AIRLINE SCHEDULING TO MINIMIZE OPERATIONAL COSTS AND VARIABILITY

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By

Deniz Şimşek

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By Deniz Şimşek
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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.

M. Selim Aktürk(Advisor)

Firdevs Ulus

Sinan Gürel

Approved for the Graduate School of Engineering and Science:

Ezhan Karaşan
Director of the Graduate School

ABSTRACT

AIRLINE SCHEDULING TO MINIMIZE OPERATIONAL COSTS AND VARIABILITY

Deniz Şimşek
M.S. in Industrial Engineering
Advisor: M. Selim Aktürk
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Airlines tend to design their flights schedules with the primary concern of the minimization of operational costs. However, the recently emerging idea of resilient scheduling defined as staying operational in case of unexpected disruptions and adaptability should be of great importance for airlines as well due to the high opportunity costs caused by the flight cancellations and passenger inconvenience caused by delays in the schedule. In this study, we integrate resilient airline schedule design, aircraft routing and fleet assignment problems with uncertain non-cruise times and controllable cruise times. We follow a data-driven method to estimate flight delay probabilities to calculate the airport congestion coefficients required for the probability distributions of non-cruise time random variables. We formulate the problem as a bi-criteria nonlinear mixed integer mathematical model with chance constraints. The nonlinearity caused by the fuel consumption and CO_2 emission function associated with the controllable cruise times in our first objective is handled by second order conic inequalities. We minimize the total absolute deviation of the aircraft path variabilities from the average in our second objective to generate balanced schedules in terms of resilience. We follow an ε-constraint approach to scalarize and solve our problem via commercial solvers and we also devise a discretized approximation and search algorithm to solve large instances. We compare the recovery performances of our proposed schedules to the minimum cost schedules by a scenario-based posterior analysis. As a key contribution, we show that in the schedule generation phase, designing resilient schedules by allowing them to deviate from the minimum cost within the trade-off between the operational costs and the variability, the potential recovery costs in case of unexpected disruptions can be reduced significantly.

Keywords: Resilient airline scheduling, aircraft routing and fleeting, cruise time controllability, chance constraints, second order cone programming.

ÖZET

OPERASYONAL MALİYETLERİ VE DEĞİŞKENLİĞİ ENAZLAYAN HAVAYOLU ÇİZELGELEME

Deniz Şimşek
Endüstri Mühendisliği, Yüksek Lisans
Tez Danışmanı: M. Selim Aktürk
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Havayolları, uçuş çizelgelerini geliştirirken öncelikle operasyonel maliyetlerin enazlanmasını amaçlar. Ancak uçuş iptallerinden kaynaklanan yüksek fırsat maliyetleri ve uzun rötarların yolcu memnuniyetsizliğine yol açması sebebiyle, beklenmedik aksaklıklara karşı operasyona devam edebilmek de havayolu şirketleri için önem taşımalıdır. Dirençli havayolu çizelgeleme, aksaklıklara adapte olup operasyona devam edebilen uçuş çizelgeleri geliştirmeyi hedefler. Bu çalışma dirençli havayolu çizelgeleme, uçak rotalama ve filo atama problemlerini bütünleşik bir yaklaşımla ele almakta, belirsiz seyir dışı süreler ile kontrol edilebilir seyir süreleri varsaymaktadır. Uçuş rötar olasılıklarını tahmin etmek için veri tabanlı bir metot önerilmiş, havalimanı yoğunluk katsayıları hesaplanmış ve katsayılar seyir dışı sürelere ait rassal değişkenlerin olasılık dağılımlarında kullanılmıştır. Problem iki amaçlı karma tamsayılı doğrusal olmayan şans kısıtlı bir matematiksel model ile formüle edilmiştir. Birinci amaç fonksiyonundaki yakıt tüketimi ve CO_2 emisyonunun yarattığı doğrusalsızlık, ikinci derece konik eşitsizlikler ile ele alınmıştır. İkinci amaç fonksiyonunda ise uçak rota değişkenliklerinin ortalamadan mutlak sapması enazlanmıştır. ε-kısıt yöntemiyle problem skalarize edilmiş ve ticari çözücüler kullanarak çözülebilir hâle getirilmiştir. Büyük ölçekli problemleri makul zamanlarda çözebilmek için bir algoritma geliştirilmiştir. Farklı aksaklık senaryoları üretilerek yapılan ikincil analizde, önerilen uçuş çizelgeleri ile en az maliyetli uçuş çizelgeleri onarım performansı açısından kıyaslanmıştır. Havayolu şirketlerinin çizelgeleme aşamasında dirençli çizelgeler elde edebilmek için kabul edilebilir sınırlar altında en az maliyetten uzaklaşmasının, beklenmedik aksaklıklarda onarım maliyetlerini önemli ölçüde azaltabileceği gösterilmiştir.

Anahtar sözcükler: Dirençli havayolu çizelgeleme, uçak rotalama, filo atama, kontrol edilebilir seyir süreleri, şans kısıtları, ikinci derece konik programlama.

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Chapter 1

Introduction

The resilient airline scheduling problem aims to create schedules which are adaptable to unexpected disruptions by integrating aircraft routing, fleet assignment and schedule design decisions such that variability levels in the schedules are minimized within the limits of their trade-off to the total operational costs. Because the complexity of the problem caused by the large number of problem parameters and decision variables, it is challenging to solve this problem manually. Therefore, the use of an optimization tool is required to tackle the large-scale problems. In this study, the problem is formulated via a bi-objective nonlinear mixed-integer mathematical model with chance constraints and it is implemented in Java programming language with a connection to IBM ILOG CPLEX.

1.1 Motivation

Airlines are one of the most complex industries which consist of large scale networks. Therefore, they need to maintain their planning to manage their resources efficiently. Indeed, after the United States airline deregulations, competition amongst airlines has increased and the use of optimization throughout airline operations has gained importance.

Airline schedules are composed of several different elements such as the set of flights to be operated, origin and destination airports, fleet types, crew assignments, etc. These are not the only elements that increase the complexity of the airline scheduling problems. Besides these, airlines run in an uncertain environment which causes the airlines to be open to unpredicted changes. So, airlines should also be able to manage disruptions. This situation forces airlines to create schedules which are capable of adapting or withstanding disruptions.

Different types of schedules are defined in the literature regarding airline scheduling. The most common term that we can use for an airline schedule is "robust". Cook et al. [1] define robustness as the resistance to withstand stresses beyond normal limits. There are several studies available in the literature which aim to create robust airline schedules and they aim to increase the robustness through increasing the passenger connection service levels. As new optimization and prediction techniques are developed, other terms started to be used in this sector as well. Lufthansa [2] mentions in their blog that minimizing the delay risks can be achieved through the use of resilient scheduling rather than robust scheduling. Resilience can be defined as the ability of a system to withstand and stay operational in the face of an unexpected disturbance or unpredicted change as discussed in Wang et al. [3].

In fact, resilience is a more comprehensive term than robustness and where they differ is that robust schedule design aims to accommodate any uncertain future events such that the initially desired future state can still be achieved whereas resilient schedule design aims to adapt to disruptions by changing its methods while continuing to operate and to be able to return to the original state of the system or move to a new desirable state after disruptions. Clearly, resilient schedule design is an emerging area and not much of a literature has been developed where resilience is considered as an objective besides the total cost or profit of the generated schedules. This study aims to create resilient airline schedules by decreasing the variability level of the systems within the limits of the trade-off between that and the operational cost of the generated schedules.

1.2 Contributions

In our study, we integrate aircraft routing, fleet assignment and schedule design decisions. In contrary to the single-criterion approaches which focus on minimizing the total costs of schedules, we follow a bi-criteria framework to increase the resilience of the system while keeping the operational cost within acceptable limits. To achieve that, we introduce the variability of the system as an indicator of resilience. We propose that the variability of the system depends on the fleet assignments due to the different characteristics of the aircraft and also the flight departure times which affect the uncertain non-cruise times. Thus, we calculate the variability of an aircraft path based on its characteristics and flight assignments. Then, our proposed objective is to minimize total absolute deviation of the variabilities of aircraft paths from their average such that the resulting schedule would be as balanced as possible. The motivation behind aiming for balanced schedules is that the disruptions that we are aiming to handle are uncertain and which aircraft is going to be affected by them cannot be known for sure beforehand. This is the key contribution of this study to the resilient airline scheduling literature.

Another important contribution to the related literature is to incorporate empirical techniques to capture the effects of airport congestions in the random variables that we use for uncertain non-cruise times. We followed a data-driven methodology to estimate departure and arrival delay probabilities of flights which were generally taken as the equal to each other in the existing literature.

We also contribute to the literature by introducing a data-driven procedure to calculate turnaround times required to prepare aircraft between consecutive flights which provides a more thoroughgoing way than normalizing the number of passengers visiting the airports as it was done in the literature.

We propose a bi-objective nonlinear mixed-integer mathematical model with chance constraints in order to tackle the problem. Then, we reformulate it to handle the nonlinearity by using second order conic inequalities and to handle chance constraints by using value-at-risk risk measure. We also follow the ε-constraint approach to be able to solve the problem via commercial solvers.

To be able to solve the problem for large-sized instances, we devise a math-heuristic algorithm to generate flight schedules by making aircraft routing and fleeting decision first to minimize total costs and making swapping decisions to balance out the aircraft path variabilities iteratively.

We develop an integrated flight and passenger recovery algorithm in order to evaluate the performance of our proposed formulation via a posterior analysis. Finally, we conducted several what if analyses to gain some managerial insight on the behavior and performance of our proposed methodology. To summarize, main contributions of this study are as follows:

– We introduce the variability of the system depending on aircraft characteristics, fleet assignment and schedule design decisions. To capture its effect on resilience, we propose a bi-objective framework by minimizing the deviation of aircraft path variabilities from the average while keeping the operational cost within acceptable limits.

– We propose a novel data-driven methodology for calculating the parameters required for the probability distributions of non-cruise time random variables in which delay probabilities occurred in origin and destination airports are distinguished from each other.

– We utilize value-at-risk risk measure to reformulate our chance constraints instead of previously used expected non-cruise time in the literature.

– We devise a math-heuristic algorithm to generate flight schedules by making aircraft routing and fleeting decision first to minimize total costs and making swapping decisions to balance out the aircraft path variabilities iteratively.

– We develop an integrated flight and passenger recovery algorithm in order to evaluate the performance of our proposed formulation via a scenario-based posterior analysis.

1.3 Overview

Remaining chapters of this thesis are organized in the following way. In Chapter 2, an extensive review of literature focusing on robust airline scheduling and airline recovery is given as well as the related information about cruise time controllability, fuel consumption and CO_2 emission costs, SOCP-representable functions and value-at-risk measure.

In Chapter 3, the problem definition and formulation is given. First, the problem is defined in detail and the notation that is utilized is provided. In addition, the mathematical characteristics of the non-cruise time random variable including its cumulative distribution, probability density, quantile functions and its variance are given. After the problem is defined, the proposed problem formulation as a bi-criteria nonlinear mixed-integer mathematical model with chance constraints is provided with the detailed explanation of objective functions and constraints that we introduce. Finally, its reformulation as an ε-constraint mathematical model is explicitly given.

Chapter 4 is devoted to the empirical study that we conducted on the historical airline on-time performance data. Development of the regression models which estimate delay probabilities and turnaround times are explained as well as the data and variables that we select to use. Finally, the estimation results for the corresponding parameters are provided.

Chapter 5 describes the proposed discretized approximation and aircraft swapping algorithm. The notation used in the Discretized Approximation Model (DAM) and Aircraft Swapping Search Algorithm (ASSA) are explicitly stated together with their mathematical formulations. In addition, a numerical example is provided in this chapter in order to illustrate how the algorithm works.

In Chapter 6, the integrated flight and passenger recovery algorithm is provided. First, the methodology to quantify the resilience of flight schedules is explained and the selected performance measures are given explicitly. Then, the flight recovery model and the re-routing model used in the recovery algorithm are given together with the associated notation.

An extensive computational study is provided in Chapter 7, starting with the explanation of the parameter setting, followed by a brief CPU time analysis on the proposed solution methodologies. Then, for the networks containing 50 and 150 flights, results for the computational analysis are discussed in detail and posterior analyses on resilience are conducted separately for each network. Finally, the managerial insights gained by the several what if analyses on different problem parameters are provided.

Chapter 8 concludes the thesis and gives potential future directions for this study.

Chapter 2

Literature Review

Although the term 'resilience' has been used in network design problems, this is a relatively new idea in airline scheduling. Thus, the literature on the resilient airline scheduling is rather limited. Therefore, we mainly focus on the robust scheduling literature including the pioneering works for resilient airline scheduling as well. In addition, since we define resilience as the performance of recovery, we also examine and provide a review on the airline disruption management literature. Together with the papers related to these areas and how they differ from our perspective, some background information regarding the cruise time controllability, fuel and CO_2 emission costs, second order cone programming and risk measures will be summarized in the following sections.

2.1 Robust Airline Scheduling

In a flight schedule, block times of flights consist of cruise times which can be controlled by adjusting the speed of the aircraft and non-cruise times that are uncertain. Majority of the non-cruise times are allocated to taxi-in and taxi-out times of the aircraft which are subject to high uncertainty so they cause significant delays which result in passengers missing their flight connections. Because of this uncertainty, many works in the literature focus on robust airline scheduling in order to satisfy passenger connection service levels.

Duran et al. [4] propose a mathematical model which inserts slacks into the schedule and speed up the aircraft if necessary as well as using chance constraints on passenger connection service levels. Similarly, Gürkan et al. [5] use chance constraints on the passenger connection service levels while aiming to generate better flight sequences in terms of robustness. They also incorporate aircraft fleeting and routing into robust schedule design.

Şafak et al. [6] introduce an integrated aircraft-path assignment and robust schedule design with cruise speed control. They also use chance constraints in order to handle random non-cruise times. Another approach by Şafak et al. [7] to capture the uncertainty of non-cruise times is stochastic programming. They suggest a multi-stage airline scheduling problem with stochastic passenger demand and non-cruise time. They consider not only flight timings and passenger demands but also expected operational expenses including cruise time controllability. They also suggest a cutting plane algorithm to efficiently solve the problem.

