103000 | GeomDiff | 0.2 | 0 | 103 | 99099 | 1.2 | 3 | 66 | **98238** | Comp | 0.1 | 6 | 47 | DB-Agg. |
| | 200 | 2000 | 1000 | 600 | **103000** | GeomDiff | 0.2 | 0 | 103 | **103000** | 1.6 | 0 | 103 | **103000** | GeomDiff | 0.1 | 0 | 103 | Agg., DB-KM, DB-Agg. |

| | | | | | | Agglomerative (Agg) | | | | | DBSCAN - KMeans (DB-KM) | | | | | DBSCAN - Agglomerative (DB-Agg) | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | F3 | Cost | Type | Time | M | N | Cost | Time | M | N | Cost | Type | Time | M | N | |
| POTOU - 3 | 30 | 1000 | 750 | 500 | 49500 | GeomDiff | 0 | 0 | 66 | **49104** | 0 | 3 | 46 | **49104** | GeomDiff | 0 | 3 | 46 | DB-KM, DB-Agg. |
| | 30 | 1000 | 750 | 600 | **49500** | GeomDiff | 0 | 0 | 66 | **49500** | 0 | 0 | 66 | **49500** | GeomDiff | 0 | 0 | 66 | Agg., DB-KM, DB-Agg. |
| | 30 | 1000 | 1000 | 500 | 54765 | GeomDiff | 0 | 11 | 15 | 54667 | 0 | 9 | 19 | **54652** | GeomDiff | 0 | 9 | 19 | DB-Agg. |
| | 30 | 1000 | 1000 | 600 | 59865 | GeomDiff | 0.1 | 11 | 15 | **59352** | 0 | 9 | 19 | **59352** | GeomDiff | 0 | 9 | 19 | DB-KM, DB-Agg. |
| | 30 | 2000 | 750 | 500 | **49500** | GeomDiff | 0.1 | 0 | 66 | **49500** | 0 | 0 | 66 | **49500** | GeomDiff | 0 | 0 | 66 | Agg., DB-KM, DB-Agg. |
| | 30 | 2000 | 750 | 600 | **49500** | GeomDiff | 0 | 0 | 66 | **49500** | 0 | 0 | 66 | **49500** | GeomDiff | 0 | 0 | 66 | Agg., DB-KM, DB-Agg. |
| | 30 | 2000 | 1000 | 500 | 66000 | GeomDiff | 0 | 0 | 66 | 61488 | 0 | 6 | 27 | **61441** | Comp | 0 | 6 | 27 | DB-Agg. |
| | 30 | 2000 | 1000 | 600 | 66000 | GeomDiff | 0 | 0 | 66 | **64921** | 0 | 2 | 50 | 65518 | GeomDiff | 0 | 1 | 58 | DB-KM |
| | 50 | 1000 | 750 | 500 | 49500 | GeomDiff | 0.1 | 0 | 66 | **48139** | 0 | 5 | 27 | **48139** | GeomDiff | 0 | 5 | 27 | DB-KM, DB-Agg. |
| | 50 | 1000 | 750 | 600 | **49500** | GeomDiff | 0.1 | 0 | 66 | **49500** | 0 | 0 | 66 | **49500** | GeomDiff | 0 | 0 | 66 | Agg., DB-KM, DB-Agg. |
| | 50 | 1000 | 1000 | 500 | **50732** | Comp | 0 | 9 | 4 | 51290 | 0 | 9 | 9 | 51290 | GeomDiff | 0 | 9 | 9 | Agg. |
| | 50 | 1000 | 1000 | 600 | **56847** | Comp | 0 | 9 | 5 | 56990 | 0 | 9 | 9 | 56990 | GeomDiff | 0 | 9 | 9 | Agg. |
| | 50 | 2000 | 750 | 500 | **49500** | GeomDiff | 0 | 0 | 66 | **49500** | 0 | 0 | 66 | **49500** | GeomDiff | 0 | 0 | 66 | Agg., DB-KM, DB-Agg. |
| | 50 | 2000 | 750 | 600 | **49500** | GeomDiff | 0 | 0 | 66 | **49500** | 0 | 0 | 66 | **49500** | GeomDiff | 0 | 0 | 66 | Agg., DB-KM, DB-Agg. |
| | 50 | 2000 | 1000 | 500 | **59222** | Comp | 0 | 7 | 13 | 59446 | 0 | 7 | 16 | 59446 | GeomDiff | 0 | 7 | 16 | Agg. |
| | 50 | 2000 | 1000 | 600 | 66000 | GeomDiff | 0 | 0 | 66 | **63712** | 0 | 3 | 39 | **63712** | GeomDiff | 0 | 3 | 39 | DB-KM, DB-Agg. |
| | 100 | 1000 | 750 | 500 | 49500 | GeomDiff | 0.0 | 0 | 66 | **48334** | 0 | 3 | 37 | 48421 | GeomDiff | 0.0 | 2 | 45 | DB-KM |
| | 100 | 1000 | 750 | 600 | **49500** | GeomDiff | 0.0 | 0 | 66 | **49500** | 0.1 | 0 | 66 | **49500** | GeomDiff | 0.0 | 0 | 66 | Agg., DB-KM, DB-Agg. |
| | 100 | 1000 | 1000 | 500 | **49905** | GeomDiff | 0.0 | 9 | 0 | **49905** | 0 | 9 | 0 | **49905** | GeomDiff | 0.2 | 9 | 0 | Agg., DB-KM, DB-Agg. |
| | 100 | 1000 | 1000 | 600 | **56505** | GeomDiff | 0.0 | 9 | 0 | **56505** | 0 | 9 | 0 | **56505** | GeomDiff | 0.0 | 9 | 0 | Agg., DB-KM, DB-Agg. |
| | 100 | 2000 | 750 | 500 | **49500** | GeomDiff | 0.0 | 0 | 66 | **49500** | 0 | 0 | 66 | **49500** | GeomDiff | 0.0 | 0 | 66 | Agg., DB-KM, DB-Agg. |
| | 100 | 2000 | 750 | 600 | **49500** | GeomDiff | 0.0 | 0 | 66 | **49500** | 0 | 0 | 66 | **49500** | GeomDiff | 0.0 | 0 | 66 | Agg., DB-KM, DB-Agg. |
| | 100 | 2000 | 1000 | 500 | **58332** | GeomDiff | 0.0 | 7 | 8 | **58332** | 0 | 7 | 8 | **58332** | GeomDiff | 0.0 | 7 | 8 | Agg., DB-KM, DB-Agg. |
| | 100 | 2000 | 1000 | 600 | **63423** | GeomDiff | 0.0 | 4 | 29 | **63423** | 0 | 4 | 29 | 63734 | GeomDiff | 0.0 | 3 | 38 | Agg., DB-KM |
| | 200 | 1000 | 750 | 500 | 49500 | GeomDiff | 0.1 | 0 | 66 | **49073** | 0 | 1 | 56 | **49073** | GeomDiff | 0.0 | 1 | 56 | DB-KM, DB-Agg. |
| | 200 | 1000 | 750 | 600 | **49500** | GeomDiff | 0.1 | 0 | 66 | **49500** | 0 | 0 | 66 | **49500** | GeomDiff | 0.0 | 0 | 66 | Agg., DB-KM, DB-Agg. |
| | 200 | 1000 | 1000 | 500 | **49787** | GeomDiff | 0.1 | 9 | 0 | 58196 | 0 | 5 | 23 | 58196 | GeomDiff | 0.0 | 5 | 23 | Agg. |
| | 200 | 1000 | 1000 | 600 | **56387** | GeomDiff | 0.1 | 9 | 0 | 62070 | 0 | 4 | 36 | 62070 | GeomDiff | 0.0 | 4 | 36 | Agg. |
| | 200 | 2000 | 750 | 500 | **49500** | GeomDiff | 0.1 | 0 | 66 | **49500** | 0 | 0 | 66 | **49500** | GeomDiff | 0.0 | 0 | 66 | Agg., DB-KM, DB-Agg. |
| | 200 | 2000 | 750 | 600 | **49500** | GeomDiff | 0.1 | 0 | 66 | **49500** | 0 | 0 | 66 | **49500** | GeomDiff | 0.0 | 0 | 66 | Agg., DB-KM, DB-Agg. |
| | 200 | 2000 | 1000 | 500 | **58105** | GeomDiff | 0.1 | 7 | 5 | 62866 | 0 | 3 | 41 | 62866 | GeomDiff | 0.1 | 3 | 41 | Agg. |
| | 200 | 2000 | 1000 | 600 | **63547** | GeomDiff | 0.2 | 5 | 16 | 65006 | 0 | 2 | 46 | 65006 | GeomDiff | 0.0 | 2 | 46 | Agg. |

| | DLim | F1 | F2 | F3 | Agglomerative (Agg) Cost | Type | Time | M | N | DBSCAN - KMeans (DB-KM) Cost | Time | M | N | DBSCAN - Agglomerative (DB-Agg) Cost | Type | Time | M | N | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| POTOU - 4 | 30 | 1000 | 750 | 500 | 96000 | GeomDiff | 0.1 | 0 | 128 | **92018** | 1.3 | 8 | 59 | 93004 | Comp | 0 | 6 | 78 | DB-KM |
| | 30 | 1000 | 750 | 600 | **96000** | GeomDiff | 0.2 | 0 | 128 | **96000** | 1.1 | 0 | 128 | **96000** | GeomDiff | 0 | 0 | 128 | Agg., DB-KM, DB-Agg. |