Gürel et al. [8] define flexible schedules as schedules which can be repaired at minimum possible cost and they also consider leaving idle times or time buffers to create flexible schedules using a so-called anticipative scheduling algorithm. This work can be considered as a basis for the anticipative airline scheduling. A different perspective in the literature is proposed by AhmadBeygi et al. [9] where they aim to minimize the expected value of delay propagation by modifying the flight departure times to re-allocate the existing slack in the flight networks. By moving a flight's departure earlier, they increase the slack in its outbound connections and decrease the slack in its inbound connections so that the passenger connections are preserved.

Sohoni et al. [10] contribute to the literature by developing a comprehensive model that includes block-time uncertainty. They explicitly model block-time distributions through chance constraints while incorporating network service levels. They propose a new cut generation algorithm to solve these stochastic binary integer programming models. Even though their model is constructed for maximizing operational profits, they also construct a model for maximizing the service levels. A newsvendor framework is presented by Deshpande and Arıkan [11]. By constructing overage and shortage costs, they examine how on-time performance is affected by the scheduled block time of flights. They also show that the stochastic non-cruise times fit a symmetric Log-laplace distribution.

Cadarso et al. [12] propose an integrated approach for airline planning where the aim is to update flight schedules when a disruption occurs in a way that the robustness is achieved against demand uncertainty. The aim of their study is to decrease the number of miss-connected passengers by creating robust itineraries. Ben Ahmed et al. [13] propose a hybrid approach to obtain robust decisions for aircraft routing and retiming through the use of optimization and simulation in terms of the flight delays and their propagation through the flight network.

Recently, there have been few studies which follow data-driven frameworks focusing on flight delays. Herring et al. [14] focus on passenger connections by examining their connection time preferences to reduce the risk of missing their following flights. They propose a multinominal logit model to estimate the probabilities of passengers selecting itineraries based on the flight departure times and buffer times between flights. Arora et al. [15] analyze the impact of delayed departure of flights on their arrivals by multinomial logistic regression. Lambelho et al. [16] propose a machine-learning based mechanism to assess the flight schedules of airlines with respect to their cancellation and delay predictions.

A different approach is proposed by Prakash [17] which focuses on generating reliable routes on networks where reliability is defined as the probability of on-time arrival at the destination, given a threshold arrival-time. Xu et al. [18] propose an integrated robust scheduling approach that decides on the schedule design, fleet assignment, and aircraft routing, while considering the effects of propagated delays. Since they aim to enhance the robustness of the schedules by decreasing the effects of the propagated delays, their work is very much in line with this study.

Since the taxi-out and taxi-in times of the aircraft constitute a significant portion of the uncertain non-cruise times of flights, the taxi operations in airports are heavily affecting the robustness of the flight schedules. To support, Wang et al. [19] focus on the importance of the prediction of taxi times, which is important for creating robust schedules. Soltani et al. [20] include eco-friendly concerns to the literature on the aircraft taxi operations through the minimization of fuel consumption.

Although Katsigiannis et al. [21] do not directly propose a robust or resilient airline planning approach, they recently proposed a multi-objective framework to solve the airport slot-scheduling framework. The main idea behind their study is to decide on a prioritization scheme for the assignments of airport slots to flights considering total schedule displacement, maximum schedule displacement and demand-based fairness which was previously done by a hierarchical order based on the historical data. Zeng et al. [22] also consider the slot allocation in airline planning and they propose a data-driven optimization model for flight scheduling to capture the uncertainty caused by the operational displacement. They create displacement probability distributions based on the historical data and aim to minimize the time of delay occurred in the schedules after these operational displacements thanks to the punctuality of the proposed schedules.

Finally, some pioneering works which consider the resilience of the airline networks are as follows: Janić [23] develops a methodology to estimate the resilience of the air transport networks and defines resilience as the ability of the network to neutralize the effects of disruptive events. He introduces friability as an implication of reduced resilience due to an alteration made in the network such as cancelling a disrupted flight leg. Besides the resilience and friability of the networks, Janić also develops a methodology for measuring the costs incurred by delaying, cancelling and re-routing the affected flights.

Moreover, Clark et al. [24] consider the resilience of the airport network of the U.S. National Airspace System and propose an approach to characterize the resilience of the airport systems after disruptive events. That way, they provide the decision makers with insights about which resources in the network to prioritize more. More recently, Wong et al. [25] propose a data-driven approach which utilizes the Mahalanobis distance metric to quantify abnormalities across the flight networks. They discuss the trends in the resilience of the several U.S. airlines and claim that their proposed data-driven methodology results in more detailed insights than the traditional network methods.

2.2 Airline Recovery

Since the aim in this study is to create flight schedules such that the schedule responds to unexpected events well with respect to certain performance metrics, airline recovery plays an important role on observing the performance of the schedules under disruptions through posterior analyses. There is a rich amount of literature on airline disruption management. For an extensive review, the recent work by Hassan et al. [26] can be referred. Some other papers focusing on different portions of airline recovery can be summarized as follows.

Petersen et al. [27] define the airline recovery problem as the composition of the schedule recovery problem, the aircraft recovery problem, the crew recovery problem, and the passenger recovery problem. They suggest an optimization approach to integrated airline recovery by decomposing the problem into several reasonably sized disruptions in order to be able to solve it quickly. Their work is one of the first attempts to solve the fully integrated problem. Following, Aktürk et al. [28] constitute one of the pioneering works which include cruise speed control into the recovery procedure of flights. They propose three alternatives; first is where delay propagation or right shifting is considered, second is only compressing the cruise speed of the aircraft, third and last alternative is where both aircraft swaps and cruise speed control is considered. They propose a mixed integer nonlinear optimization model with convex cost functions in the objective and nonlinear constraints.

Arıkan et al. [29] consider aircraft and passenger recovery and they handle related costs simultaneously by deciding on which flights to postpone, how much to postpone, which itineraries to disrupt, cruise times of which flights to compress, how much to compress, the aircraft of which flights to swap to achieve the minimum cost. Following this work, Arıkan et al. [30] contribute to the literature by suggesting that recovery decisions for all entities namely, aircraft, crew and passengers can be integrated. Common recovery decisions are departure delays, aircraft and crew rerouting, passenger accommodations, ticket and flight cancellations. Their objective is to find the optimal set of actions that minimizes the costs of disruptions provided that the original schedule will be resumed at the end of a specified recovery period.

Yetimoğlu et al. [31] consider an integrated aircraft and passenger recovery problem where the sources of disruption are mechanical failures and unexpected delays of maintenance which result in unavailability periods for the aircraft. Besides a mathematical formulation that they propose which utilizes second order cone programming, a novel math-heuristic algorithm which makes itinerary based recovery decisions is developed in their study.

Some recent works on the airline recovery literature includes the one by Vink et al. [32] in which they present a new approach for the aircraft recovery problem where a selection heuristic with integer linear programming is proposed dynamically to capture the effects of disruptions costs fully compared to the static approaches. Evler et al. [33] propose a resource-constrained project scheduling problem (RCPSP) to obtain recovery actions for disruptions created due to the unavailability of different resources. They define the resilience as the schedule recovery performance and by providing resilient solutions, they claim that the total cost and delay caused by the schedule deviations are minimized. This study is also one of the recent works that include resilience into the airline planning and scheduling problems which in fact is in line with the scope of our study.

2.3 Cruise Time Controllability, Fuel and CO_2 Emission Costs

According to the IATA report [34], among all cost terms, fuel cost has been the largest cost term for the airlines. Based on the information gathered from the 45 major airlines, fuel costs represent approximately 32% of the total operating costs. Thus, reducing the operational costs by minimizing of the fuel consumption is one of the primary concerns of the airlines. Further, each kg of fuel used by aircraft produces approximately 3.15 kilograms of CO_2. This means, reducing the fuel consumption is aimed under environmentalist concerns as well. Therefore, many studies in the literature aim to decrease the fuel consumption and CO_2 emission of the aircraft in order to reduce the operational costs of the airlines.

Besides the costs related to the fuel consumption, there are also several other cost terms. In many studies, costs incurred due to the idle time spent by the aircraft, maintenance of the aircraft, crew related costs, etc. are considered as well as fuel costs. Although cruise time of a flight is the longest portion of the flight where the most of the fuel consumption by aircraft is made, airlines may want to operate their flights at speeds different than the maximum range cruise (MRC) speed at which the highest fuel efficiency is achieved by the aircraft. This results in controllable cruise times and consequently different trade-offs among all of these cost terms. To illustrate, if one speeds up the aircraft, then the fuel costs and idle time costs increase but costs incurred by the crew, maintenance or rental costs may decrease due to the reduction in the cruise time of flights. In order to balance all these terms, Airbus [35] published a cost index defined by the ratio of time-related cost per minute of flight to the cost of fuel consumption per kg. By using this, airlines minimize operational costs by adjusting increased fuel consumption for compressed cruise time and vice versa. Detailed information on the trade-offs between cost terms can be found in the technical reports provided by Boeing [36] as well. Therefore, cruise time controllability is an important element in the related studies to represent the trade-off between fuel cost and the other cost terms.

Many studies in the robust airline scheduling area consider cruise time controllability. Duran et al. [4] propose a robust scheduling model which utilizes controllable cruise times and idle time insertion to increase robustness by satisfying minimum passenger connection service levels. Şafak et al. [7] also use cruise time controllability in their study to handle operational expenses. Arıkan et al. [29] added the cruise time controllability into the integrated aircraft and passenger recovery problem besides the traditional recovery strategies. In this study, we also consider cruise times as controllable by integrating them into our mathematical models as decision variables. Decision variables denoting the cruise times also play a major role in the chance constraints regarding the random non-cruise times. By decreasing the cruise time of a flight, probability of the non-cruise time spent by the aircraft being less than some desired level increases. Detailed explanation regarding the chance constraints will be given in the related sections.

2.4 Second Order Cone Programming

The impact of cruise time controllability and fuel costs on our problem is already explained in the previous section. One major challenge regarding the fuel consumption costs is that the cost function is nonlinear in the cruise speed of the aircraft. In order to handle this nonlinearity, second order cone programming (SOCP) has been used in optimization. Günlük and Linderoth [37] discuss how to represent several problems as SOCP. Aktürk et al. [38] consider the conic quadratic reformulation for machine-job assignment with controllable processing times which is one of the pioneering works. Gürkan et al. [5] also use second order cone programming in order to handle the nonlinearity in the objective function. More extensive information on conic programming can be found in Ben-Tal and Nemirovski [39]. In this study, nonlinearity of the fuel cost function in the objective is handled via SOCP and further explanation will be given in the related sections.

2.5 Value-at-Risk Measure

In stochastic programming, there may occur some situations where using only the expected values of random variables is not enough to formulate the complexity of the problem. Thus, a concept called "risk measure" is defined in the following fashion.

Definition 2.1. *A risk measure* ρ *is a function* $f : \mathcal{M} \rightarrow \bar{\mathbb{R}}$ *with mapping* $Z \mapsto \rho(Z)$ *where* $\mathcal{M}$ *is a space of random variables.*

There are various number of risk measures that can be considered. In this study, *Value-at-Risk* (VaR) is used to represent the risk carried out by the random non-cruise times. Further information regarding *Value-at-Risk* can be obtained from the following definitions [40].

Definition 2.2. *Given a random variable* Z *with the cumulative distribution function* $F_Z(z) = \mathbb{P}\{Z \leq z\}$*, for* $0 < \gamma < 1$*, the* $\gamma-$ *quantile is defined as*

$$F_Z^{-1}(\gamma) = \min\{z \ : \ F_Z(z) \geq \gamma\}.$$

Definition 2.3. *Given a random variable* Z *with the cumulative distribution function* $F_Z(t)$*, for* $0 < \gamma < 1$*, Value-at-Risk of* Z *at level* γ *is defined as the* $(1-\gamma)-$ *quantile of* Z*, i.e.,*

$$VaR_\gamma(Z) = F_Z^{-1}(1-\gamma).$$

2.6 Summary

Fuel consumption cost is one of the most important and most common factors that many airlines as well as a major part of the literature mainly focus on. As discussed, both fleet assignment decisions and cruise speed controllability have effects on the total costs of the schedules. Therefore, several studies, including this study, consider integrating these decisions while trying to keep the total costs at the minimum possible.

Another most important decision when generating schedules for the airlines is the flight departures. There are many works which include departure time decisions in a way that the passenger misconnections between flights due to delays is aimed to be minimized. These works which utilize robust optimization approaches constitutes a foundation for robust airline scheduling while maximizing passenger connection service levels.

However, there is a gap in the related literature due to the fact that most of the works focus only on the passenger connections to the best of our knowledge. Therefore, we follow a data-driven bi-criteria framework where the schedules are generated with the aim of maximizing the resilience of the system by minimizing the variability as a surrogate measure and while doing so the total operational costs of the schedules are allowed to deviate from the minimum but kept within acceptable limits.

Chapter 3

Problem Definition and Formulation

In this chapter, the problem is defined and the problem setting is explained with the notation that we utilized. Additionally, mathematical expressions for the functions related to non-cruise time random variables are given. After the problem is defined, the proposed problem formulation as a bi-criteria nonlinear mixed-integer mathematical model with chance constraints is provided with the detailed explanation of its objective functions and constraints. Finally, its reformulation as an ε-constraint mathematical model is explicitly given.

3.1 Problem Definition and Notation

We consider aircraft routing, fleet assignment and schedule design through flight departure times in an integrated manner while we also handle uncertainty caused by non-cruise times, fuel consumption and CO_2 emission costs, and the variability of the system which is related to the resilience of the schedule against unexpected challenges. Given the set of flights to be operated and the set of available aircraft, the problem is to determine the routes of the aircraft, block times of the flights, idle times of the aircraft, and fleet assignments to the determined routes while minimizing the total operational cost as well as the variability of the system. Block times of the flights consists of cruise and non-cruise times. Cruise times are controllable which means that they can be changed within some upper and lower limits whereas non-cruise times are random variables which are the main source of uncertainty in the system.

We claim that the variability of the system depends on the aircraft characteristics and the uncertain portion of the flights, i.e., non-cruise times. Thus, variability is heavily affected by the congestion levels of origin and destination airports of flights. To increase the resilience of the system, we use variability in a way that each aircraft path has a variability value as close to each other as possible since it is not known beforehand that which aircraft is going to be disrupted unexpectedly.

Similarly, turnaround times, which are times required to prepare the aircraft between consecutive flights, are also uncertain due to the congestion in the airports. Therefore, we handle the uncertain non-cruise times by using chance constraints in order to satisfy connections up to desired service levels to capture the delay risks of the aircrafts.

In the remainder of this section; sets, parameters and decision variables of the proposed mathematical model will be introduced. After that, random variable denoting the non-cruise times will be given together with its mathematical properties.

Sets:

T : set of aircrafts

F : set of all flight legs

B : set of airports

A : set of all possible consecutive flight pairs

U^i : set of flights which can connect to flight i, $i \in F$

D^i : set of flights which flight i can connect, $i \in F$

F_e^t : set of flights which aircraft t can use as a last flight in the schedule, $t \in T$

F_s^t : set of flights which aircraft t can use as a first flight in the schedule, $t \in T$

Parameters:

$Idle_t$: cost of idle time of aircraft $t \in T$ per minute

Cap_t : seat capacity of aircraft $t \in T$

Dem_i : passenger demand of flight $i \in F$

c_{fuel} : cost of fuel per ton of fuel consumption

c_{CO_2} : cost of emission per ton of aircraft CO_2 emission

O_i : origin airport of flight $i \in F$

D_i : destination airport of flight $i \in F$

NC_i : random parameter denoting the non-cruise time of flight $i \in F$

TA_{ij} : turnaround time needed between flights $(i, j) \in A$ to prepare aircraft

λ_t : total available cruise time of aircraft t on a day, $t \in T$

bf_t : base value for aircraft $t \in T$

f_i^l : lower time limit on the cruise time of flight $i \in F$

f_i^u : upper time limit on the cruise time of flight $i \in F$

e_b : airport congestion coefficient of airport $b \in B$

d_i^l : lower time limit on the departure time of flight $i \in F$

d_i^u : upper time limit on the departure time of flight $i \in F$

γ_i : desired probability level for the chance constraint for flight $i \in F$

Decision Variables:

d_i : departure time of flight $i \in F$

s_i^t : idle time of aircraft t after flight i, $t \in T,\ i \in F$

f_i^t : cruise time of flight i performed by aircraft t, $i \in F,\ t \in T$

q_i : scheduled block time of flight $i \in F$

$$x_{ij}^t := \begin{cases} 1 & \text{if flight } i \text{ is followed by flight } j \text{ performed by aircraft } t,\ i \in F, \\ & j \in F,\ t \in T \\ 0 & \text{otherwise} \end{cases}$$

$$y_i^t := \begin{cases} 1 & \text{if flight } i \text{ is the first flight performed by aircraft } t,\ i \in F,\ t \in T \\ 0 & \text{otherwise} \end{cases}$$

$$z_i^t := \begin{cases} 1 & \text{if flight } i \text{ is the last flight performed by aircraft } t,\ i \in F,\ t \in T \\ 0 & \text{otherwise} \end{cases}$$

Recall that the random variable NC_i denotes the non-cruise time of flight $i \in F$. According to the study of Deshpande and Arıkan [11], non-cruise times fit a symmetric Log-laplace distribution. Therefore, NC_i's are assumed to have Log-laplace distribution where each random variable is associated with two parameters, α for scale and $\beta_i > 0$ for shape. For each flight $i \in F$, the parameter β_i is calculated as

$$\beta_i = \beta(e_{O_i})^2(e_{D_i})^2 \tag{3.1}$$

where e_{O_i} is the congestion coefficient of origin and e_{D_i} is the congestion coefficient of destination airport of flight i and β is the base shape parameter. Congestion coefficients for different origin and destination airports are calculated based on the data-driven methodology explained later.

Then, let NC_i be a symmetric Log-laplace random variable with parameters α and $\beta_i > 0$. Then, e^α is the scale parameter and $1/\beta_i$ is the tail parameter. Cumulative distribution and probability density functions of NC_i are given respectively as:

$$F_{NC_i}(z) = \begin{cases} \frac{1}{2} e^{\frac{\ln z - \alpha}{\beta_i}}, & \text{if } \ln z < \alpha \\ 1 - \frac{1}{2} e^{\frac{-\ln z + \alpha}{\beta_i}}, & \text{if } \ln z \geq \alpha \end{cases} \tag{3.2}$$

$$f_{NC_i}(z) = \begin{cases} \frac{1}{2\beta_i z} e^{\frac{\ln z - \alpha}{\beta_i}}, & \text{if } \ln z < \alpha \\ \frac{1}{2\beta_i z} e^{\frac{-\ln z + \alpha}{\beta_i}}, & \text{if } \ln z \geq \alpha. \end{cases} \tag{3.3}$$

Then, the $\gamma - quantile$ of NC_i is as follows:

$$F^{-1}_{NC_i}(\gamma) = \begin{cases} (2\gamma)^{\beta_i} e^{\alpha}, & \text{if } \ln z < \alpha \\ \frac{e^{\alpha}}{(2-2\gamma)^{\beta_i}}, & \text{if } \ln z \geq \alpha. \end{cases} \tag{3.4}$$

For $\beta_i < 1/2$, the variance of NC_i is denoted by the following expression [41]:

$$Var(NC_i) = e^{2\alpha}\left(\frac{1}{(\alpha-2)(\beta_i+2)} - \left[\frac{1}{(\alpha-1)(\beta_i+1)}\right]^2\right) \tag{3.5}$$

3.2 Problem Formulation

We formulate the problem as a bi-criteria nonlinear mixed-integer mathematical model with chance constraints. The mathematical model and the detailed explanation of its objective functions and constraints are as follows:

$$\min \quad F_1: \quad \sum_{i\in F}\sum_{t\in T}(c_{fuel} + c_{CO_2})F_i^t(f_i^t) + \sum_{i\in F}\sum_{t\in T} s_i^t \cdot Idle_t \tag{3.6}$$

$$\min \quad F_2: \quad \frac{1}{|T|}\sum_{t\in T}\left|\mathbb{V}^t - \bar{\mathbb{V}}\right| \tag{3.7}$$

$$\text{s.t.} \quad \sum_{j\in U^i} x_{ji}^t + y_i^t - \sum_{j\in D^i} x_{ij}^t - z_i^t = 0 \qquad \forall i \in F,\ t \in T \tag{3.8}$$

$$\sum_{i\in F} y_i^t \leq 1 \qquad \forall t \in T \tag{3.9}$$

$$\sum_{t\in T}(y_i^t + \sum_{j\in U^i} x_{ij}^t) = 1 \qquad \forall i \in F \tag{3.10}$$

$$\sum_{i\in F} f_i^t \leq \lambda_t \qquad \forall t \in T \tag{3.11}$$

$$\text{IF} \quad \sum_{t \in T} x_{ij}^t = 1 \quad \text{THEN}$$

$$\mathbb{P}\{NC_i \leq q_i - \sum_{t \in T}(f_i^t + s_i^t) - TA_{ij}\} \geq \gamma_i \quad \forall (i,j) \in A \tag{3.12}$$

$$q_i = d_j - d_i \quad \forall (i,j) \in A \tag{3.13}$$

$$\text{IF} \quad (y_i^t + \sum_{j \in U^i} x_{ji}^t) = 1 \quad \text{THEN}$$

$$f_i^l \leq f_i^t \leq f_i^u \quad \forall i \in F,\ t \in T \tag{3.14}$$

$$\text{ELSE}$$

$$f_i^t = 0 \quad \forall i \in F,\ t \in T \tag{3.15}$$

$$s_i^t = 0 \quad \forall i \in F,\ t \in T \tag{3.16}$$

$$d_i^l \leq d_i \leq d_i^u \quad \forall i \in F \tag{3.17}$$

$$y_i^t = 0 \quad \forall t \in T,\ i \in F \backslash F_s^t \tag{3.18}$$

$$z_i^t = 0 \quad \forall t \in T,\ i \in F \backslash F_e^t \tag{3.19}$$

$$q_i \geq 0 \quad \forall i \in F \tag{3.20}$$

$$s_i^t \geq 0 \quad \forall i \in F,\ t \in T \tag{3.21}$$

$$x_{ij}^t \in \{0,1\} \quad \forall (i,j) \in A,\ t \in T \tag{3.22}$$

$$y_i^t \in \{0,1\} \quad \forall i \in F,\ t \in T \tag{3.23}$$

$$z_i^t \in \{0,1\} \quad \forall i \in F,\ t \in T \tag{3.24}$$

The first objective function (3.6) is the operational cost which is the sum of the fuel consumption and CO_2 emission costs and the idle time cost of the aircraft. The second objective function (3.7) is the total absolute deviation of the aircraft path variabilities from the average variability. Constraint (3.8) is the network balance constraint. Constraint (3.9) ensures that each aircraft can be used for at most one path. Constraint (3.10) ensures that each flight can be performed by exactly one aircraft. Constraint (3.11) ensures that the total cruise time of an aircraft does not exceed a predetermined time limit for maintenance feasibility. The chance constraint (3.12) requires that if two flights are performed by the same aircraft, then the probability of the non-cruise time of the earlier flight being less than or equal to the difference of departure times minus the sum of the cruise, idle, and the aircraft turnaround times should be at least the desired service level γ_i. Constraint (3.13) ensures that the block times of two flights that are performed by the same aircraft equals to the difference between their departure times. If flight i is performed by aircraft t then constraints (3.14)-(3.16) limit cruise time change; cruise time of a flight cannot exceed the upper and lower bounds, else the corresponding variables f_i^t and s_i^t are set to zero. Constraint (3.17) puts lower and upper bounds on the flight departure times based on the desired times which are available in the set of flights to be operated as input. Constraints (3.18) and (3.19) sustain a maintenance policy by preventing some flights from being the first or the last flight that is operated in a day. Constraints (3.20) and (3.21) make block times and idle times nonnegative. Constraints (3.22)-(3.24) are integrality constraints for the binary variables x_{ij}^t, y_i^t, and z_i^t.

This formulation is a bi-criteria mixed-integer non-linear programming model with chance constraints. The constraint (3.12) utilizes non-cruise time random variables NC_i which follow Loglaplace distribution. The same constraint can be written as

$$d_j - d_i - \sum_{t \in T}(f_i^t + s_i^t) - TA_{ij} \geq \mathrm{VaR}_{1-\gamma_i}(NC_i) \tag{3.25}$$

where $\mathrm{VaR}_{1-\gamma_i}(NC_i)$ represents the value-at-risk at the service level γ_i. By Definition 2.3 and Equation 3.4 it is calculated as

$$\mathrm{VaR}_{1-\gamma_i}(NC_i) = \begin{cases} (2\gamma_i)^{\beta_i} e^{\alpha}, & \text{if } \ln z < \alpha \\ \frac{e^{\alpha}}{(2-2\gamma_i)^{\beta_i}}, & \text{if } \ln z \geq \alpha \end{cases} \tag{3.26}$$

where the parameter β_i is calculated as $\beta_i = \beta(e_{O_i})^2(e_{D_i})^2$ in which β is the base shape parameter and e_{O_i} and e_{D_i} represent the congestion coefficients of origin and destination airports of flight i respectively. Airport congestion coefficients are calculated based on the following data-driven methodology. Intuitively, departure and arrival delay probabilities of flights are closely related to the congestion levels in airports. Therefore, we aim to first estimate these probabilities using the historical Airline On-Time Performance Data provided by BTS [42]. Many studies in the literature consider logit models to explain the impact of variables on on-time performance of flight schedules. In this study, two logistic regression models are constructed to estimate the departure and arrival delay probabilities.

To estimate the departure delay probability of flight i, denoted as $p_i \in (0, 1)$, the origin airport of the flight and the time segment that the departure time of the flight lies in are determined to be the variables denoted as $x_{i,origin}$ and $x_{i,deptime}$. Then, the linear predictor $\eta_i \in \mathbb{R}$ is constructed by

$$\eta_i = \theta_0 + \theta_{origin} x_{i,origin} + \theta_{deptime} x_{i,deptime}$$

where θ_0, θ_{origin}, and $\theta_{deptime}$ are the corresponding coefficients. Finally, through the use of the logit link function, p_i is calculated by the following characterization [43]:

$$\eta_i = \log\left(\frac{p_i}{1-p_i}\right).$$

A similar logistic regression model is constructed for estimating the arrival delay probabilities, denoted as $q_i \in (0,1)$ for flight i, where the variable $x_{i,origin}$ is changed to $x_{i,destination}$ to capture the effect of the destination airport of a flight on the arrival delays.

After the departure and arrival delay probabilities are estimated, the airport congestion coefficients for flight $i \in F$ are calculated as follows:

$$e_{O_i} = (1+p_i)^2, \; e_{D_i} = (1+q_i)^2.$$

In addition, for each possible consecutive flight pair $(i,j) \in A$, the turnaround time TA_{ij} to prepare the aircraft between flights i and j is estimated by linear regression as follows:

$$TA_{ij} = \mu_0 + \mu_{origin} x_{j,origin}$$

where μ_{origin} is the corresponding coefficient to the variable $x_{j,origin}$ denoting the airport that the aircraft spends its preparation time between the flights. Detailed explanation of the development of these estimation models and their results are available in Chapter 4.

By replacing constraint (3.12) with inequality 3.25 in the mathematical model, chance constraints are handled via the closed-form representation of the quantile function of Loglaplace probability distribution.

In the objective function (3.7), the aircraft path variability of aircraft t denoted by $\mathbb{V}^t$ is calculated as $\sum_{i\in F} \mathcal{V}_i^t(O_i, D_i, d_i, f_i^t)$ where the variability of a flight leg i is calculated as

$$\mathcal{V}_i^t(O_i, D_i, d_i, f_i^t) = \begin{cases} bf_t \cdot Var(NC_i) & \text{if flight } i \text{ is operated by aircraft } t \\ 0 & \text{otherwise.} \end{cases}$$

Note that bf_t denotes the base value for aircraft t which is calculated by normalizing the base turntime of different aircraft provided by EUROCONTROL [44] and $Var(NC_i)$ denotes the variance value of the Log-laplace random variable corresponding to the non-cruise time of flight leg i which is calculated by Equation 3.5 as follows

$$Var(NC_i) = e^{2\alpha}\left(\frac{1}{(\alpha-2)(\beta_i+2)} - \left[\frac{1}{(\alpha-1)(\beta_i+1)}\right]^2\right).$$

Also, $\bar{\mathbb{V}}$ denotes the arithmetic mean of the aircraft path variabilities $\mathbb{V}^t$ over all $t \in T$ which allows us to calculate the total absolute deviation of the aircraft path variabilities from the average variability. This creates a nonlinearity due to the use of absolute value and it can be linearized by using the following set of inequalities:

$$\begin{aligned} \min \quad F_2 : \quad & \frac{1}{|T|}\sum_{t\in T} \nu^t \\ \text{s.t.} \quad & \nu^t \geq \mathbb{V}^t - \bar{\mathbb{V}} && \forall t \in T \\ & \nu^t \geq \bar{\mathbb{V}} - \mathbb{V}^t && \forall t \in T \end{aligned}$$

The other nonlinearity of the model stems from the objective function (3.6). In the objective, for flight $i \in F$ and aircraft $t \in T$, the fuel consumption function $F_i^t(f_i^t)$ is represented as

$$F_i^t(f_i^t) = \begin{cases} \left(c_1^{it}\frac{1}{f_i^t} + c_2^{it}\frac{1}{(f_i^t)^2} + c_3^{it}(f_i^t)^3 + c_4^{it}(f_i^t)^2\right) & \text{if } y_i^t + \sum_{j\in U^i} x_{ji}^t = 1 \\ 0 & \text{if } y_i^t + \sum_{j\in U^i} x_{ji}^t = 0 \end{cases} \tag{3.27}$$

where f_i^t denotes the cruise time of flight i operated by aircraft t. The parameters that are required to calculate the fuel consumption can be found in EUROCONTROL [44].