| | 30 | 1000 | 1000 | 500 | 100718 | Comp | 0 | 20 | 19 | **100596** | 1.1 | 16 | 27 | 101937 | Comp | 0 | 18 | 27 | DB-KM |
| | 30 | 1000 | 1000 | 600 | 111961 | Comp | 0.1 | 19 | 24 | **110565** | 1.3 | 16 | 27 | 112037 | Comp | 0 | 18 | 27 | DB-KM |
| | 30 | 2000 | 750 | 500 | 96000 | GeomDiff | 0.1 | 0 | 128 | **95694** | 1 | 1 | 115 | 96000 | GeomDiff | 0.1 | 0 | 128 | DB-KM |
| | 30 | 2000 | 750 | 600 | **96000** | GeomDiff | 0.1 | 0 | 128 | **96000** | 0.8 | 0 | 128 | **96000** | GeomDiff | 0.1 | 0 | 128 | Agg., DB-KM, DB-Agg. |
| | 30 | 2000 | 1000 | 500 | 117639 | Comp | 0 | 12 | 49 | **114302** | 0.9 | 11 | 44 | 117080 | GeomDiff | 0.1 | 12 | 47 | DB-KM |
| | 30 | 2000 | 1000 | 600 | 128000 | GeomDiff | 0.1 | 0 | 128 | **122203** | 1.1 | 8 | 61 | 127170 | GeomDiff | 0.1 | 1 | 119 | DB-KM |
| | 50 | 1000 | 750 | 500 | **91015** | Comp | 0.1 | 8 | 39 | 91066 | 1 | 8 | 34 | 91332 | GeomDiff | 0.2 | 7 | 44 | Agg. |
| | 50 | 1000 | 750 | 600 | **96000** | GeomDiff | 0.1 | 0 | 128 | **96000** | 1.4 | 0 | 128 | **96000** | GeomDiff | 0.2 | 0 | 128 | Agg., DB-KM, DB-Agg. |
| | 50 | 1000 | 1000 | 500 | **93748** | Ward | 0 | 16 | 3 | 95218 | 0.8 | 15 | 9 | 93956 | GeomDiff | 0.2 | 14 | 7 | Agg. |
| | 50 | 1000 | 1000 | 600 | 106131 | Comp | 0.1 | 14 | 8 | 106853 | 1.4 | 13 | 14 | **106056** | GeomDiff | 0.2 | 14 | 7 | DB-Agg. |
| | 50 | 2000 | 750 | 500 | 96000 | GeomDiff | 0.1 | 0 | 128 | 95416 | 1.2 | 1 | 107 | **95377** | GeomDiff | 0.2 | 2 | 92 | DB-Agg. |
| | 50 | 2000 | 750 | 600 | **96000** | GeomDiff | 0.1 | 0 | 128 | **96000** | 1 | 0 | 128 | **96000** | GeomDiff | 0.2 | 0 | 128 | Agg., DB-KM, DB-Agg. |
| | 50 | 2000 | 1000 | 500 | 107342 | Comp | 0 | 12 | 16 | 107490 | 1 | 12 | 16 | **107167** | GeomDiff | 0.2 | 12 | 15 | DB-Agg. |
| | 50 | 2000 | 1000 | 600 | 117665 | Comp | 0.1 | 8 | 39 | **116800** | 1.4 | 7 | 40 | 117935 | GeomDiff | 0.1 | 5 | 57 | DB-KM |
| | 100 | 1000 | 750 | 500 | **90546** | Ward | 0.1 | 7 | 22 | 92573 | 0.8 | 6 | 21 | 90740 | Ward | 0.1 | 7 | 18 | Agg. |
| | 100 | 1000 | 750 | 600 | **96000** | GeomDiff | 0.2 | 0 | 128 | **96000** | 0.5 | 0 | 128 | **96000** | GeomDiff | 0.2 | 0 | 128 | Agg., DB-KM, DB-Agg. |
| | 100 | 1000 | 1000 | 500 | 91217 | GeomDiff | 0.2 | 10 | 1 | **91143** | 1 | 8 | 1 | 91294 | GeomDiff | 0.3 | 9 | 1 | DB-KM |
| | 100 | 1000 | 1000 | 600 | **103917** | GeomDiff | 0.2 | 10 | 1 | 106907 | 0.8 | 8 | 0 | 103994 | GeomDiff | 0.3 | 9 | 1 | Agg. |
| | 100 | 2000 | 750 | 500 | 96000 | GeomDiff | 0.2 | 0 | 128 | **93900** | 1 | 2 | 73 | 94336 | Ward | 0.0 | 1 | 97 | DB-KM |
| | 100 | 2000 | 750 | 600 | **96000** | GeomDiff | 0.2 | 0 | 128 | **96000** | 0.7 | 0 | 128 | **96000** | GeomDiff | 0.3 | 0 | 128 | Agg., DB-KM, DB-Agg. |
| | 100 | 2000 | 1000 | 500 | 99383 | GeomDiff | 0.2 | 8 | 1 | **99143** | 1.4 | 8 | 1 | 99383 | GeomDiff | 0.2 | 8 | 1 | DB-KM |
| | 100 | 2000 | 1000 | 600 | **112083** | GeomDiff | 0.1 | 8 | 1 | 112302 | 0.6 | 7 | 2 | **112083** | GeomDiff | 0.3 | 8 | 1 | Agg., DB-Agg. |
| | 200 | 1000 | 750 | 500 | **90546** | Ward | 0.1 | 7 | 22 | 94138 | 0.9 | 3 | 61 | **90546** | Ward | 0.3 | 7 | 22 | Agg., DB-Agg. |
| | 200 | 1000 | 750 | 600 | **96000** | GeomDiff | 0.1 | 0 | 128 | **96000** | 0.6 | 0 | 128 | **96000** | GeomDiff | 0.3 | 0 | 128 | Agg., DB-KM, DB-Agg. |
| | 200 | 1000 | 1000 | 500 | **91314** | GeomDiff | 0.1 | 10 | 0 | 99707 | 1.2 | 5 | 0 | **91314** | GeomDiff | 0.3 | 10 | 0 | Agg., DB-Agg. |
| | 200 | 1000 | 1000 | 600 | **104059** | Ward | 0.2 | 10 | 1 | 117568 | 0.5 | 3 | 26 | **104059** | Ward | 0.1 | 10 | 1 | Agg., DB-Agg. |
| | 200 | 2000 | 750 | 500 | 96000 | GeomDiff | 0.1 | 0 | 128 | **95592** | 0.9 | 1 | 88 | 96000 | GeomDiff | 0.2 | 0 | 128 | DB-KM |
| | 200 | 2000 | 750 | 600 | **96000** | GeomDiff | 0.1 | 0 | 128 | **96000** | 0.9 | 0 | 128 | **96000** | GeomDiff | 0.2 | 0 | 128 | Agg., DB-KM, DB-Agg. |
| | 200 | 2000 | 1000 | 500 | **99341** | GeomDiff | 0.1 | 7 | 0 | 110368 | 0.7 | 3 | 26 | **99341** | GeomDiff | 0.2 | 7 | 0 | Agg., DB-Agg. |
| | 200 | 2000 | 1000 | 600 | **112141** | GeomDiff | 0.1 | 7 | 0 | 117507 | 0.9 | 5 | 0 | **112141** | GeomDiff | 0.2 | 7 | 0 | Agg., DB-Agg. |

Table H.7: Results of the Model-based Heuristics on Ruhiira (Fixed and Variable Cost)

| | | | | | MB-I | | | | | MB-II | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | F3 | Cost | Time | Gap | M | N | Cost | Time | Gap | M | N | |
| RUHIIRA- 1 | 30 | 1000 | 750 | 500 | **101874** | 4.7 | 0 | 1 | 129 | **101874** | 4.9 | 0 | 1 | 129 | MB-I, MB-II |
| | 30 | 1000 | 750 | 600 | **102000** | 2.9 | 0 | 0 | 136 | **102000** | 5.8 | 0 | 0 | 136 | MB-I, MB-II |
| | 30 | 1000 | 1000 | 500 | 129803 | 1.5 | 0 | 13 | 91 | **129636** | 2.1 | 0 | 14 | 88 | MB-II |
| | 30 | 1000 | 1000 | 600 | **133916** | 4.1 | 0 | 7 | 109 | **133916** | 20.7 | 0 | 7 | 109 | MB-I, MB-II |
| | 30 | 2000 | 750 | 500 | **102000** | 2.8 | 0 | 0 | 136 | **102000** | 5 | 0 | 0 | 136 | MB-I, MB-II |
| | 30 | 2000 | 750 | 600 | **102000** | 2.6 | 0 | 0 | 136 | **102000** | 6 | 0 | 0 | 136 | MB-I, MB-II |
| | 30 | 2000 | 1000 | 500 | **135124** | 3.5 | 0 | 1 | 129 | **135124** | 7.5 | 0 | 1 | 129 | MB-I, MB-II |
| | 30 | 2000 | 1000 | 600 | **135824** | 3.2 | 0 | 1 | 129 | **135824** | 5.7 | 0 | 1 | 129 | MB-I, MB-II |
| | 50 | 1000 | 750 | 500 | **101610** | 4 | 0 | 1 | 127 | **101610** | 5.7 | 0 | 1 | 127 | MB-I, MB-II |
| | 50 | 1000 | 750 | 600 | **102000** | 2.2 | 0 | 0 | 136 | **102000** | 5.5 | 0 | 0 | 136 | MB-I, MB-II |
| | 50 | 1000 | 1000 | 500 | 126078 | 1 | 0 | 19 | 62 | **125865** | 1.8 | 0 | 20 | 59 | MB-II |