For flight $i \in F$ and aircraft $t \in T$, $F_i^t(f_i^t)$ is discontinuous and its epigraph $E_F = \{(f_i^t, \tau) \in \mathbb{R}^2 : F_i^t(f_i^t) \leq \tau\}$ is nonconvex. In the Proposition 3.2.1 by Şafak et al. [6], the assumptions that yield the convexity of E_F are obtained. Detailed information can be found in Aktürk et al. [38] and Günlük and Linderoth [37].

Proposition 3.2.1. *The convex hull of E_F can be expressed as*

$$\tau \geq (c_{fuel} + c_{CO_2}) \cdot (c_1^{it}\kappa_i^t + c_2^{it}\delta_i^t + c_3^{it}\phi_i^t + c_4^{it}\vartheta_i^t) \tag{3.28}$$

$$(y_i^t + \sum_{j \in U^i} x_{ji}^t)^2 \leq \kappa_i^t \cdot f_i^t \tag{3.29}$$

$$(y_i^t + \sum_{j \in U^i} x_{ji}^t)^4 \leq (f_i^t)^2 \cdot \delta_i^t \cdot 1 \tag{3.30}$$

$$(f_i^t)^4 \leq (y_i^t + \sum_{j \in U^i} x_{ji}^t)^2 \cdot \phi_i^t \cdot f_i^t \tag{3.31}$$

$$(f_i^t)^2 \leq \vartheta_i^t \cdot (y_i^t + \sum_{j \in U^i} x_{ji}^t) \tag{3.32}$$

in the constraint set. Each inequalities (3.29)-(3.32) can be represented by conic quadratic inequalities.

Proof. Let $w = y_i^t + \sum_{j \in U^i} x_{ji}^t$ for the ease of notation. Perspective of a convex function $k(f)$ is $zk(f/z)$ [45]. Since each of the nonlinear terms $\frac{1}{f_i^t}$, $\frac{1}{(f_i^t)^2}$, $(f_i^t)^3$, and $(f_i^t)^2$ is a convex function for $f_i^t \geq 0$, then epigraph of the perspective of each term can be stated as

$$\frac{w^2}{f_i^t} \leq \kappa$$
$$\frac{w^4}{(f_i^t)^2} \leq \delta$$
$$\frac{(f_i^t)^3}{w^2} \leq \phi$$
$$\frac{(f_i^t)^2}{w} \leq \vartheta$$

respectively. Since $w,\ f_i^t \geq 0$, they can be written as described in the proposition. Finally, observe that (3.29) and (3.32) are hyperbolic inequalities, (3.30) can be written as two hyperboic inequalities

$$w^2 \leq z f_i^t \quad \text{and} \quad z^2 \leq \delta \cdot 1$$

and (3.31) can be restated as

$$(f_i^t)^2 \leq zw \quad \text{and} \quad z^2 \leq \phi \cdot f_i^t$$

which can be written as a conic quadratic inequality. □

The corresponding conic representation of the fuel consumption function is as follows:

$$\begin{aligned}
\min \quad F_1 : \quad & \sum_{i \in F} \sum_{t \in T} (c_{fuel} + c_{CO_2}) \cdot (c_1^{it} \kappa_i^t + c_2^{it} \delta_i^t + c_3^{it} \phi_i^t + c_4^{it} \vartheta_i^t) + \sum_{i \in F} \sum_{t \in T} s_i^t \cdot Idle_t \\
\text{s.t.} \quad & (y_i^t + \sum_{j \in U^i} x_{ji}^t)^2 \leq \kappa_i^t \cdot f_i^t \\
& (y_i^t + \sum_{j \in U^i} x_{ji}^t)^4 \leq (f_i^t)^2 \cdot \delta_i^t \cdot 1 \\
& (f_i^t)^4 \leq (y_i^t + \sum_{j \in U^i} x_{ji}^t)^2 \cdot \phi_i^t \cdot f_i^t \\
& (f_i^t)^2 \leq \vartheta_i^t \cdot (y_i^t + \sum_{j \in U^i} x_{ji}^t)
\end{aligned}$$

Therefore, the mathematical model can be reformulated by using the above conic inequalities in the constraint set in order to tackle the nonlinearity in the first objective function via second order cone programming. The conic reformulation is as follows:

$$\min \quad F_1 : \quad \sum_{i \in F} \sum_{t \in T} (c_{fuel} + c_{CO_2}) \cdot (c_1^{it} \kappa_i^t + c_2^{it} \delta_i^t + c_3^{it} \phi_i^t + c_4^{it} \vartheta_i^t) + \sum_{i \in F} \sum_{t \in T} s_i^t \cdot Idle_t \tag{3.33}$$

$$\min \quad F_2 : \quad \frac{1}{|T|} \sum_{t \in T} |\mathbb{V}^t - \bar{\mathbb{V}}|$$

$$\text{s.t.} \quad (3.8) - (3.24)$$

$$(y_i^t + \sum_{j \in U^i} x_{ji}^t)^2 \leq \kappa_i^t \cdot f_i^t \qquad \forall i \in F,\ t \in T \tag{3.34}$$

$$(y_i^t + \sum_{j \in U^i} x_{ji}^t)^4 \leq (f_i^t)^2 \cdot \delta_i^t \cdot 1 \qquad \forall i \in F,\ t \in T \tag{3.35}$$

$$(f_i^t)^4 \leq (y_i^t + \sum_{j \in U^i} x_{ji}^t)^2 \cdot \phi_i^t \cdot f_i^t \qquad \forall i \in F,\ t \in T \tag{3.36}$$

$$(f_i^t)^2 \leq \vartheta_i^t \cdot (y_i^t + \sum_{j \in U^i} x_{ji}^t)^2 \qquad \forall i \in F,\ t \in T \tag{3.37}$$

To solve the above bi-criteria nonlinear mixed-integer programming problem, the ε-constraint approach as discussed in T'kindt and Billaut [46] is applied. In this approach, the problem of minimizing F_2 for a given upper bound on F_1 is solved. We add the following constraint into our proposed model to bound the operational cost above.

$$\sum_{i\in F}\sum_{t\in T}(c_{fuel}+c_{CO_2})\cdot(c_1^{it}\kappa_i^t+c_2^{it}\delta_i^t+c_3^{it}\phi_i^t+c_4^{it}\vartheta_i^t)+\sum_{i\in F}\sum_{t\in T}s_i^t\cdot Idle_t\leq\varepsilon \quad (3.38)$$

The ε-constraint approach is frequently used in the literature since it provides the decision maker with flexibility to modify bounds on one objective to analyze the changes on the other. Therefore, we propose the following ε-constraint mathematical model denoted as (ε-CM) by bounding the operational cost by ε to analyze its effects on the total deviation of aircraft path variabilities.

$$(\varepsilon\text{-CM}) \qquad \min \quad \frac{1}{|T|}\sum_{t\in T}\nu^t$$

$$\text{s.t.} \quad (3.8)-(3.24),\ (3.34)-(3.37)$$

$$\sum_{i\in F}\sum_{t\in T}(c_{fuel}+c_{CO_2})\cdot(c_1^{it}\kappa_i^t+c_2^{it}\delta_i^t+c_3^{it}\phi_i^t+c_4^{it}\vartheta_i^t)+\sum_{i\in F}\sum_{t\in T}s_i^t\cdot Idle_t\leq\varepsilon$$

$$\nu^t\geq\mathbb{V}^t-\bar{\mathbb{V}} \qquad \forall t\in T \qquad (3.39)$$

$$\nu^t\geq\bar{\mathbb{V}}-\mathbb{V}^t \qquad \forall t\in T \qquad (3.40)$$

It is only guaranteed that ε-constraint approach yields weak efficient solutions to the multi-objective optimization problems. Hence, as a future direction, the weighted sum approach might be considered where the scalarization is achieved by multiplying the total operational cost by a small constant and adding it to the objective function.

3.3 Summary

In this chapter, the problem definition is provided in detail. Properties of the random variables that we utilize throughout this study, sets, parameters and decision variables of the problem are described. Then, the formulation of the problem as a bi-criteria nonlinear mixed-integer mathematical model with chance constraint is given. Chance constraints are handled with the use of value-at-risk measure. Nonlinear fuel consumption and CO_2 cost function in the objective is handled with second order conic inequalities. Finally, ε-constraint formulation is proposed to be able to solve the problem via commercial solvers.

Chapter 4

Data Analysis and Parameter Estimation

In this chapter, the aim is to explain how the available on-performance data is utilized in order to estimate departure and arrival delay probabilities of flights and the turnaround times of the aircraft. These estimates are used in our proposed mathematical models such that the empirical evidence that we found helps increasing the resilience of the system.

4.1 Model Development

In order to estimate departure and arrival delays, and turnaround times of the aircraft, we develop several models. To explain the factors that are affecting our estimates, several hypotheses which are developed in the literature are examined as follows.

Delay probabilities of flights are heavily affected by the propagation patterns as suggested by Lambelho et al. [16]. To capture these propagation effects, position of a flight in the path of an aircraft is considered in their study. We consider using the flight departure time as a surrogate measure to position of a flight. Indeed, the existing literature provides some studies which take flight departure times into account when estimating the required parameters. According to Deshpande and Arıkan [11], airline schedule planners tend to schedule larger number of flights in the interval of 5 P.M. - 6 P.M. to capture the business travel demand. Arora et al. [15] suggest that afternoon and evening flights are more likely to depart late. Şafak et al. [7] propose a segmentation based on the time intervals that the flights departure times lie in and they claim that in different time segments, passenger volumes are different in airports. Similarly, Herring et al. [14] claim that passengers prefer itineraries with more than 25 minutes buffer time in order to satisfy their connection between flights. This shows that the departure times of scheduled flights are affecting the passenger volumes in airports at different time intervals. All of these clearly indicate that the flight departure times are affecting the congestion levels in the airports and consecutively the delay probabilities significantly. On the other hand, Prakash [17] assumes that the planned arrival time of a flight also has an effect on the probability of having a delayed arrival. In our proposed mathematical models, we capture the effect of arrival time on the delay probabilities of flights by approximating it with the addition of the air time of flights to their departure times. Therefore, we take flight departure times as factors that affect the estimates of departure and arrival delay probabilities of flights.

Also, naturally, not all airports have the same level of congestion due to geographical reasons. Intuitively, one can expect the hubs to be more congested. Since the level of congestion differs in the airports, we assume departure and arrival delays occurred in different origin and destination airports have different means and variances which have effects on the on-time probabilities. Similarly, flight departure time has also an effect on the turnaround time required to prepare the aircraft between two flights. Therefore, in our proposed models, origin and destination airports of flights are taken as factors to estimate both departure and arrival delays and also turnaround times. In short, we consider flight departure times, origin and destination airports as the factors that affect our estimation of the related response variables.

4.2 Data and Variables

Detailed data is obtained from the Airline On-Time Performance Data [42] provided by the Bureau of Transportation Statistics of the U.S. Department of Transportation on each flight operated between major airports in the United Stated by United Airlines in the years 2018 and 2019. The data set contains origin and destination airports of flights, tail numbers of the aircraft that operate these flights, scheduled and actual arrival and departure times, arrival and departure delays, taxi-in and taxi-out times, air times and distances of the flights. Tail numbers uniquely identify the aircraft but having only the tail number does not give further information on the type of the aircraft and its characteristics. Thus, Aircraft Registry Database [47] is used to obtain aircraft specific information of the United States.

Data set consists of 269,349 observations, one for each flight flown, across two years covering 21 major U.S. airports. Description of the variables can be found in Table 4.1.

Table 4.1: Description of the Variables

Variable	**Description**
ORIGIN	Origin Airport
DEST	Destination Airport
TAIL_NUM	Tail Number
CRS_DEP_TIME	Planned Departure Time (in local time: hhmm)
CRS_ARR_TIME	Planned Arrival Time (in local time: hhmm)
DEP_TIME	Actual Departure Time (in local time: hhmm)
ARR_TIME	Actual Arrival Time (in local time: hhmm)
DEP_DEL15	Departure Delay Indicator: 15 Minutes or More (1 = Yes)
ARR_DEL15	Arrival Delay Indicator: 15 Minutes or More (1 = Yes)
DEP_DEL_NEW	Difference in minutes between scheduled and actual departure time
ARR_DEL_NEW	Difference in minutes between scheduled and actual arrival time
TAXI_OUT	Taxi Out Time, in Minutes
TAXI_IN	Taxi In Time, in Minutes
AIR_TIME	Flight Time, in Minutes
DISTANCE	Distance between Airports in Miles

In order to use departure time of a flights as a factor in our estimation models, we convert it into a categorical variable based on the segmentation proposed by Şafak et al. [7] with the addition of the segment IV to satisfy completeness. The segmentation used is available in Table 4.2. Therefore, the departure time of flights are used in all of the estimation models as a factor with four levels.

Table 4.2: Segmentation for the Departure Time of Flights

Segment	**Time Interval**
I	06:00 A.M. - 08:59 A.M. and after 05:00 P.M.
II	09:00 A.M. - 11:59 A.M. and 03:00 P.M. - 04:59 P.M.
III	12:00 noon - 02:59 P.M.
IV	Before 06:00 A.M.

4.3 Estimation Results

Using logistic regression models, departure and arrival delay probabilities for 269,349 flights across 21 major U.S. airports are estimated. Since we distinguish the departure and arrival delay probabilities of a flight from each other, to see the effects of this difference on the probabilities of having a delayed departure from or a delayed arrival to each airport are given in Table 4.3 without considering the effects of the departure times of flights.

As it can be seen from the Table 4.3, for a given airport, delay probability of a flight departing from there and arriving to there are different. For example, delay probability of a flight departing from FLL (Fort Lauderdale-Hollywood Intl. Airport) is up to 9.68% whereas delay probability of a flight arriving to FLL is up to 20.14%. In the existing literature, it was assumed that for a flight, having a particular airport as either its origin or destination airport has the same effect on its delay probabilities. By distinguishing the departure and arrival delay probabilities, we are able to capture the effects of the different congestion levels of origin and destination airports of flights.

Table 4.3: Departure and Arrival Delay Probabilities of 21 Major U.S. Airports

Airport	**Departure Delay Probability**	**Airport**	**Arrival Delay Probability**
EWR	0.1502	FLL	0.2014
SLC	0.1452	DFW	0.1823
ATL	0.1442	MIA	0.1794
SFO	0.1272	MCI	0.1675
ORD	0.1263	LGA	0.1672
STL	0.1159	BOS	0.1567
DFW	0.1098	PHL	0.1565
MIA	0.1088	EWR	0.1524
DEN	0.1056	PHX	0.1501
BOS	0.1009	ATL	0.1460
LGA	0.0995	SFO	0.1453
FLL	0.0968	DCA	0.1440
PHL	0.0936	MSP	0.1428
PHX	0.0928	LAS	0.1370
LAS	0.0907	SAN	0.1362
SAN	0.0867	SLC	0.1353
MSP	0.0829	AUS	0.1352
LAX	0.0797	LAX	0.1334
AUS	0.0796	ORD	0.1284
DCA	0.0699	DEN	0.1214
MCI	0.0561	STL	0.1114

An important observation, the earlier studies estimated the airport congestion coefficients based on the number of passengers visiting a particular airport provided in T-100 Domestic Market Data [48] regardless of departure or arrival events, that may not be a realistic representation as can be seen from Table 4.3. For example, MIA (Miami Intl. Airport) has the highest number passengers and consequently assigned the largest airport congestion coefficient in earlier studies, followed by ORD (Chicago O'Hare Intl. Airport), DEN (Denver Intl. Airport) and DFW (Dallas/Fort Worth Intl. Airport). In contrary, DEN has one of the lowest arrival delay occurrence and consequently one of the lowest arrival congestion coefficients according to our data analysis. The corresponding airport congestion coefficients are provided in Table 4.4.

Table 4.4: Departure and Arrival Congestion Coefficients of 21 Major U.S. Airports

Airport	**Departure Cong. Coefficient**	**Airport**	**Arrival Cong. Coefficient**
EWR	1.32	FLL	1.44
SLC	1.31	DFW	1.40
ATL	1.31	MIA	1.39
SFO	1.27	MCI	1.36
ORD	1.27	LGA	1.36
STL	1.25	BOS	1.34
DFW	1.23	PHL	1.34
MIA	1.23	EWR	1.33
DEN	1.22	PHX	1.32
BOS	1.21	ATL	1.31
LGA	1.21	SFO	1.31
FLL	1.20	DCA	1.31
PHL	1.20	MSP	1.31
PHX	1.19	LAS	1.29
LAS	1.19	SAN	1.29
SAN	1.18	SLC	1.29
MSP	1.17	AUS	1.29
LAX	1.17	LAX	1.28
AUS	1.17	ORD	1.27
DCA	1.14	DEN	1.26
MCI	1.12	STL	1.24

In addition to the previous results, we also consider the effects of the time segments of the flight departure times on the delay probabilities. The resulting delay probability estimations for the same set of flights operated between 21 major U.S. airports and departing in each of the four time segments are available in Table 4.5.

Table 4.5: Departure and Arrival Delay Probabilities of 21 Major U.S. Airports in Four Time Segments

Departure Delay Probability					**Arrival Delay Probability**				
Airport	Time Segment				Airport	Time Segment			
	I	II	III	IV		I	II	III	IV
ATL	0.142	0.145	0.162	0.025	ATL	0.174	0.111	0.115	0.130
AUS	0.079	0.081	0.091	0.013	AUS	0.170	0.108	0.113	0.127
BOS	0.102	0.104	0.116	0.017	BOS	0.182	0.116	0.121	0.136
DCA	0.071	0.073	0.082	0.012	DCA	0.176	0.112	0.117	0.131
DEN	0.103	0.105	0.118	0.018	DEN	0.148	0.093	0.097	0.109
DFW	0.110	0.112	0.125	0.019	DFW	0.224	0.146	0.152	0.170
EWR	0.149	0.152	0.169	0.026	EWR	0.181	0.115	0.120	0.135
FLL	0.094	0.096	0.107	0.016	FLL	0.246	0.162	0.168	0.187
LAS	0.089	0.091	0.102	0.015	LAS	0.166	0.105	0.110	0.123
LAX	0.078	0.080	0.090	0.013	LAX	0.162	0.103	0.107	0.121
LGA	0.096	0.099	0.110	0.016	LGA	0.200	0.129	0.134	0.150
MCI	0.057	0.058	0.066	0.009	MCI	0.189	0.121	0.126	0.142
MIA	0.105	0.108	0.120	0.018	MIA	0.215	0.139	0.145	0.162
MSP	0.084	0.085	0.096	0.014	MSP	0.175	0.112	0.116	0.130
ORD	0.123	0.125	0.140	0.021	ORD	0.157	0.099	0.103	0.116
PHL	0.095	0.097	0.109	0.016	PHL	0.182	0.116	0.121	0.136
PHX	0.091	0.094	0.105	0.015	PHX	0.181	0.115	0.120	0.135
SAN	0.084	0.086	0.096	0.014	SAN	0.165	0.105	0.109	0.122
SFO	0.125	0.128	0.142	0.022	SFO	0.176	0.112	0.117	0.131
SLC	0.149	0.152	0.169	0.027	SLC	0.182	0.116	0.121	0.136
STL	0.114	0.117	0.130	0.020	STL	0.154	0.097	0.101	0.114

Besides the delay probabilities, base turnaround times needed to prepare the aircraft between consecutive flights in 21 different airports are estimated by a linear regression model. Results for turnaround time estimations are given in Table 4.6.

Table 4.6: Turnaround Times in 21 Major U.S. Airports

Airport	**Turnaround Time (mins)**	**Airport**	**Turnaround Time (mins)**	**Airport**	**Turnaround Time (mins)**
ATL	29	FLL	39	ORD	31
AUS	24	LAS	29	PHL	28
BOS	29	LAX	30	PHX	24
DCA	28	LGA	33	SAN	29
DEN	26	MCI	27	SFO	32
DFW	29	MIA	39	SLC	26
EWR	32	MSP	30	STL	26

4.4 Summary

In this chapter, the historical airline on-time performance data that we use to estimate some problem parameters are described. The logistic regression models to estimate departure and arrival probabilities of flights are discussed in terms of the development of the models and variable selection provess. Results for the estimation are given as well as the airport congestion coefficients which are calculated based on these estimations. After the probability estimations, results for the turnaround time estimations are provided.

Chapter 5

Proposed Discretized Approximation and Aircraft Swapping Algorithm

Even though the proposed mathematical model (ε-CM) in Chapter 3.2 can be applied for solving the small-sized problem instances, due to the increasing difficulty of solving the problem to optimality with the increasing problem size, a solution approach called discretized approximation and aircraft swapping algorithm is proposed. The main idea of the algorithm is to solve Discretized Approximation Model (DAM) first to get an initial feasible solution for aircraft routing and fleeting and then to solve the cruise speed control model (CSCM) proposed by Duran et al. [4] to obtain the minimum cost schedule. Then, Aircraft Swapping Search Algorithm (ASSA) is applied in order to decrease the deviation of the aircraft path variabilities from the average without exceeding the upper limit for the total operational cost. Flow of the algorithm can be found in Figure 5.1.

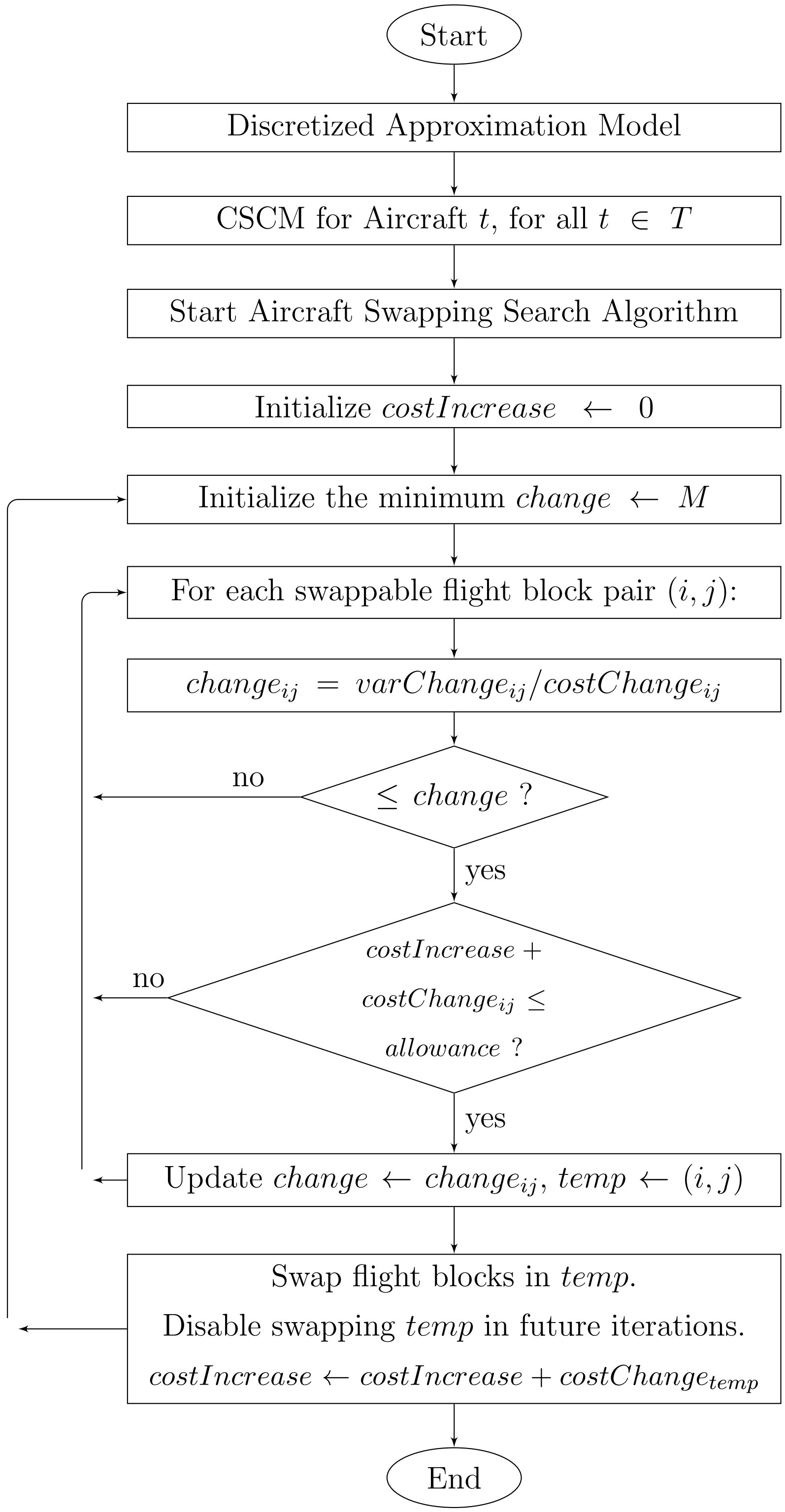

Figure 5.1: Flow Chart of the Discretized Approximation and Aircraft Swapping Algorithm

5.1 Discretized Approximation Model

In our proposed mathematical model, complexity of the formulation is heavily due to the SOCP-representable fuel consumption and CO_2 emission functions. Therefore, in order to reduce the complexity to be able to solve the problem within reasonable solution times, we first use the discretized approximation model (DAM) proposed by Gürkan et al. [5] where the cruise times of flights can only take discrete values from a pre-determined set instead of continuous values from a range. The following parameters are introduced:

crs_{ik}^t : the k^{th} cruise time option of flight i operated by aircraft t, $k \in K$

$cost_{ik}^t$: the cost of crs_{ik}^t which is equal to $(c_{fuel} + c_{CO_2}) \cdot F(crs_{ik}^t)$

Also, the following binary variable is defined for each flight i, aircraft t, and cruise time option k:

$$\sigma_{ik}^t := \begin{cases} 1 & \text{if cruise time of flight } i \text{ takes the } k^{th} \text{ value for aircraft } t \\ 0 & \text{otherwise} \end{cases}$$

The formulation of DAM is as follows:

$$\min \quad \sum_{t\in T}\sum_{i\in F}\sum_{k\in K} \sigma_{ik}^t \cdot cost_{ik}^t + \sum_{t\in T}\sum_{i\in F} s_i^t \cdot Idle_t \tag{5.1}$$

$$\text{s.t.} \quad (3.8) - (3.24)$$

$$\sum_{k\in K} \sigma_{ik}^t = (y_i^t + \sum_{j\in U^i} x_{ji}^t) \qquad \forall i \in F,\ t \in T \tag{5.2}$$

$$\sum_{k\in K} \sigma_{ik}^t \cdot crs_{ik}^t = f_i^t \qquad \forall i \in F,\ t \in T \tag{5.3}$$

$$\sigma_{ik}^t \in \{0,1\} \qquad \forall i \in F,\ t \in T,\ k \in K \tag{5.4}$$

(DAM) gives a solution to aircraft routing, fleet assignment and schedule generation without any consideration of variability terms.