| | 50 | 1000 | 1000 | 600 | **132087** | 2.8 | 0 | 10 | 91 | **132087** | 3.8 | 0 | 10 | 91 | MB-I, MB-II |
| | 50 | 2000 | 750 | 500 | **102000** | 4 | 0 | 0 | 136 | **102000** | 8.4 | 0 | 0 | 136 | MB-I, MB-II |
| | 50 | 2000 | 750 | 600 | **102000** | 2.9 | 0 | 0 | 136 | **102000** | 7.9 | 0 | 0 | 136 | MB-I, MB-II |
| | 50 | 2000 | 1000 | 500 | **134360** | 2.8 | 0 | 1 | 127 | **134360** | 6.2 | 0 | 1 | 127 | MB-I, MB-II |
| | 50 | 2000 | 1000 | 600 | **135260** | 2.9 | 0 | 1 | 127 | **135260** | 8.9 | 0 | 1 | 127 | MB-I, MB-II |
| | 100 | 1000 | 750 | 500 | **101610** | 3.0 | 0 | 1 | 127 | **101610** | 4.4 | 0 | 1 | 127 | MB-I, MB-II |
| | 100 | 1000 | 750 | 600 | **102000** | 1.9 | 0 | 0 | 136 | **102000** | 3.7 | 0 | 0 | 136 | MB-I, MB-II |
| | 100 | 1000 | 1000 | 500 | **123294** | 2.3 | 0 | 21 | 43 | **123294** | 5.2 | 0 | 21 | 43 | MB-I, MB-II |
| | 100 | 1000 | 1000 | 600 | **131203** | 2.9 | 0 | 12 | 74 | **131203** | 3.3 | 0 | 12 | 74 | MB-I, MB-II |
| | 100 | 2000 | 750 | 500 | **102000** | 2.4 | 0 | 0 | 136 | **102000** | 5.5 | 0 | 0 | 136 | MB-I, MB-II |
| | 100 | 2000 | 750 | 600 | **102000** | 2.5 | 0 | 0 | 136 | **102000** | 7.2 | 0 | 0 | 136 | MB-I, MB-II |
| | 100 | 2000 | 1000 | 500 | **133551** | 4.1 | 0 | 4 | 107 | **133551** | 3.9 | 0 | 4 | 107 | MB-I, MB-II |
| | 100 | 2000 | 1000 | 600 | **135175** | 3.9 | 0 | 1 | 126 | **135175** | 4.8 | 0 | 1 | 126 | MB-I, MB-II |
| | 200 | 1000 | 750 | 500 | **101610** | 4.1 | 0 | 1 | 127 | **101610** | 5.7 | 0 | 1 | 127 | MB-I, MB-II |
| | 200 | 1000 | 750 | 600 | **102000** | 2.7 | 0 | 0 | 136 | **102000** | 3.7 | 0 | 0 | 136 | MB-I, MB-II |
| | 200 | 1000 | 1000 | 500 | **123052** | 7.2 | 0 | 20 | 38 | **123052** | 9.2 | 0 | 20 | 38 | MB-I, MB-II |
| | 200 | 1000 | 1000 | 600 | **131203** | 5.7 | 0 | 12 | 74 | **131203** | 6.8 | 0 | 12 | 74 | MB-I, MB-II |
| | 200 | 2000 | 750 | 500 | **102000** | 4.4 | 0 | 0 | 136 | **102000** | 4.6 | 0 | 0 | 136 | MB-I, MB-II |
| | 200 | 2000 | 750 | 600 | **102000** | 2.0 | 0 | 0 | 136 | **102000** | 2.7 | 0 | 0 | 136 | MB-I, MB-II |
| | 200 | 2000 | 1000 | 500 | **133512** | 7.0 | 0 | 4 | 106 | **133512** | 9.5 | 0 | 4 | 106 | MB-I, MB-II |
| | 200 | 2000 | 1000 | 600 | **135175** | 5.7 | 0 | 1 | 126 | **135175** | 13.4 | 0 | 1 | 126 | MB-I, MB-II |

| | | | | | MB-I | | | | | MB-II | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | F3 | Cost | Time | Gap | M | N | Cost | Time | Gap | M | N | |
| RUHIIRA- 2 | 30 | 1000 | 750 | 500 | **181424** | 11.5 | 0 | 3 | 222 | **181424** | 18.5 | 0 | 3 | 222 | MB-I, MB-II |
| | 30 | 1000 | 750 | 600 | **182250** | 8.9 | 0 | 0 | 243 | **182250** | 15.9 | 0 | 0 | 243 | MB-I, MB-II |
| | 30 | 1000 | 1000 | 500 | 226765 | 5.2 | 0 | 28 | 140 | **226490** | 8.5 | 0 | 28 | 139 | MB-II |
| | 30 | 1000 | 1000 | 600 | 236463 | 12 | 0 | 16 | 176 | **236288** | 13 | 0 | 16 | 175 | MB-II |
| | 30 | 2000 | 750 | 500 | **182250** | 8.6 | 0 | 0 | 243 | **182250** | 39.2 | 0 | 0 | 243 | MB-I, MB-II |
| | 30 | 2000 | 750 | 600 | **182250** | 8.8 | 0 | 0 | 243 | **182250** | 16.1 | 0 | 0 | 243 | MB-I, MB-II |
| | 30 | 2000 | 1000 | 500 | **239713** | 8.7 | 0 | 4 | 217 | **239713** | 16.1 | 0 | 4 | 217 | MB-I, MB-II |
| | 30 | 2000 | 1000 | 600 | **242009** | 10.4 | 0 | 2 | 228 | **242009** | 16.9 | 0 | 2 | 228 | MB-I, MB-II |
| | 50 | 1000 | 750 | 500 | **181243** | 10.5 | 0 | 3 | 220 | **181243** | 13.4 | 0 | 3 | 220 | MB-I, MB-II |
| | 50 | 1000 | 750 | 600 | **182250** | 8.8 | 0 | 0 | 243 | **182250** | 13.2 | 0 | 0 | 243 | MB-I, MB-II |
| | 50 | 1000 | 1000 | 500 | 220800 | 6.2 | 0 | 28 | 117 | **220412** | 8.1 | 0 | 30 | 110 | MB-II |
| | 50 | 1000 | 1000 | 600 | 233509 | 9.1 | 0 | 22 | 143 | **232978** | 10.7 | 0 | 22 | 137 | MB-II |
| | 50 | 2000 | 750 | 500 | **182250** | 8.1 | 0 | 0 | 243 | **182250** | 16.7 | 0 | 0 | 243 | MB-I, MB-II |
| | 50 | 2000 | 750 | 600 | **182250** | 9.5 | 0 | 0 | 243 | **182250** | 12.5 | 0 | 0 | 243 | MB-I, MB-II |
| | 50 | 2000 | 1000 | 500 | **237907** | 8.3 | 0 | 7 | 195 | **237907** | 13.9 | 0 | 7 | 195 | MB-I, MB-II |
| | 50 | 2000 | 1000 | 600 | **241255** | 8.3 | 0 | 3 | 217 | **241255** | 14.3 | 0 | 3 | 217 | MB-I, MB-II |
| | 100 | 1000 | 750 | 500 | **181266** | 12.1 | 0 | 3 | 217 | **181266** | 15.9 | 0 | 3 | 217 | MB-I, MB-II |
| | 100 | 1000 | 750 | 600 | **182250** | 8.7 | 0 | 0 | 243 | **182250** | 11.9 | 0 | 0 | 243 | MB-I, MB-II |
| | 100 | 1000 | 1000 | 500 | **213350** | 6.6 | 0 | 38 | 53 | 213358 | 9.4 | 0 | 38 | 51 | MB-I |
| | 100 | 1000 | 1000 | 600 | **230247** | 14.1 | 0 | 24 | 104 | **230247** | 14.7 | 0 | 24 | 104 | MB-I, MB-II |
| | 100 | 2000 | 750 | 500 | **182250** | 10.9 | 0 | 0 | 243 | **182250** | 13.8 | 0 | 0 | 243 | MB-I, MB-II |
| | 100 | 2000 | 750 | 600 | **182250** | 6.1 | 0 | 0 | 243 | **182250** | 12.5 | 0 | 0 | 243 | MB-I, MB-II |
| | 100 | 2000 | 1000 | 500 | **233606** | 13.2 | 0 | 10 | 155 | **233606** | 23.5 | 0 | 10 | 155 | MB-I, MB-II |
| | 100 | 2000 | 1000 | 600 | **240321** | 20.7 | 0 | 3 | 206 | **240321** | 19.7 | 0 | 3 | 206 | MB-I, MB-II |
| | 200 | 1000 | 750 | 500 | **181266** | 22.7 | 0 | 3 | 217 | **181266** | 25.4 | 0 | 3 | 217 | MB-I, MB-II |
| | 200 | 1000 | 750 | 600 | **182250** | 9.8 | 0 | 0 | 243 | **182250** | 16.0 | 0 | 0 | 243 | MB-I, MB-II |
| | 200 | 1000 | 1000 | 500 | **212623** | 19.4 | 0 | 36 | 42 | **212623** | 24.4 | 0 | 36 | 42 | MB-I, MB-II |
| | 200 | 1000 | 1000 | 600 | **230247** | 17.9 | 0 | 24 | 104 | **230247** | 26.8 | 0 | 24 | 104 | MB-I, MB-II |
| | 200 | 2000 | 750 | 500 | **182250** | 24.2 | 0 | 0 | 243 | **182250** | 31.3 | 0 | 0 | 243 | MB-I, MB-II |
| | 200 | 2000 | 750 | 600 | **182250** | 5.9 | 0 | 0 | 243 | **182250** | 7.9 | 0 | 0 | 243 | MB-I, MB-II |
| | 200 | 2000 | 1000 | 500 | **233033** | 43.8 | 0 | 10 | 143 | **233033** | 46.5 | 0 | 10 | 143 | MB-I, MB-II |
| | 200 | 2000 | 1000 | 600 | **240321** | 42.0 | 0 | 3 | 206 | **240321** | 55.1 | 0 | 3 | 206 | MB-I, MB-II |

| | DLim | F1 | F2 | F3 | MB-I Cost | MB-I Time | MB-I Gap | MB-I M | MB-I N | MB-II Cost | MB-II Time | MB-II Gap | MB-II M | MB-II N | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| RUHIIRA- 3 | 30 | 1000 | 750 | 500 | 201369 | 12.2 | 0 | 8 | 218 | **201328** | 17.8 | 0 | 8 | 217 | MB-II |
| | 30 | 1000 | 750 | 600 | **203250** | 9.8 | 0 | 0 | 271 | **203250** | 23.9 | 0 | 0 | 271 | MB-I, MB-II |
| | 30 | 1000 | 1000 | 500 | **242448** | 7.2 | 0 | 32 | 129 | 242482 | 12.8 | 0 | 31 | 131 | MB-I |
| | 30 | 1000 | 1000 | 600 | **256278** | 9.8 | 0 | 26 | 146 | **256278** | 18.9 | 0 | 26 | 146 | MB-I, MB-II |
| | 30 | 2000 | 750 | 500 | **203250** | 11.8 | 0 | 0 | 271 | **203250** | 18.2 | 0 | 0 | 271 | MB-I, MB-II |
| | 30 | 2000 | 750 | 600 | **203250** | 11.2 | 0 | 0 | 271 | **203250** | 17.1 | 0 | 0 | 271 | MB-I, MB-II |
| | 30 | 2000 | 1000 | 500 | 263152 | 10.6 | 0 | 10 | 206 | **263116** | 19.6 | 0 | 12 | 196 | MB-II |
| | 30 | 2000 | 1000 | 600 | **268774** | 11.4 | 0 | 6 | 228 | **268774** | 25.1 | 0 | 6 | 228 | MB-I, MB-II |
| | 50 | 1000 | 750 | 500 | **200429** | 13.7 | 0 | 8 | 205 | **200429** | 16.3 | 0 | 8 | 205 | MB-I, MB-II |
| | 50 | 1000 | 750 | 600 | **203250** | 10 | 0 | 0 | 271 | **203250** | 18.1 | 0 | 0 | 271 | MB-I, MB-II |
| | 50 | 1000 | 1000 | 500 | 233525 | 6 | 0 | 33 | 92 | **233363** | 10.7 | 0 | 34 | 89 | MB-II |
| | 50 | 1000 | 1000 | 600 | 250909 | 8.8 | 0 | 29 | 107 | **250654** | 14.5 | 0 | 30 | 102 | MB-II |
| | 50 | 2000 | 750 | 500 | **203250** | 12.7 | 0 | 0 | 271 | **203250** | 28.6 | 0 | 0 | 271 | MB-I, MB-II |
| | 50 | 2000 | 750 | 600 | **203250** | 9.3 | 0 | 0 | 271 | **203250** | 18 | 0 | 0 | 271 | MB-I, MB-II |
| | 50 | 2000 | 1000 | 500 | 257649 | 14.6 | 0 | 11 | 182 | **257480** | 17.6 | 0 | 12 | 175 | MB-II |
| | 50 | 2000 | 1000 | 600 | **265720** | 12.4 | 0 | 7 | 206 | **265720** | 15.1 | 0 | 7 | 206 | MB-I, MB-II |
| | 100 | 1000 | 750 | 500 | **200373** | 28.3 | 0 | 8 | 199 | **200373** | 37.1 | 0 | 8 | 199 | MB-I, MB-II |
| | 100 | 1000 | 750 | 600 | **203250** | 12.0 | 0 | 0 | 271 | **203250** | 14.5 | 0 | 0 | 271 | MB-I, MB-II |
| | 100 | 1000 | 1000 | 500 | **226787** | 15.1 | 0 | 35 | 49 | **226787** | 27.5 | 0 | 35 | 49 | MB-I, MB-II |
| | 100 | 1000 | 1000 | 600 | **247984** | 23.1 | 0 | 29 | 76 | **247984** | 44.2 | 0 | 29 | 76 | MB-I, MB-II |
| | 100 | 2000 | 750 | 500 | **203250** | 25.1 | 0 | 0 | 271 | **203250** | 37.0 | 0 | 0 | 271 | MB-I, MB-II |
| | 100 | 2000 | 750 | 600 | **203250** | 8.5 | 0 | 0 | 271 | **203250** | 13.4 | 0 | 0 | 271 | MB-I, MB-II |
| | 100 | 2000 | 1000 | 500 | **251524** | 35.3 | 0 | 18 | 98 | **251524** | 69.7 | 0 | 18 | 98 | MB-I, MB-II |
| | 100 | 2000 | 1000 | 600 | **264146** | 35.6 | 0 | 8 | 183 | **264146** | 48.0 | 0 | 8 | 183 | MB-I, MB-II |
| | 200 | 1000 | 750 | 500 | 200373 | 47.8 | 0 | 8 | 199 | **200339** | 51.2 | 0 | 8 | 200 | MB-II |
| | 200 | 1000 | 750 | 600 | **203250** | 15.0 | 0 | 0 | 271 | **203250** | 21.5 | 0 | 0 | 271 | MB-I, MB-II |
| | 200 | 1000 | 1000 | 500 | **226481** | 26.4 | 0 | 35 | 41 | **226481** | 26.0 | 0 | 35 | 41 | MB-I, MB-II |
| | 200 | 1000 | 1000 | 600 | **247967** | 39.3 | 0 | 29 | 76 | **247967** | 35.9 | 0 | 29 | 76 | MB-I, MB-II |
| | 200 | 2000 | 750 | 500 | **203250** | 78.8 | 0 | 0 | 271 | **203250** | 61.1 | 0 | 0 | 271 | MB-I, MB-II |
| | 200 | 2000 | 750 | 600 | **203250** | 9.8 | 0 | 0 | 271 | **203250** | 13.4 | 0 | 0 | 271 | MB-I, MB-II |
| | 200 | 2000 | 1000 | 500 | **250939** | 191.9 | 0 | 17 | 94 | **250939** | 226.7 | 0 | 17 | 94 | MB-I, MB-II |
| | 200 | 2000 | 1000 | 600 | **264121** | 153.0 | 0 | 8 | 183 | **264121** | 178.6 | 0 | 8 | 183 | MB-I, MB-II |

| | | | | | MB-I | | | | | MB-II | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | F3 | Cost | Time | Gap | M | N | Cost | Time | Gap | M | N | |
| RUHIIRA- 4 | 30 | 1000 | 750 | 500 | **181500** | 9.1 | 0 | 0 | 242 | **181500** | 13.6 | 0 | 0 | 242 | MB-I, MB-II |
| | 30 | 1000 | 750 | 600 | **181500** | 10.3 | 0 | 0 | 242 | **181500** | 14.7 | 0 | 0 | 242 | MB-I, MB-II |
| | 30 | 1000 | 1000 | 500 | **231227** | 6.3 | 0 | 27 | 154 | **231227** | 8.7 | 0 | 27 | 154 | MB-I, MB-II |
| | 30 | 1000 | 1000 | 600 | **239191** | 7.3 | 0 | 15 | 190 | **239191** | 13.4 | 0 | 15 | 190 | MB-I, MB-II |
| | 30 | 2000 | 750 | 500 | **181500** | 8.3 | 0 | 0 | 242 | **181500** | 15 | 0 | 0 | 242 | MB-I, MB-II |
| | 30 | 2000 | 750 | 600 | **181500** | 7.5 | 0 | 0 | 242 | **181500** | 15.2 | 0 | 0 | 242 | MB-I, MB-II |
| | 30 | 2000 | 1000 | 500 | **241546** | 8.4 | 0 | 1 | 236 | **241546** | 13.6 | 0 | 1 | 236 | MB-I, MB-II |
| | 30 | 2000 | 1000 | 600 | **242000** | 7.6 | 0 | 0 | 242 | **242000** | 29.8 | 0 | 0 | 242 | MB-I, MB-II |
| | 50 | 1000 | 750 | 500 | **181424** | 6.7 | 0 | 1 | 234 | **181424** | 18.2 | 0 | 1 | 234 | MB-I, MB-II |
| | 50 | 1000 | 750 | 600 | **181500** | 6.5 | 0 | 0 | 242 | **181500** | 14.7 | 0 | 0 | 242 | MB-I, MB-II |
| | 50 | 1000 | 1000 | 500 | 225523 | 4.7 | 0 | 34 | 115 | **225093** | 7.1 | 0 | 34 | 113 | MB-II |
| | 50 | 1000 | 1000 | 600 | 237444 | 6.4 | 0 | 20 | 163 | **236955** | 9.8 | 0 | 22 | 152 | MB-II |
| | 50 | 2000 | 750 | 500 | **181500** | 8 | 0 | 0 | 242 | **181500** | 14.5 | 0 | 0 | 242 | MB-I, MB-II |