5.2 Aircraft Swapping Search Algorithm

Since (DAM) combined with (CSCM) does not generate a schedule where the aircraft path variabilities is considered, a search algorithm is proposed in order to decrease the deviation of aircraft path variabilities from the average variability by swapping the aircraft. Let E denote the set of flight blocks and S be the set of flight block pairs whose operating aircraft can be swapped. Then, new set of parameters and decision variables are introduced as follows:

$minCost$: the minimum cost value of the schedule

ϱ : the percentage allowance for the cost increase

$blockVar_i^t$: variability of block i if it is operated by aircraft t, $i \in E,\ t \in T$

$pathVar^t$: variability over the path of aircraft t, $t \in T$

$aircraft^i$: aircraft assignment of flight block i, $i \in E$

a_{ij} := 1 if $(i,j) \in S,$ 0 otherwise

w_i^t := 1 if block i is performed by aircraft t, $i \in E,\ t \in T,$ 0 otherwise

u_{ij} := 1 if block i is swapped with flight block j, $(i,j) \in S,$ 0 otherwise

The search algorithm is available in Algorithm 1 and the idea is to decide on the flight blocks whose aircraft assignments are swapped in order to have the maximum amount of decrease in the deviation of the aircraft path variabilities from the average while satisfying the upper limit for the total operational cost. To be able to achieve that, the swap which gives the maximum decrease in the deviation of variabilities with the minimum increase in the total operational cost is selected in a knapsack framework.

Algorithm 1 Aircraft Swapping Search Algorithm

1: **Initialize:** $costOfSchedule \leftarrow minCost$

2: **Set:** $maxCost \leftarrow minCost \times (1 + \varrho)$

3: **for** each $t \in T$ **do**

4: **for** each $j \in \{0, \ldots, |E|\}$ **do**

5: $pathVar^t \leftarrow pathVar^t + w_j^t \cdot blockVar_j^t$ {Calculate path variabilities.}

6: **end for**

7: **end for**

8: **for** each $j \in \{0, \ldots, |E|\}$ **do**

9: **for** each $k \in \{0, \ldots, |E|\}$ **do**

10: $varChange_{jk} \leftarrow$ change in the absolute deviation of path variabilities from average if flight block j is swapped with k.

11: $costChange_{jk} \leftarrow$ increase in the total operational cost if flight block j is swapped with k.

12: **end for**

13: $k^\star \leftarrow \arg\min_{k \in \{0,\ldots,|E|\}\ :\ aircraft^j \neq aircraft^k,\ a_{jk}=1} \{\frac{varChange_{jk}}{costChange_{jk}}\}$

14: **if** $varChange_{jk^\star} \leq 0$ **and** $costOfSchedule + costChange_{jk^\star} \leq maxCost$ **then**

15: $w_j^{aircraft^j} \leftarrow 0$ **and** $w_{k^\star}^{aircraft^{k^\star}} \leftarrow 0$ {Remove initial aircraft assignments.}

16: $aircraft^j \leftrightarrow aircraft^{k^\star}$ {Swap the aircraft assignments.}

17: $u_{jk^\star} \leftarrow 1$ {Swap flight blocks j and $k^\star$.}

18: $w_j^{aircraft^j} \leftarrow 1$ **and** $w_{k^\star}^{aircraft^{k^\star}} \leftarrow 1$ {Reassign aircraft to flight blocks j, $k^\star$.}

19: $costOfSchedule \leftarrow costOfSchedule + costChange_{jk^\star}$ {Update the cost.}

20: **end if**

21: Re-calculate path variabilities $pathVar^t$ for all $t \in T$ (same as in steps 2-6).

22: **end for**

5.3 Numerical Example

In this section, a numerical example is provided to illustrate the model mechanics and how the proposed algorithm works. The problem takes the set of flights to be operated and the set of available aircraft as input. We consider a sample schedule of 25 flights to be operated and each of them either departs from the selected hub airport ORD or arrive to ORD. There are 5 available aircraft whose manufacturers and models can be seen in Table 5.1.

Table 5.1: The Set of Available Aircraft

Tail Number	Aircraft Type
N678UA	B737 50
N802WA	MD 83
N805WA	MD 83
N309US	A320 111
N334NW	A320 212

Table 5.2 shows the aircraft assignments, flights numbers, origin and destination airports and the planned departure and arrival times of the flights in local ORD time, idle times and cruise times for the the minimum cost schedule $\mathcal{P}_1$ obtained by solving (DAM) and (CSCM) consecutively.

Figure 5.2 gives the time-space network representation of the minimum cost schedule $\mathcal{P}_1$. Vertical and horizontal axes represent the airports and time line, respectively. Arcs starting from the origin airport at the planned departure time and ending at the destination airport at the planned arrival time correspond to flight arcs. Ground arcs at the destination airports represent the turnaround time needed for aircraft preparation for the next flight. Afterwards, the aircraft stay idle on the ground until next flight.

Table 5.2: Minimum Cost Schedule $\mathcal{P}_1$

Tail No.	Flight No.	Origin	Dest.	Departure Time	Arrival Time	Idle Time (mins)	Cruise Time (mins)
N678UA	0	ORD	LGA	08:09	09:51	0	102
	1	LGA	ORD	10:44	12:42	39	118
	7	ORD	LGA	14:15	15:57	30	102
	8	LGA	ORD	17:20	19:17	77	117
	19	ORD	BOS	21:29	23:13	0	104
N802WA	20	ORD	DFW	09:44	11:14	25	90
	21	DFW	ORD	12:32	13:56	29	84
	22	ORD	STL	15:16	16:49	1	93
	23	STL	ORD	17:41	19:07	6	86
	9	ORD	SAN	19:59	21:38	0	99
N805WA	5	ORD	DFW	07:44	09:14	14	90
	6	DFW	ORD	10:22	11:46	55	84
	2	ORD	DFW	13:32	15:02	82	90
	3	DFW	ORD	17:18	18:42	46	84
	4	ORD	LGA	20:19	22:01	0	102
N309US	15	ORD	MSP	07:14	08:19	4	65
	16	MSP	ORD	09:15	10:17	39	62
	17	ORD	SAN	11:47	13:26	148	99
	18	SAN	ORD	16:46	18:09	1	83
	24	ORD	SAN	18:59	20:38	0	99
N334NW	10	ORD	MCI	07:14	08:15	6	61
	11	MCI	ORD	09:12	10:12	20	60
	12	ORD	DFW	11:20	12:50	49	90
	13	DFW	ORD	14:32	15:57	42	85
	14	ORD	DEN	17:29	19:20	0	101

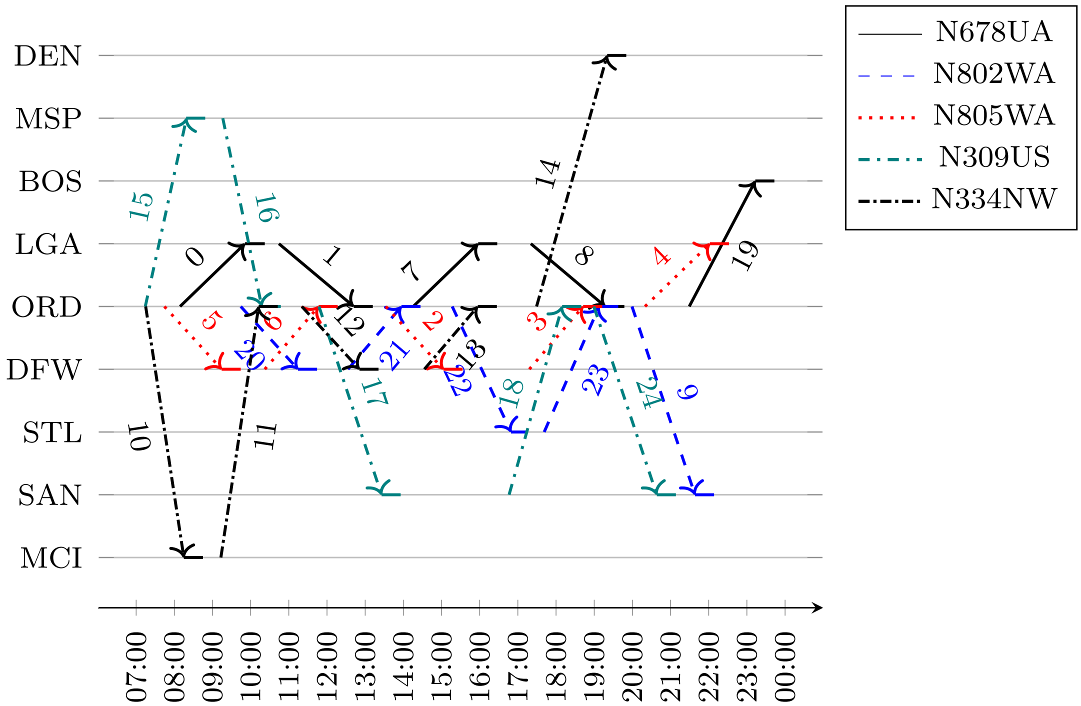

Figure 5.2: Time-Space Network of the Minimum Cost Schedule $\mathcal{P}_1$

When the Aircraft Swapping and Search Algorithm is applied to the minimum cost schedule $\mathcal{P}_1$, one aircraft assignment swap is made between two flight block pairs and the proposed schedule $\mathcal{P}_2$ is obtained. In Table 5.3, the proposed schedule is provided along with the new aircraft assignments, flight numbers, airports and updated departure, arrival, idle and cruise times. In addition, Figure 5.3 gives the time-space network representation of the proposed schedule $\mathcal{P}_2$.

Table 5.3: Proposed Schedule $\mathcal{P}_2$

Tail No.	Flight No.	Origin	Dest.	Departure Time	Arrival Time	Idle Time (mins)	Cruise Time (mins)
N678UA	0	ORD	LGA	08:09	09:51	0	102
	1	LGA	ORD	10:44	12:42	39	118
	7	ORD	LGA	14:15	15:57	30	102
	8	LGA	ORD	17:20	19:17	77	117
	10	ORD	BOS	21:29	23:13	0	104
N802WA	20	ORD	DFW	09:44	11:14	25	90
	21	DFW	ORD	12:32	13:56	29	84
	2	ORD	DFW	15:15	16:46	82	91
	3	DFW	ORD	19:01	20:26	170	85
	9	ORD	SAN	00:07	01:54	0	107
N805WA	5	ORD	DFW	07:44	09:14	14	90
	6	DFW	ORD	10:22	11:46	55	84
	22	ORD	STL	13:32	15:05	1	93
	23	STL	ORD	15:57	17:23	116	86
	4	ORD	LGA	20:06	21:55	0	109
N309US	15	ORD	MSP	07:14	08:19	4	65
	16	MSP	ORD	09:15	10:17	39	62
	17	ORD	SAN	11:47	13:26	148	99
	18	SAN	ORD	16:46	18:09	1	83
	24	ORD	SAN	18:59	20:38	0	99
N334NW	10	ORD	MCI	07:14	08:15	6	61
	11	MCI	ORD	09:12	10:12	20	60
	12	ORD	DFW	11:20	12:50	49	90
	13	DFW	ORD	14:32	15:57	42	85
	14	ORD	DEN	17:29	19:20	0	101

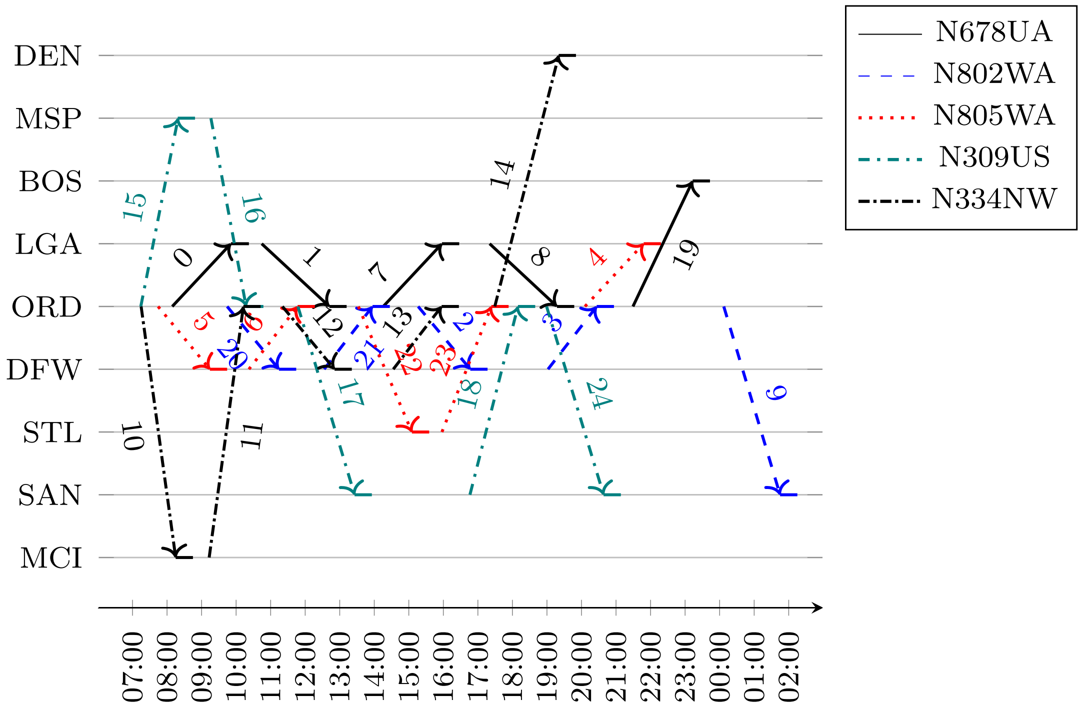

Figure 5.3: Time-Space Network of the Proposed Schedule $\mathcal{P}_2$

The algorithm swaps the aircraft assigned to the flights 22 and 23 with the aircraft assigned to the flights 2 and 3. In the minimum cost schedule $\mathcal{P}_1$, the flights 22 and 23 are assigned to the aircraft with tail number N802WA. The algorithm assigns them to the aircraft N805WA in the proposed schedule $\mathcal{P}_2$. Conversely, in $\mathcal{P}_1$, the flights 2 and 3 are assigned to the aircraft with tail number N805WA, the algorithm assigns them to the aircraft N802WA in $\mathcal{P}_2$.

The total operational cost of the schedule $\mathcal{P}_1$ is equal to \$392,170. This means that, when the allowance for the cost increase is set to 10%, then the algorithm is allowed to increase the total operational cost of the schedule by at most \$39,217. After the algorithm is applied, the total operational cost of the proposed schedule $\mathcal{P}_2$ is observed to be equal to \$417,832. The net increase in the total cost which is equal to \$25,662 is explained as follows.

Both of the aircraft with tail numbers N802WA and N805WA are of the type MD 83. Thus, the unit idle time costs of the two aircraft do not differ from each other and it is equal to \$142 per minute of an idle time. In $\mathcal{P}_2$, the algorithm inserts an additional idle time of 110 minutes after the flight 23 on top the existing idle time in the minimum cost schedule $\mathcal{P}_1$. Similarly, an additional idle time of 124 minutes is inserted after the flight 3 in schedule $\mathcal{P}_2$. In total, the addition of an 224 minute idle time causes the operational cost of the schedule to increase by \$33,228 which exceeds the the net increase \$25,662.