| | 50 | 2000 | 750 | 600 | **181500** | 7.8 | 0 | 0 | 242 | **181500** | 28.9 | 0 | 0 | 242 | MB-I, MB-II |
| | 50 | 2000 | 1000 | 500 | **240924** | 7.5 | 0 | 1 | 234 | **240924** | 14.7 | 0 | 1 | 234 | MB-I, MB-II |
| | 50 | 2000 | 1000 | 600 | **241724** | 8.1 | 0 | 1 | 234 | **241724** | 13.6 | 0 | 1 | 234 | MB-I, MB-II |
| | 100 | 1000 | 750 | 500 | **181414** | 7.6 | 0 | 1 | 234 | **181414** | 12.7 | 0 | 1 | 234 | MB-I, MB-II |
| | 100 | 1000 | 750 | 600 | **181500** | 5.5 | 0 | 0 | 242 | **181500** | 9.4 | 0 | 0 | 242 | MB-I, MB-II |
| | 100 | 1000 | 1000 | 500 | **220059** | 8.2 | 0 | 38 | 72 | **220059** | 9.9 | 0 | 38 | 72 | MB-I, MB-II |
| | 100 | 1000 | 1000 | 600 | **235002** | 10.0 | 0 | 26 | 112 | **235002** | 10.8 | 0 | 26 | 112 | MB-I, MB-II |
| | 100 | 2000 | 750 | 500 | **181500** | 7.7 | 0 | 0 | 242 | **181500** | 11.8 | 0 | 0 | 242 | MB-I, MB-II |
| | 100 | 2000 | 750 | 600 | **181500** | 8.2 | 0 | 0 | 242 | **181500** | 16.3 | 0 | 0 | 242 | MB-I, MB-II |
| | 100 | 2000 | 1000 | 500 | 239050 | 16.0 | 0 | 4 | 201 | **238909** | 14.3 | 0 | 4 | 198 | MB-II |
| | 100 | 2000 | 1000 | 600 | **241528** | 11.0 | 0 | 1 | 230 | **241528** | 13.4 | 0 | 1 | 230 | MB-I, MB-II |
| | 200 | 1000 | 750 | 500 | **181414** | 15.8 | 0 | 1 | 234 | **181414** | 10.5 | 0 | 1 | 234 | MB-I, MB-II |
| | 200 | 1000 | 750 | 600 | **181500** | 5.2 | 0 | 0 | 242 | **181500** | 6.5 | 0 | 0 | 242 | MB-I, MB-II |
| | 200 | 1000 | 1000 | 500 | **219629** | 11.3 | 0 | 36 | 66 | **219629** | 18.3 | 0 | 36 | 66 | MB-I, MB-II |
| | 200 | 1000 | 1000 | 600 | **235002** | 6.9 | 0 | 26 | 112 | **235002** | 20.7 | 0 | 26 | 112 | MB-I, MB-II |
| | 200 | 2000 | 750 | 500 | **181500** | 6.7 | 0 | 0 | 242 | **181500** | 9.3 | 0 | 0 | 242 | MB-I, MB-II |
| | 200 | 2000 | 750 | 600 | **181500** | 4.7 | 0 | 0 | 242 | **181500** | 5.7 | 0 | 0 | 242 | MB-I, MB-II |
| | 200 | 2000 | 1000 | 500 | **238437** | 27.8 | 0 | 5 | 183 | **238437** | 25.5 | 0 | 5 | 183 | MB-I, MB-II |
| | 200 | 2000 | 1000 | 600 | **241528** | 19.6 | 0 | 1 | 230 | **241528** | 24.9 | 0 | 1 | 230 | MB-I, MB-II |

Table H.8: Results of the Clustering-based Heuristics on Ruhiira (Fixed and Variable Cost)

| | | | | | Agglomerative (Agg) | | | | | DBSCAN - KMeans (DB-KM) | | | | DBSCAN - Agglomerative (DB-Agg) | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | F3 | Cost | Type | Time | M | N | Cost | Time | M | N | Cost | Type | Time | M | N | |
| RUHIIRA- 1 | 30 | 1000 | 750 | 500 | 102000 | GeomDiff | 0 | 0 | 136 | **101717.2** | 0.2 | 1 | 128 | **101717.2** | GeomDiff | 0 | 1 | 128 | DB-KM, DB-Agg. |
| | 30 | 1000 | 750 | 600 | **102000** | GeomDiff | 0 | 0 | 136 | **102000** | 0 | 0 | 136 | **102000** | GeomDiff | 0 | 0 | 136 | Agg., DB-KM, DB-Agg. |
| | 30 | 1000 | 1000 | 500 | 132209.4 | Ward | 0 | 8 | 110 | **131831.7** | 0 | 6 | 113 | **131831.7** | GeomDiff | 0 | 6 | 113 | DB-KM, DB-Agg. |
| | 30 | 1000 | 1000 | 600 | 136000 | GeomDiff | 0.1 | 0 | 136 | **134131.7** | 0 | 6 | 113 | **134131.7** | GeomDiff | 0 | 6 | 113 | DB-KM, DB-Agg. |
| | 30 | 2000 | 750 | 500 | **102000** | GeomDiff | 0.1 | 0 | 136 | **102000** | 0 | 0 | 136 | **102000** | GeomDiff | 0 | 0 | 136 | Agg., DB-KM, DB-Agg. |
| | 30 | 2000 | 750 | 600 | **102000** | GeomDiff | 0.1 | 0 | 136 | **102000** | 0 | 0 | 136 | **102000** | GeomDiff | 0 | 0 | 136 | Agg., DB-KM, DB-Agg. |
| | 30 | 2000 | 1000 | 500 | 136000 | GeomDiff | 0 | 0 | 136 | **134717.2** | 0 | 1 | 128 | **134717.2** | GeomDiff | 0 | 1 | 128 | DB-KM, DB-Agg. |
| | 30 | 2000 | 1000 | 600 | 136000 | GeomDiff | 0.1 | 0 | 136 | **135517.2** | 0 | 1 | 128 | **135517.2** | GeomDiff | 0 | 1 | 128 | DB-KM, DB-Agg. |
| | 50 | 1000 | 750 | 500 | 102000 | GeomDiff | 0.1 | 0 | 136 | **101610.2** | 0 | 1 | 127 | **101610.2** | GeomDiff | 0 | 1 | 127 | DB-KM, DB-Agg. |
| | 50 | 1000 | 750 | 600 | **102000** | GeomDiff | 0.1 | 0 | 136 | **102000** | 0 | 0 | 136 | **102000** | GeomDiff | 0 | 0 | 136 | Agg., DB-KM, DB-Agg. |
| | 50 | 1000 | 1000 | 500 | **125799** | Ward | 0 | 21 | 56 | 127626.8 | 0 | 12 | 87 | 127617.6 | GeomDiff | 0 | 12 | 87 | Agg. |
| | 50 | 1000 | 1000 | 600 | 136000 | GeomDiff | 0 | 0 | 136 | **132469.2** | 0 | 10 | 92 | 132589.9 | GeomDiff | 0 | 10 | 94 | DB-KM |
| | 50 | 2000 | 750 | 500 | **102000** | GeomDiff | 0.1 | 0 | 136 | **102000** | 0 | 0 | 136 | **102000** | GeomDiff | 0 | 0 | 136 | Agg., DB-KM, DB-Agg. |
| | 50 | 2000 | 750 | 600 | **102000** | GeomDiff | 0 | 0 | 136 | **102000** | 0.5 | 0 | 136 | **102000** | GeomDiff | 0 | 0 | 136 | Agg., DB-KM, DB-Agg. |
| | 50 | 2000 | 1000 | 500 | 136000 | GeomDiff | 0 | 0 | 136 | 134364.8 | 0 | 2 | 122 | **134355.6** | GeomDiff | 0 | 2 | 122 | DB-Agg. |
| | 50 | 2000 | 1000 | 600 | 136000 | GeomDiff | 0 | 0 | 136 | 136000 | 0 | 0 | 136 | **135260.2** | GeomDiff | 0 | 1 | 127 | DB-Agg. |
| | 100 | 1000 | 750 | 500 | 102000 | GeomDiff | 0.1 | 0 | 136 | **101963** | 0.5 | 1 | 125 | **101963** | GeomDiff | 0.0 | 1 | 125 | DB-KM, DB-Agg. |
| | 100 | 1000 | 750 | 600 | **102000** | GeomDiff | 0.1 | 0 | 136 | **102000** | 0.5 | 0 | 136 | **102000** | GeomDiff | 0.0 | 0 | 136 | Agg., DB-KM, DB-Agg. |
| | 100 | 1000 | 1000 | 500 | 123888 | Comp | 0.0 | 20 | 42 | **123644** | 0.5 | 20 | 42 | 123840 | GeomDiff | 0.0 | 20 | 41 | DB-KM |
| | 100 | 1000 | 1000 | 600 | 136000 | GeomDiff | 0.1 | 0 | 136 | **131537** | 0.5 | 11 | 75 | 131943 | GeomDiff | 0.0 | 9 | 85 | DB-KM |
| | 100 | 2000 | 750 | 500 | **102000** | GeomDiff | 0.1 | 0 | 136 | **102000** | 0.5 | 0 | 136 | **102000** | GeomDiff | 0.0 | 0 | 136 | Agg., DB-KM, DB-Agg. |
| | 100 | 2000 | 750 | 600 | **102000** | GeomDiff | 0.1 | 0 | 136 | **102000** | 0.9 | 0 | 136 | **102000** | GeomDiff | 0.0 | 0 | 136 | Agg., DB-KM, DB-Agg. |
| | 100 | 2000 | 1000 | 500 | 136000 | GeomDiff | 0.0 | 0 | 136 | **133621** | 0.6 | 4 | 106 | 134050 | GeomDiff | 0.0 | 2 | 119 | DB-KM |
| | 100 | 2000 | 1000 | 600 | 136000 | GeomDiff | 0.1 | 0 | 136 | **135313** | 0.8 | 1 | 125 | **135313** | GeomDiff | 0.0 | 1 | 125 | DB-KM, DB-Agg. |
| | 200 | 1000 | 750 | 500 | **102000** | GeomDiff | 0.3 | 0 | 136 | **102000** | 2.7 | 0 | 136 | **102000** | GeomDiff | 0.2 | 0 | 136 | Agg., DB-KM, DB-Agg. |
| | 200 | 1000 | 750 | 600 | **102000** | GeomDiff | 0.2 | 0 | 136 | **102000** | 3.3 | 0 | 136 | **102000** | GeomDiff | 0.4 | 0 | 136 | Agg., DB-KM, DB-Agg. |
| | 200 | 1000 | 1000 | 500 | **123282** | Ward | 0.0 | 20 | 39 | 133557 | 2.3 | 6 | 80 | 124354 | GeomDiff | 0.3 | 18 | 42 | Agg. |
| | 200 | 1000 | 1000 | 600 | 136000 | GeomDiff | 0.3 | 0 | 136 | 136000 | 2.7 | 0 | 136 | **135899** | GeomDiff | 0.2 | 1 | 132 | DB-Agg. |
| | 200 | 2000 | 750 | 500 | **102000** | GeomDiff | 0.2 | 0 | 136 | **102000** | 2.8 | 0 | 136 | **102000** | GeomDiff | 0.2 | 0 | 136 | Agg., DB-KM, DB-Agg. |
| | 200 | 2000 | 750 | 600 | **102000** | GeomDiff | 0.2 | 0 | 136 | **102000** | 3.1 | 0 | 136 | **102000** | GeomDiff | 0.3 | 0 | 136 | Agg., DB-KM, DB-Agg. |
| | 200 | 2000 | 1000 | 500 | **136000** | GeomDiff | 0.2 | 0 | 136 | **136000** | 2.5 | 0 | 136 | **136000** | GeomDiff | 0.3 | 0 | 136 | Agg., DB-KM, DB-Agg. |
| | 200 | 2000 | 1000 | 600 | **136000** | GeomDiff | 0.2 | 0 | 136 | **136000** | 2.4 | 0 | 136 | **136000** | GeomDiff | 0.2 | 0 | 136 | Agg., DB-KM, DB-Agg. |

| | | | | | Agglomerative (Agg) | | | | | DBSCAN - KMeans (DB-KM) | | | | DBSCAN - Agglomerative (DB-Agg) | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | F3 | Cost | Type | Time | M | N | Cost | Time | M | N | Cost | Type | Time | M | N | |
| RUHIIRA- 2 | 30 | 1000 | 750 | 500 | 182250 | GeomDiff | 0.1 | 0 | 243 | **181634** | 0 | 2 | 229 | **181634** | GeomDiff | 0 | 2 | 229 | DB-KM, DB-Agg. |
| | 30 | 1000 | 750 | 600 | **182250** | GeomDiff | 0.2 | 0 | 243 | **182250** | 0 | 0 | 243 | **182250** | GeomDiff | 0 | 0 | 243 | Agg., DB-KM, DB-Agg. |
| | 30 | 1000 | 1000 | 500 | **228384.2** | Comp | 0.2 | 23 | 157 | 231793.5 | 0 | 14 | 187 | 231793.5 | GeomDiff | 0 | 14 | 187 | Agg. |
| | 30 | 1000 | 1000 | 600 | 241071.8 | GeomDiff | 0.1 | 4 | 227 | **237393.5** | 0 | 14 | 187 | **237393.5** | GeomDiff | 0 | 14 | 187 | DB-KM, DB-Agg. |
| | 30 | 2000 | 750 | 500 | **182250** | GeomDiff | 0.2 | 0 | 243 | **182250** | 0 | 0 | 243 | **182250** | GeomDiff | 0 | 0 | 243 | Agg., DB-KM, DB-Agg. |
| | 30 | 2000 | 750 | 600 | **182250** | GeomDiff | 0.1 | 0 | 243 | **182250** | 0 | 0 | 243 | **182250** | GeomDiff | 0 | 0 | 243 | Agg., DB-KM, DB-Agg. |
| | 30 | 2000 | 1000 | 500 | 243000 | GeomDiff | 0.2 | 0 | 243 | **240272.7** | 0 | 3 | 223 | **240272.7** | GeomDiff | 0 | 3 | 223 | DB-KM, DB-Agg. |
| | 30 | 2000 | 1000 | 600 | 243000 | GeomDiff | 0.1 | 0 | 243 | **242269.5** | 0 | 1 | 235 | **242269.5** | GeomDiff | 0 | 1 | 235 | DB-KM, DB-Agg. |
| | 50 | 1000 | 750 | 500 | 182250 | GeomDiff | 0.3 | 0 | 243 | **181633.5** | 0.5 | 2 | 229 | 182164.5 | GeomDiff | 0 | 1 | 237 | DB-KM |
| | 50 | 1000 | 750 | 600 | **182250** | GeomDiff | 0.2 | 0 | 243 | **182250** | 0.2 | 0 | 243 | **182250** | GeomDiff | 0 | 0 | 243 | Agg., DB-KM, DB-Agg. |
| | 50 | 1000 | 1000 | 500 | **221461.9** | Ward | 0 | 39 | 95 | 221971.4 | 0.3 | 29 | 122 | 222046.8 | Ward | 0 | 28 | 124 | Agg. |
| | 50 | 1000 | 1000 | 600 | 240295.9 | GeomDiff | 0.3 | 4 | 224 | **233556.7** | 0.2 | 25 | 132 | 233659.4 | Comp | 0 | 22 | 140 | DB-KM |
| | 50 | 2000 | 750 | 500 | **182250** | GeomDiff | 0.1 | 0 | 243 | **182250** | 0.4 | 0 | 243 | **182250** | GeomDiff | 0 | 0 | 243 | Agg., DB-KM, DB-Agg. |
| | 50 | 2000 | 750 | 600 | **182250** | GeomDiff | 0.2 | 0 | 243 | **182250** | 0.4 | 0 | 243 | **182250** | GeomDiff | 0 | 0 | 243 | Agg., DB-KM, DB-Agg. |
| | 50 | 2000 | 1000 | 500 | 243000 | GeomDiff | 0.2 | 0 | 243 | 238948.7 | 0.3 | 8 | 194 | **237875.7** | Comp | 0 | 7 | 194 | DB-Agg. |
| | 50 | 2000 | 1000 | 600 | 243000 | GeomDiff | 0.2 | 0 | 243 | **241915.8** | 0.2 | 2 | 227 | 243000 | GeomDiff | 0.1 | 0 | 243 | DB-KM |
| | 100 | 1000 | 750 | 500 | 182250 | GeomDiff | 0.2 | 0 | 243 | **182226** | 2.1 | 1 | 230 | 182250 | GeomDiff | 0.2 | 0 | 243 | DB-KM |
| | 100 | 1000 | 750 | 600 | **182250** | GeomDiff | 0.2 | 0 | 243 | **182250** | 3.4 | 0 | 243 | **182250** | GeomDiff | 0.2 | 0 | 243 | Agg., DB-KM, DB-Agg. |
| | 100 | 1000 | 1000 | 500 | 215021 | Comp | 0.1 | 38 | 47 | 215810 | 3.5 | 36 | 46 | **213772** | GeomDiff | 0.2 | 37 | 47 | DB-Agg. |
| | 100 | 1000 | 1000 | 600 | **231071** | GeomDiff | 0.3 | 24 | 101 | 232902 | 2.7 | 22 | 99 | 231675 | Ward | 0.1 | 21 | 111 | Agg. |
| | 100 | 2000 | 750 | 500 | **182250** | GeomDiff | 0.3 | 0 | 243 | **182250** | 3.5 | 0 | 243 | **182250** | GeomDiff | 0.2 | 0 | 243 | Agg., DB-KM, DB-Agg. |
| | 100 | 2000 | 750 | 600 | **182250** | GeomDiff | 0.4 | 0 | 243 | **182250** | 2.2 | 0 | 243 | **182250** | GeomDiff | 0.2 | 0 | 243 | Agg., DB-KM, DB-Agg. |
| | 100 | 2000 | 1000 | 500 | 243000 | GeomDiff | 0.1 | 0 | 243 | 235661 | 2.8 | 12 | 146 | **234839** | Comp | 0.1 | 9 | 163 | DB-Agg. |
| | 100 | 2000 | 1000 | 600 | 243000 | GeomDiff | 0.1 | 0 | 243 | **241705** | 2.9 | 3 | 206 | 242998 | GeomDiff | 0.2 | 1 | 236 | DB-KM |
| | 200 | 1000 | 750 | 500 | **182250** | GeomDiff | 0.3 | 0 | 243 | **182250** | 4.2 | 0 | 243 | **182250** | GeomDiff | 0.8 | 0 | 243 | Agg., DB-KM, DB-Agg. |