This means that there is a decrease in the fuel consumption and CO_2 emission costs by \$7,566. Indeed, the durations of the cruise time of flights 2, 3, 4, and 9 are increased by the amounts of 1, 1, 7, and 8 minutes, respectively. This corresponds to a \$7,566 decrease in the fuel consumption and CO_2 emission cost. Therefore, the net increase in the total operational cost becomes equal to \$25,662.

Besides the total operational cost, in the proposed schedule $\mathcal{P}_2$, the value for our second objective F_2, which is defined as the deviation of the aircraft path variabilities from the average, is reduced to 4.90 which was equal to 6.41 in the minimum cost schedule $\mathcal{P}_1$. This corresponds to a 24% improvement in F_2.

We claim that decreasing the value of F_2 without increasing the value of F_1 beyond acceptable limits would increase the resilience of the schedules. Indeed, the insertion of the additional idle times and the increase in the cruise time of some flights in $\mathcal{P}_2$ indicate that the recovery performance of the proposed schedule would be higher compared to the minimum cost schedule $\mathcal{P}_1$. A scenario-based posterior analysis can be conducted on the schedules $\mathcal{P}_1$ and $\mathcal{P}_2$ in order to compare their recovery performances against different disruptions. Such analysis is made for larger networks in Chapter 7 which can be referred to gain insights on how to evaluate the resilience of flight schedules.

5.4 Summary

In this study, a math-heuristic algorithm is devised to solve the large-sized problem instances in reasonable computation times. The Proposed Discretized Approximation and Aircraft Swapping Algorithm first generates the near minimum cost schedule by solving the Discretized Approximation Model (DAM) and the Cruise Speed Control Model (CSCM) consecutively. Then, the Aircraft Swapping Search Algorithm (ASSA) balances out the aircraft path variabilities and decreases the absolute deviation of those from the average by making swaps in the aircraft and flight block assignments.

When making the aircraft assignment swaps, the total operational cost of the proposed schedule is not allowed to exceed a predetermined upper limit. In each iteration of the algorithm, the additional cost of making a swap and the improvement it yields in the deviation of the path variabilities from the average are calculated for each possible swap. Then, the algorithm is forced to make the swaps which provide the highest utility. If there remains no possible swaps to be made or the upper limit for the total operational cost is going to be reached in the next iteration, the algorithm terminates and returns the proposed schedule.

This chapter was devoted to the explanation of the algorithm in detail. The idea behind the proposed approach is explained throughly and the mathematical models used in the steps of the algorithm are given explicitly. Moreover, a numerical example on a small-sized flight network is provided to illustrate the mechanics of the algorithm.

Chapter 6

Integrated Flight and Passenger Recovery Algorithm

To be able to quantify resilience of the schedules and compare the recovery performances of minimum cost schedules and the proposed schedules with each other, a bi-criteria framework is followed. First performance indicator ξ_1 is the number of cancelled flights after the schedule is recovered from a disruption and the second indicator ξ_2 is the total time of delay occurred in the schedule after the recovery. Therefore, for a flight schedule $\mathcal{P}$, under the disruption scenario ω which is caused by the availability of an aircraft, we have

$$
\begin{aligned}
n(\mathcal{P},\omega) &: \text{number of disrupted flights in schedule } \mathcal{P} \text{ under scenario } \omega \\
\xi_1(\mathcal{P},\omega) &: \text{number of cancelled flights in schedule } \mathcal{P} \text{ after recovered from} \\
&\quad\ \text{disruption } \omega \\
\xi_2(\mathcal{P},\omega) &: \text{total time of delay occurred in schedule } \mathcal{P} \text{ after recovered from} \\
&\quad\ \text{disruption } \omega.
\end{aligned}
$$

To generate recovery solutions for flight schedules against disruptions, the Integrated Flight and Passenger Recovery Algorithm is proposed. The main idea of the algorithm is to solve Flight Recovery Model (FRM) first to minimize the number of cancelled flights and then to solve Re-Routing Model (RRM) to route each of the aircraft considering cruise time controllability to minimize the total delay iteratively. In each iteration, eligibility for swapping or accommodating disrupted flights is removed to obtain alternative solutions and the algorithm terminates if it cannot find an alternative solution. Sets and parameters that the algorithm utilizes are as follows:

Sets:

E_D : set of disrupted flight blocks

E_N : set of existing, i.e., non-disrupted flight blocks

E : set of flight blocks, i.e., $E_D \cup E_N$

F_i : set of flights in flight block $i \in E$

Parameters:

t^i : aircraft operating the flight block $i \in E$

c^i : number of flights in the flight block $i \in E$

$$a_i^t : \begin{cases} 1 & \text{if flight block } i \text{ can be accommodated in the existing path of} \\ & \text{aircraft } t,\ i \in E_D,\ t \in T \backslash t^i \\ 0 & \text{otherwise} \end{cases}$$

$$b_{ij} : \begin{cases} 1 & \text{if flight blocks } i \text{ and } j \text{ can be swapped, } i \in E_D,\ j \in E_N \\ 0 & \text{otherwise} \end{cases}$$

$$c_i^{t^i} : \begin{cases} 1 & \text{if flight block } i \text{ can be recovered with delayed departure in} \\ & \text{the path of aircraft } t^i,\ i \in E_D \\ 0 & \text{otherwise} \end{cases}$$

Flow of the algorithm can be found in Figure 6.1 whereas the pseudo-code can be found in Appendix A.

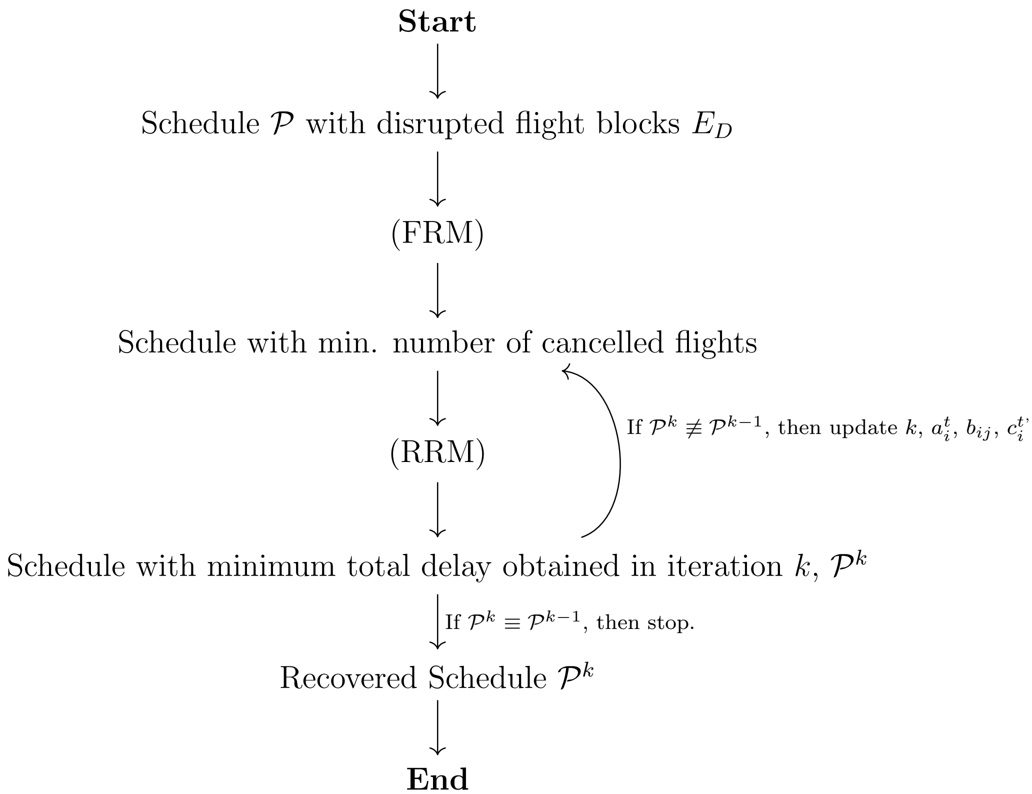

Figure 6.1: Integrated Flight and Passenger Recovery Algorithm

6.1 Flight Recovery Model

The parameters a_i^t and b_{ij}, which denote the eligibility for accommodating and swapping a flight block, are calculated by simply checking if the disrupted flight block can be compressed by speeding up the assigned aircraft if necessary and accommodated into the existing schedule by utilizing the slack times created by the idle times and the times that can be created by compressing the other existing flights. Detailed methodology to calculate these parameters can be found in Appendix B. We introduce the following decision variables to be used in the

Flight Recovery Model (FRM):

$$cancel_i := \begin{cases} 1 & \text{if flight block } i \text{ is cancelled, } i \in E_D \\ 0 & \text{otherwise} \end{cases}$$

$$swap_{ij} := \begin{cases} 1 & \text{if flight blocks } i \text{ and } j \text{ are swapped, } i \in E_D,\ j\ \in E_N \\ 0 & \text{otherwise} \end{cases}$$

$$accom_i^t := \begin{cases} 1 & \text{if flight block } i \text{ is accommodated in the path of} \\ & \text{aircraft } t,\ i \in E_D,\ t \in T \backslash t^i \\ 0 & \text{otherwise} \end{cases}$$

$$delay_i^{t^i} := \begin{cases} 1 & \text{if flight block } i \text{ is recovered with delayed departure in the} \\ & \text{path of aircraft } t^i,\ i \in E_D \\ 0 & \text{otherwise} \end{cases}$$

Flight Recovery Model:

$$\xi_1 = \min \sum_{i \in E_D} c^i \times cancel_i + \sum_{i \in E_D} \sum_{j \in E_N} c^j \times swap_{ij} \tag{6.1}$$

$$\text{s.t.} \quad cancel_i + \sum_{j \in E_N} swap_{ij} + \sum_{t \in T \backslash t^i} accom_i^t + delay_i^{t^i} = 1 \forall i \in E_D \tag{6.2}$$

$$\sum_{i \in E_D} swap_{ij} \leq 1 \qquad \forall j \in E_N \tag{6.3}$$

$$\sum_{i \in E_D} accom_i^t \leq 1 \qquad \forall t \in T \backslash t^i \tag{6.4}$$

$$accom_i^t \leq a_i^t \qquad \forall i \in E_D,\ t \in T \backslash t^i \tag{6.5}$$

$$swap_{ij} \leq b_{ij} \qquad \forall i \in E_D,\ j \in E_N \tag{6.6}$$

$$delay_i^{t^i} \leq c_i^{t^i} \qquad \forall i \in E_D \tag{6.7}$$

$$swap_{ij} \in \{0, 1\} \qquad \forall i \in E_D,\ j \in E_N \tag{6.8}$$

$$accom_i^t \in \{0, 1\} \qquad \forall i \in E_D,\ t \in T \backslash t^i \tag{6.9}$$

$$delay_i^{t^i} \in \{0, 1\} \qquad \forall i \in E_D \tag{6.10}$$

The objective function (6.1) minimizes the number of cancelled flights. Constraint (6.2) ensures that a disrupted flight block can either be cancelled, swapped with a non-disrupted flight block, recovered in the path of its originally assigned aircraft with a delayed departure or accommodated into the existing path of another aircraft. Constraint (6.3) ensures that a non-disrupted flight block can be swapped with at most one disrupted flight block. Constraint (6.4) ensures that the existing path of an aircraft can accommodate at most one disrupted flight block. Constraints (6.5) -(6.7) make sure that accommodating and swapping a disrupted flight block are possible if the corresponding parameters are equal to one. Constraint (6.8)-(6.10) are binary constraints. Note that it is not necessary to have binary constraints for variable $cancel_i$ due to the constraints (6.2) and (6.8)-(6.10).

6.2 Re-Routing Model

After (FRM) is solved to obtain the minimum number of flight cancellations and the corresponding recovery decisions, for each aircraft $t \in T$ with changed flight block assignments, we define the following updated notation associated with the re-routing model:

Sets and Parameters:

F^t : set of flights assigned to aircraft t

A^t : set of all possible flight pairs assigned to aircraft t

U^i, D^i : upstream and downstream flights of flight $i \in F^t$

TA_{ij} : turnaround time needed to prepare aircraft between $(i, j) \in A^t$

d_i^{min} : departure time of flight i obtained in ε-CM, $i \in F^t$

d_i^{max} : upper bound for departure time of flight $i \in F^t$

f_i^l, f_i^u : lower and upper bounds for cruise time of flight $i \in F^t$

Decision Variables:

d_i : departure time of flight $i \in F^t$

s_i : idle time of aircraft after flight $i \in F^t$

f_i : cruise time of flight $i \in F^t$

$$x_{ij} := \begin{cases} 1 & \text{if flight } i \text{ is followed by flight } j,\ (i,j) \in A^t \\ 0 & \text{otherwise} \end{cases}$$

$$y_i := \begin{cases} 1 & \text{if flight } i \text{ is the first flight performed by aircraft } t,\ i \in F^t \\ 0 & \text{otherwise} \end{cases}$$

$$z_i := \begin{cases} 1 & \text{if flight } i \text{ is the last flight performed by aircraft } t,\ i \in F^t \\ 0 & \text{otherwise} \end{cases}$$

Re-Routing Model:

$$\xi_2 = \min \sum_{i \in F^t} \left(d_i - d_i^{min}\right) \tag{6.11}$$

$$\text{s.t.} \quad \sum_{j \in U^i} x_{ji} + y_i - \sum_{j \in D^i} x_{ij} - z_i = 0 \qquad \forall i \in F^t \tag{6.12}$$

$$\sum_{j \in U^i} x_{ji} + y_i = 1 \qquad \forall i \in F^t \tag{6.13}$$

$$\sum_{i \in F^t} y_i \leq 1 \tag{6.14}$$

$$f_i^l \leq f_i \leq f_i^u \qquad \forall i \in F^t \tag{6.15}$$

$$d_i^{min} \leq d_i \leq d_i^{max} \qquad \forall i \in F^t \tag{6.16}$$

$$\text{IF } x_{ij} = 1 \text{ THEN} \tag{6.17}$$

$$d_j - d_i - TA_{ij} - f_i - \text{VaR}_{1-\gamma_i}(NC_i) - s_i = 0 \ \forall (i,j) \in A^t \tag{6.18}$$

$$\sum_{i \in F^t} f_i \leq \lambda_t \tag{6.19}$$

$$s_i \geq 0 \qquad \forall i \in F^t \tag{6.20}$$

$$x_{ij} \in \{0,1\} \qquad \forall (i,j) \in A^t \tag{6.21}$$

$$y_i \in \{0,1\} \qquad \forall i \in F^t \tag{6.22}$$

The objective function (6.11) minimizes the total delay occurred in the schedule by summing the differences between the departure times of the flights and the published departure times over all flights. Constraint (6.12) is the network balance constraint and together with the constraint (6.13), they determine the aircraft routes and assign individual aircraft to those routes. Constraint (6.14) ensures that there is at mose one aircraft route is assigned to an aircraft. Constraint (6.15) limits the cruise time controllability. Constraint (6.16) limits the departure time from below by the published departure times and from above to keep the delay of the flights within acceptable limits. Constraint (6.18) is the chance constraint which is the same as in ε-model. Constraint (6.19) is the maintenance feasibility constraint. Constraints (6.20)-(6.22) are domain constraints for the idle time variables and binary variables.