| | 200 | 1000 | 750 | 600 | **182250** | GeomDiff | 0.2 | 0 | 243 | **182250** | 4.4 | 0 | 243 | **182250** | GeomDiff | 0.8 | 0 | 243 | Agg., DB-KM, DB-Agg. |
| | 200 | 1000 | 1000 | 500 | 214142 | Ward | 0.1 | 37 | 39 | 231196 | 4.3 | 11 | 139 | **214047** | Ward | 0.2 | 35 | 38 | DB-Agg. |
| | 200 | 1000 | 1000 | 600 | **230874** | GeomDiff | 0.2 | 24 | 101 | 239797 | 4.5 | 5 | 184 | 233344 | GeomDiff | 0.8 | 13 | 153 | Agg. |
| | 200 | 2000 | 750 | 500 | **182250** | GeomDiff | 0.2 | 0 | 243 | **182250** | 5.2 | 0 | 243 | **182250** | GeomDiff | 0.7 | 0 | 243 | Agg., DB-KM, DB-Agg. |
| | 200 | 2000 | 750 | 600 | **182250** | GeomDiff | 0.3 | 0 | 243 | **182250** | 5.1 | 0 | 243 | **182250** | GeomDiff | 0.7 | 0 | 243 | Agg., DB-KM, DB-Agg. |
| | 200 | 2000 | 1000 | 500 | 243000 | GeomDiff | 0.3 | 0 | 243 | 240106 | 4.1 | 3 | 193 | **236588** | Ward | 0.1 | 8 | 167 | DB-Agg. |
| | 200 | 2000 | 1000 | 600 | **243000** | GeomDiff | 0.3 | 0 | 243 | **243000** | 4.5 | 0 | 243 | **243000** | GeomDiff | 0.4 | 0 | 243 | Agg., DB-KM, DB-Agg. |

| | | | | | Agglomerative (Agg) | | | | | DBSCAN - KMeans (DB-KM) | | | | DBSCAN - Agglomerative (DB-Agg) | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | F3 | Cost | Type | Time | M | N | Cost | Time | M | N | Cost | Type | Time | M | N | |
| RUHIIRA- 3 | 30 | 1000 | 750 | 500 | 203250 | GeomDiff | 0.5 | 0 | 271 | **201418.8** | 0.4 | 8 | 219 | 201574 | GeomDiff | 0.1 | 7 | 225 | DB-KM |
| | 30 | 1000 | 750 | 600 | **203250** | GeomDiff | 0.2 | 0 | 271 | **203250** | 0.3 | 0 | 271 | **203250** | GeomDiff | 0 | 0 | 271 | Agg., DB-KM, DB-Agg. |
| | 30 | 1000 | 1000 | 500 | **244710.3** | Comp | 0.1 | 31 | 140 | 247217.7 | 0.4 | 25 | 161 | 247694.5 | Comp | 0.1 | 26 | 160 | Agg. |
| | 30 | 1000 | 1000 | 600 | **257778.6** | Comp | 0.3 | 27 | 153 | 258722.3 | 0.3 | 26 | 160 | 258492.4 | GeomDiff | 0 | 24 | 165 | Agg. |
| | 30 | 2000 | 750 | 500 | **203250** | GeomDiff | 0.2 | 0 | 271 | **203250** | 0.2 | 0 | 271 | **203250** | GeomDiff | 0 | 0 | 271 | Agg., DB-KM, DB-Agg. |
| | 30 | 2000 | 750 | 600 | **203250** | GeomDiff | 0.2 | 0 | 271 | **203250** | 0.4 | 0 | 271 | **203250** | GeomDiff | 0 | 0 | 271 | Agg., DB-KM, DB-Agg. |
| | 30 | 2000 | 1000 | 500 | 271000 | GeomDiff | 0.1 | 0 | 271 | **263833.9** | 0.5 | 10 | 209 | 264488.9 | GeomDiff | 0 | 9 | 215 | DB-KM |
| | 30 | 2000 | 1000 | 600 | 271000 | GeomDiff | 0.2 | 0 | 271 | **269148.1** | 0 | 8 | 218 | 269424 | GeomDiff | 0 | 7 | 225 | DB-KM |
| | 50 | 1000 | 750 | 500 | 203250 | GeomDiff | 0.5 | 0 | 271 | **200784.4** | 0.8 | 9 | 202 | 201499 | GeomDiff | 0.1 | 6 | 225 | DB-KM |
| | 50 | 1000 | 750 | 600 | **203250** | GeomDiff | 0.2 | 0 | 271 | **203250** | 0.5 | 0 | 271 | **203250** | GeomDiff | 0 | 0 | 271 | Agg., DB-KM, DB-Agg. |
| | 50 | 1000 | 1000 | 500 | **234212.8** | Comp | 0.2 | 39 | 77 | 236165.8 | 0.6 | 34 | 103 | 235473.5 | GeomDiff | 0.1 | 33 | 103 | Agg. |
| | 50 | 1000 | 1000 | 600 | **252097.4** | Comp | 0.2 | 27 | 114 | 252382.4 | 0.8 | 29 | 118 | 252191.6 | GeomDiff | 0.1 | 27 | 123 | Agg. |
| | 50 | 2000 | 750 | 500 | **203250** | GeomDiff | 0.2 | 0 | 271 | **203250** | 0.7 | 0 | 271 | **203250** | GeomDiff | 0.1 | 0 | 271 | Agg., DB-KM, DB-Agg. |
| | 50 | 2000 | 750 | 600 | **203250** | GeomDiff | 0.2 | 0 | 271 | **203250** | 0.9 | 0 | 271 | **203250** | GeomDiff | 0 | 0 | 271 | Agg., DB-KM, DB-Agg. |
| | 50 | 2000 | 1000 | 500 | 271000 | GeomDiff | 0.1 | 0 | 271 | 260531.8 | 0.9 | 12 | 188 | **260465.8** | GeomDiff | 0 | 12 | 188 | DB-Agg. |
| | 50 | 2000 | 1000 | 600 | 271000 | GeomDiff | 0.1 | 0 | 271 | **267550.7** | 0.8 | 7 | 214 | 268349 | GeomDiff | 0.2 | 6 | 225 | DB-KM |
| | 100 | 1000 | 750 | 500 | 203250 | GeomDiff | 0.2 | 0 | 271 | **201909** | 3.4 | 4 | 224 | 202176 | GeomDiff | 0.3 | 2 | 244 | DB-KM |
| | 100 | 1000 | 750 | 600 | **203250** | GeomDiff | 0.2 | 0 | 271 | **203250** | 3.4 | 0 | 271 | **203250** | GeomDiff | 0.2 | 0 | 271 | Agg., DB-KM, DB-Agg. |
| | 100 | 1000 | 1000 | 500 | 228748 | Ward | 0.2 | 41 | 50 | 229609 | 2.9 | 29 | 50 | **227486** | Ward | 0.0 | 34 | 45 | DB-Agg. |
| | 100 | 1000 | 1000 | 600 | 248823 | Ward | 0.2 | 28 | 89 | 250609 | 3.1 | 23 | 76 | **248716** | Ward | 0.1 | 25 | 79 | DB-Agg. |
| | 100 | 2000 | 750 | 500 | **203250** | GeomDiff | 0.3 | 0 | 271 | **203250** | 2.6 | 0 | 271 | **203250** | GeomDiff | 0.2 | 0 | 271 | Agg., DB-KM, DB-Agg. |
| | 100 | 2000 | 750 | 600 | **203250** | GeomDiff | 0.1 | 0 | 271 | **203250** | 3.2 | 0 | 271 | **203250** | GeomDiff | 0.3 | 0 | 271 | Agg., DB-KM, DB-Agg. |
| | 100 | 2000 | 1000 | 500 | 271000 | GeomDiff | 0.2 | 0 | 271 | **253395** | 2.9 | 15 | 125 | 254867 | GeomDiff | 0.2 | 15 | 138 | DB-KM |
| | 100 | 2000 | 1000 | 600 | 271000 | GeomDiff | 0.3 | 0 | 271 | **264764** | 2 | 7 | 187 | 265887 | Ward | 0.0 | 5 | 210 | DB-KM |
| | 200 | 1000 | 750 | 500 | **203250** | GeomDiff | 0.4 | 0 | 271 | **203250** | 4.6 | 0 | 271 | **203250** | GeomDiff | 0.3 | 0 | 271 | Agg., DB-KM, DB-Agg. |
| | 200 | 1000 | 750 | 600 | **203250** | GeomDiff | 0.4 | 0 | 271 | **203250** | 4.3 | 0 | 271 | **203250** | GeomDiff | 0.4 | 0 | 271 | Agg., DB-KM, DB-Agg. |
| | 200 | 1000 | 1000 | 500 | **227788** | Ward | 0.4 | 34 | 35 | 254269 | 4.5 | 13 | 94 | 231412 | Ward | 0.3 | 33 | 57 | Agg. |
| | 200 | 1000 | 1000 | 600 | **249172** | Ward | 0.3 | 24 | 84 | 265385 | 4.5 | 5 | 196 | 250596 | Ward | 0.4 | 22 | 105 | Agg. |
| | 200 | 2000 | 750 | 500 | **203250** | GeomDiff | 0.3 | 0 | 271 | **203250** | 4.4 | 0 | 271 | **203250** | GeomDiff | 0.6 | 0 | 271 | Agg., DB-KM, DB-Agg. |
| | 200 | 2000 | 750 | 600 | **203250** | GeomDiff | 0.3 | 0 | 271 | **203250** | 4.4 | 0 | 271 | **203250** | GeomDiff | 0.4 | 0 | 271 | Agg., DB-KM, DB-Agg. |
| | 200 | 2000 | 1000 | 500 | **252829** | Ward | 0.4 | 15 | 101 | 262544 | 5.4 | 4 | 201 | 255154 | GeomDiff | 0.4 | 13 | 124 | Agg. |
| | 200 | 2000 | 1000 | 600 | 271000 | GeomDiff | 0.2 | 0 | 271 | **268864** | 4.6 | 3 | 219 | 271000 | GeomDiff | 0.4 | 0 | 271 | DB-KM |

| | | | | | Agglomerative (Agg) | | | | | DBSCAN - KMeans (DB-KM) | | | | DBSCAN - Agglomerative (DB-Agg) | | | | | Best Method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DLim | F1 | F2 | F3 | Cost | Type | Time | M | N | Cost | Time | M | N | Cost | Type | Time | M | N | |
| RUHIIRA- 4 | 30 | 1000 | 750 | 500 | **181500** | GeomDiff | 0.3 | 0 | 242 | **181500** | 0 | 0 | 242 | **181500** | GeomDiff | 0 | 0 | 242 | Agg., DB-KM, DB-Agg. |
| | 30 | 1000 | 750 | 600 | **181500** | GeomDiff | 0.3 | 0 | 242 | **181500** | 0 | 0 | 242 | **181500** | GeomDiff | 0 | 0 | 242 | Agg., DB-KM, DB-Agg. |
| | 30 | 1000 | 1000 | 500 | **232069.3** | Comp | 0 | 26 | 159 | 234687.1 | 0 | 16 | 190 | 234687.1 | GeomDiff | 0 | 16 | 190 | Agg. |
| | 30 | 1000 | 1000 | 600 | 242000 | GeomDiff | 0.2 | 0 | 242 | **239877.1** | 0 | 14 | 196 | **239877.1** | GeomDiff | 0 | 14 | 196 | DB-KM, DB-Agg. |
| | 30 | 2000 | 750 | 500 | **181500** | GeomDiff | 0.1 | 0 | 242 | **181500** | 0 | 0 | 242 | **181500** | GeomDiff | 0 | 0 | 242 | Agg., DB-KM, DB-Agg. |
| | 30 | 2000 | 750 | 600 | **181500** | GeomDiff | 0.2 | 0 | 242 | **181500** | 0 | 0 | 242 | **181500** | GeomDiff | 0 | 0 | 242 | Agg., DB-KM, DB-Agg. |
| | 30 | 2000 | 1000 | 500 | **242000** | GeomDiff | 0.1 | 0 | 242 | **242000** | 0 | 0 | 242 | **242000** | GeomDiff | 0 | 0 | 242 | Agg., DB-KM, DB-Agg. |
| | 30 | 2000 | 1000 | 600 | **242000** | GeomDiff | 0.2 | 0 | 242 | **242000** | 0 | 0 | 242 | **242000** | GeomDiff | 0 | 0 | 242 | Agg., DB-KM, DB-Agg. |
| | 50 | 1000 | 750 | 500 | 181500 | GeomDiff | 0.1 | 0 | 242 | **181424.3** | 0 | 1 | 234 | 181500 | GeomDiff | 0 | 0 | 242 | DB-KM |
| | 50 | 1000 | 750 | 600 | **181500** | GeomDiff | 0.1 | 0 | 242 | **181500** | 0 | 0 | 242 | **181500** | GeomDiff | 0 | 0 | 242 | Agg., DB-KM, DB-Agg. |
| | 50 | 1000 | 1000 | 500 | **226600.3** | Comp | 0.2 | 37 | 111 | 228064.9 | 0 | 28 | 141 | 227621.5 | GeomDiff | 0 | 30 | 135 | Agg. |
| | 50 | 1000 | 1000 | 600 | 242000 | GeomDiff | 0.1 | 0 | 242 | **237501.9** | 0 | 20 | 164 | 237576.9 | GeomDiff | 0.1 | 19 | 168 | DB-KM |
| | 50 | 2000 | 750 | 500 | **181500** | GeomDiff | 0.2 | 0 | 242 | **181500** | 0 | 0 | 242 | **181500** | GeomDiff | 0 | 0 | 242 | Agg., DB-KM, DB-Agg. |
| | 50 | 2000 | 750 | 600 | **181500** | GeomDiff | 0.1 | 0 | 242 | **181500** | 0 | 0 | 242 | **181500** | GeomDiff | 0 | 0 | 242 | Agg., DB-KM, DB-Agg. |
| | 50 | 2000 | 1000 | 500 | 242000 | GeomDiff | 0.1 | 0 | 242 | **240924.3** | 0 | 1 | 234 | **240924.3** | GeomDiff | 0 | 1 | 234 | DB-KM, DB-Agg. |
| | 50 | 2000 | 1000 | 600 | 242000 | GeomDiff | 0.2 | 0 | 242 | **241724.3** | 0 | 1 | 234 | 242000 | GeomDiff | 0 | 0 | 242 | DB-KM |
| | 100 | 1000 | 750 | 500 | **181500** | GeomDiff | 0.3 | 0 | 242 | **181500** | 2 | 0 | 242 | **181500** | GeomDiff | 0.1 | 0 | 242 | Agg., DB-KM, DB-Agg. |
| | 100 | 1000 | 750 | 600 | **181500** | GeomDiff | 0.2 | 0 | 242 | **181500** | 1.5 | 0 | 242 | **181500** | GeomDiff | 0.1 | 0 | 242 | Agg., DB-KM, DB-Agg. |
| | 100 | 1000 | 1000 | 500 | 221437 | GeomDiff | 0.3 | 40 | 80 | 222658 | 1.8 | 36 | 71 | **221008** | GeomDiff | 0.1 | 38 | 70 | DB-Agg. |
| | 100 | 1000 | 1000 | 600 | 242000 | GeomDiff | 0.2 | 0 | 242 | 237608 | 1.7 | 18 | 136 | **235793** | GeomDiff | 0.1 | 21 | 137 | DB-Agg. |
| | 100 | 2000 | 750 | 500 | **181500** | GeomDiff | 0.2 | 0 | 242 | **181500** | 1.6 | 0 | 242 | **181500** | GeomDiff | 0.1 | 0 | 242 | Agg., DB-KM, DB-Agg. |
| | 100 | 2000 | 750 | 600 | **181500** | GeomDiff | 0.1 | 0 | 242 | **181500** | 1.7 | 0 | 242 | **181500** | GeomDiff | 0.1 | 0 | 242 | Agg., DB-KM, DB-Agg. |
| | 100 | 2000 | 1000 | 500 | 242000 | GeomDiff | 0.1 | 0 | 242 | 241002 | 1.7 | 2 | 220 | **240258** | GeomDiff | 0.1 | 3 | 215 | DB-Agg. |
| | 100 | 2000 | 1000 | 600 | 242000 | GeomDiff | 0.2 | 0 | 242 | **241896** | 2.5 | 1 | 228 | 242000 | GeomDiff | 0.1 | 0 | 242 | DB-KM |
| | 200 | 1000 | 750 | 500 | **181500** | GeomDiff | 0.3 | 0 | 242 | **181500** | 8 | 0 | 242 | **181500** | GeomDiff | 0.7 | 0 | 242 | Agg., DB-KM, DB-Agg. |
| | 200 | 1000 | 750 | 600 | **181500** | GeomDiff | 0.3 | 0 | 242 | **181500** | 7.1 | 0 | 242 | **181500** | GeomDiff | 0.8 | 0 | 242 | Agg., DB-KM, DB-Agg. |
| | 200 | 1000 | 1000 | 500 | **220990** | Ward | 0.2 | 35 | 55 | 234620 | 7.2 | 13 | 111 | **220990** | Ward | 0.4 | 35 | 55 | Agg., DB-Agg. |
| | 200 | 1000 | 1000 | 600 | 242000 | GeomDiff | 0.5 | 0 | 242 | 241843 | 6.9 | 2 | 226 | **239307** | GeomDiff | 0.7 | 7 | 203 | DB-Agg. |
| | 200 | 2000 | 750 | 500 | **181500** | GeomDiff | 0.3 | 0 | 242 | **181500** | 7.1 | 0 | 242 | **181500** | GeomDiff | 0.6 | 0 | 242 | Agg., DB-KM, DB-Agg. |
| | 200 | 2000 | 750 | 600 | **181500** | GeomDiff | 0.3 | 0 | 242 | **181500** | 6.9 | 0 | 242 | **181500** | GeomDiff | 0.3 | 0 | 242 | Agg., DB-KM, DB-Agg. |
| | 200 | 2000 | 1000 | 500 | 242000 | GeomDiff | 0.2 | 0 | 242 | **241537** | 6.4 | 1 | 226 | 242000 | GeomDiff | 0.2 | 0 | 242 | DB-KM |
| | 200 | 2000 | 1000 | 600 | **242000** | GeomDiff | 0.3 | 0 | 242 | **242000** | 6.6 | 0 | 242 | **242000** | GeomDiff | 0.2 | 0 | 242 | Agg., DB-KM, DB-Agg. |