6.3 Summary

In this chapter, the methodology to measure the resilience of the schedules against uncertain disruptions are explained. Two criteria which are the number of cancelled flights and the total time of delay are selected as the key performance indicators to quantify the recovery performances of the schedules. Then, the Integrated Flight and Passenger Recovery Algorithm, which aims to minimize these performance measures, is provided together with mathematical formulations of the Flight Recovery Model (FRM) and Re-Routing Model (RRM) which are solved in the steps algorithm.

Chapter 7

Computational Study

In this study, we propose a bi-criteria mixed-integer second order conic programming formulation for solving the integrated problem of resilient airline scheduling, fleet assignment and aircraft routing. While the ε-constraint mathematical model (ε-CM), which is proposed in Section 3.2, is able to solve the small scale problems, it may not be sufficient to solve the large scale problem instances to optimality. To solve the time issues for such problems, we also proposed a discretized approximation and aircraft swapping algorithm which first solves a discretized version of the problem to find a near-minimum cost schedule, then swaps aircraft assignments iteratively to decrease the absolute deviation of the aircraft path variabilities from the average. In this chapter, a computation time analysis on the performances of the schedules generated by the integrated model and the proposed algorithm is conducted. In addition, the schedules with near-minimum costs are compared with schedules having lower levels of variability. This comparison is based on the Pareto frontier caused by the trade-off between the operational cost of the schedules and the absolute deviation of the aircraft path variabilities from average. Afterwards, posterior analyses are conducted by following a scenario-based manner in order to observe the resilience of the generated schedules under different disruption scenarios. Finally, several what if analyses are conducted to gain insights about the effects of the problem setting on the performance of the schedules.

In order to obtain sample schedules and generate flight and aircraft sets, we used "Airline On-Time Performance" database of the Bureau of Transportation Statistics [42]. In all of the subsets of the flight legs that we select, Chicago O'Hare International Airport (ORD) serves as the hub airport. This means that all the available aircraft have to depart first from ORD in the beginning of the daily planning horizon.

We consider six different types of aircraft with different parameters as presented in EUROCONTROL [44]. Seat capacity, mass, wing surface area, fuel consumption coefficients, maximum range cruise (MRC) speed, idle time cost and base value parameters are available in Table 7.1. In the computational experiments, we initially assume unit cost of fuel consumption as $c_{fuel} = 1.2$ \$/kg and unit cost of CO_2 emission as $c_{CO_2} = 0.02$ \$/kg. Then, in Section 7.3, we evaluate different experimental settings.

The set A, which is the set of all possible consecutive flight pairs, is one of the main factors to affect the problem size. In order to reduce the size of the problem instances to shorten the solution times, we only allow flight pairs with at most 300 minutes time difference between the estimated arrival of the first leg and the estimated departure of the second leg. The estimated arrival and departure times are calculated based on the desired departure time of flights and the upper limits on the cruise times.

Table 7.1: Aircraft Parameters

Aircraft Type	**B737 500**	**MD 83**	**A320 111**	**A320 212**	**B767 300**	**B727 228**
Seat Capacity	122	148	172	180	218	134
Mass (kg)	50000	61200	62000	64000	135000	74000
Surface (m^2)	105.4	118	122.4	122.6	283.3	157.9
$C_{D0,CR}$	0.018	0.0211	0.024	0.024	0.021	0.018
$C_{D2,CR}$	0.055	0.0468	0.0375	0.0375	0.049	0.06
C_{f1}	0.46	0.7462	0.94	0.94	0.763	0.53178
C_{f2}	300	638.59	50000	100000	1430	276.72
C_{fcr}	1.079	0.9505	1.095	1.06	1.0347	0.954
MRC speed	859.2	867.6	855.15	868.79	876.70	867.6
Idle Time Cost (\$)	140	142	136	144	147	150
Base Value	1.90	1.65	1.70	1.75	2.00	1.80

In addition, we initially take $\beta = 0.01$ which is the base shape parameter of the Log-laplace random variables denoting the non-cruise times. Thus, the tail parameter β_i is calculated for each flight i by Equation 3.1. Also, the scale parameter α is adjusted as $e^\alpha = 20$ to have non-cruise times which are deviating from 20 minutes. In Section 7.3, we evaluate different α and β settings as well.

We assume controllable cruise times and in order to have that, we allow up to 15% decrease in the predetermined maximum cruise time of each flight by speeding up the aircraft. This means that f_i^l is equal to the 85% of f_i^u for each flight i. Maximum cruise time of each flight operating between 21 major airports located in the U.S. can be found in Appendix C. Finally, we allow a time window of 200 minutes between the lower and upper limits for the departure times of flights. That is to say, d_i^l is 200 minutes less than d_i^u for each flight i.

All computational experiments are conducted on an AMD Ryzen 7 5800X 8-core 16-thread computer with 3.8 GHz processor and 32 GB RAM. The problem is implemented in Java programming language with a connection to IBM ILOG CPLEX Optimization Studio 20.1.0.

Table 7.2: CPU Time Analysis on the Performance of Proposed Methodology

			ε-CM		DAM		ASSA
# of flights	# of aircraft	$\|A\|$	CPU Time (secs)	MIP Gap (%)	CPU Time (secs)	MIP Gap (%)	# of Iterations
25	5	65	1000	2.27	0.39	0	1
50	10	267	1000	1.89	1000	1.37	3
75	15	593	1000	3.27	1000	1.69	5
100	20	1068	2000	infeasible	2000	1.66	6
125	25	1536	2000	infeasible	2000	1.83	7
150	30	2233	2000	infeasible	2000	1.87	9

In Table 7.2, CPU time analysis for the networks with number of flights from changing 25 to 150 is given. First of all, note that the cardinality of the set A, which is defined as the set of all possible consecutive flight pairs, does not increase linearly when the number of flights to be operated does so. This is one of the main reasons for the problem getting significantly harder to solve when the number of flights increase since $|A|$ directly affects the number of constraints in the problem.

For the small-sized instances, ε-CM is able to find schedules with small optimality gaps. However, for the networks with number of flights greater than or equal to 100, it cannot find a feasible schedule in the time limit of 2000 seconds.

The most time consuming part in the proposed algorithm is solving the Discretized Approximation Model (DAM). After then, the Cruise Speed Control Model (CSCM) and the Aircraft Swapping Search Algorithm (ASSA) take so little time that they are negligible. Thus, we can conclude that the proposed algorithm is able to generate schedules with acceptable optimality gaps within the pre-determined time limits.

Also, note that the number of swaps made in the Aircraft Swapping Search Algorithm increases as the problem size increases. It is due to the fact that the larger networks have greater total operational costs which allows the algorithm to make more swaps.

For each flight network with different number of flights to be operated, let $\mathcal{P}_1$ denote the minimum cost schedule and $\mathcal{P}_2$ denote the proposed schedule. The objective function values for the schedules $\mathcal{P}_1$ and $\mathcal{P}_2$ are given in Table 7.3.

Table 7.3: Objective Values for Min. Cost and Proposed Schedules

	Total Operational Cost F_1 (\$)			Deviation of Aircraft Path Variabilities F_2		
# of flights	$\mathcal{P}_1$	$\mathcal{P}_2$	% Increase	$\mathcal{P}_1$	$\mathcal{P}_2$	% Decrease
25	392170	417832	7%	6.41	4.90	24%
50	796294	874284	10%	5.32	3.24	39%
75	1242207	1366375	10%	8.31	5.39	35%
100	1613056	1767306	10%	9.14	5.49	40%
125	1943004	2113672	9%	8.13	5.09	37%
150	2511398	2741499	9%	8.61	4.60	47%

As it can be seen from Table 7.3, in each network, the total operational cost of the schedule is at most 10% higher in $\mathcal{P}_2$ than $\mathcal{P}_1$ since we allow a 10% cost increase in the proposed algorithm. Against the increase in F_1, in each network there is a significant decrease in the deviation of the aircraft path variabilities, F_2. We observe a minimum of 24% improvement in F_2 and the maximum improvement is 47%. Therefore, we can conclude that there is a crucial trade-off between these two objectives and this strongly motivates the remaining of this computational study.

In the remaining of this chapter, the networks with 50 and 150 flights are examined in detail and posterior analyses on them are conducted to evaluate their resilience. Finally, several what if analyses are provided to gain some insights on how the problem parameters and the evaluation methods affect the schedule generation and the resilience of the schedules.

7.1 Computational Analysis on the Schedule with 50 Flights

We first analyzed the flight network containing 50 flights operated by 10 aircraft in detail. The corresponding minimum cost schedule $\mathcal{P}_1$ is given in Table 7.5. Note that, each of the available aircraft in this schedule belongs to one of the aircraft types presented in Table 7.1. Whole list of aircraft that we use in our computational experiments can be found in Appendix D. To obtain this schedule, after the initial schedule with discretized cruise times is generated by DAM, for each aircraft path, CSCM is solved individually.

Table 7.4: Minimum Operational Cost ORD Schedule $\mathcal{P}_1$

Tail No.	Aircraft No.	Flight No.	Origin	Dest.	Departure Time	Arrival Time
N678UA	0	0	ORD	LGA	08:10	09:52
		36	LGA	ORD	10:45	12:42
		42	ORD	LGA	14:18	16:00
		8	LGA	ORD	17:24	19:21
		19	ORD	BOS	21:30	23:14
N802WA	1	30	ORD	DFW	07:29	08:59
		6	DFW	ORD	10:19	11:43
		32	ORD	AUS	13:50	15:32
		33	AUS	ORD	17:22	18:59
		4	ORD	LGA	20:20	22:02
N805WA	2	5	ORD	DFW	07:45	09:15
		41	DFW	ORD	10:23	11:47
		2	ORD	DFW	13:35	15:05
		3	DFW	ORD	17:22	18:46
		44	ORD	SAN	20:00	21:39
N309US	3	15	ORD	MSP	07:15	08:19
		16	MSP	ORD	09:15	10:17
		17	ORD	SAN	11:49	13:28
		18	SAN	ORD	16:47	18:10
		24	ORD	SAN	19:00	20:39
N334NW	4	45	ORD	MCI	07:15	08:15
		11	MCI	ORD	09:12	10:11
		47	ORD	DFW	11:22	12:52
		48	DFW	ORD	14:35	15:59
		49	ORD	DEN	17:30	19:20
N312US	5	10	ORD	MCI	07:15	08:15
		46	MCI	ORD	09:12	10:11
		12	ORD	DFW	11:22	12:52
		13	DFW	ORD	14:35	15:59
		14	ORD	DEN	17:30	19:20
N801WA	6	25	ORD	DFW	08:45	10:15
		26	DFW	ORD	11:09	12:33
		7	ORD	LGA	14:18	16:00
		43	LGA	ORD	17:24	19:21
		34	ORD	LGA	20:40	22:22
N807TR	7	40	ORD	DFW	07:45	09:15
		31	DFW	ORD	10:29	11:53
		37	ORD	DFW	13:35	15:05
		38	DFW	ORD	17:22	18:46
		39	ORD	LGA	20:20	22:02
N695UA	8	35	ORD	LGA	08:06	09:48
		1	LGA	ORD	10:41	12:39
		27	ORD	LGA	13:33	15:15
		28	LGA	ORD	16:08	18:06
		29	ORD	BOS	19:01	20:44
N422BN	9	20	ORD	DFW	09:45	11:15
		21	DFW	ORD	12:34	13:58
		22	ORD	STL	15:17	16:49
		23	STL	ORD	17:42	19:08
		9	ORD	SAN	20:00	21:39

After the minimum cost schedule $\mathcal{P}_1$ is obtained, Aircraft Swapping Search Algorithm is applied to $\mathcal{P}_1$ and the so-called bi-criteria schedule denoted by $\mathcal{P}_2$ is proposed. The proposed schedule $\mathcal{P}_2$ can be seen in Table 7.5.

Table 7.5: Proposed Bi-Criteria Schedule $\mathcal{P}_2$

Tail No.	Aircraft No.	Flight No.	Origin	Dest.	Departure Time	Arrival Time
N678UA	0	0	ORD	LGA	08:10	09:52
		36	LGA	ORD	10:44	12:42
		42	ORD	LGA	14:17	15:59
		8	LGA	ORD	17:24	19:22
		14	ORD	DEN	21:30	23:20
N802WA	1	30	ORD	DFW	07:29	08:59
		6	DFW	ORD	10:19	11:43
		32	ORD	AUS	13:50	15:32
		33	AUS	ORD	17:22	18:59
		4	ORD	LGA	20:20	22:02
N805WA	2	5	ORD	DFW	07:45	09:15
		41	DFW	ORD	10:23	11:47
		2	ORD	DFW	13:35	15:05
		3	DFW	ORD	17:22	18:46
		44	ORD	SAN	20:00	21:38
N309US	3	15	ORD	MSP	07:15	08:20
		16	MSP	ORD	09:16	10:17
		17	ORD	SAN	11:49	13:28
		18	SAN	ORD	16:47	18:10
		24	ORD	SAN	19:00	20:38
N334NW	4	45	ORD	MCI	07:15	08:16
		11	MCI	ORD	09:12	10:11
		47	ORD	DFW	11:22	12:52
		48	DFW	ORD	14:35	15:59
		29	ORD	BOS	17:31	19:14
N312US	5	10	ORD	MCI	07:15	08:16
		46	MCI	ORD	09:12	10:11
		12	ORD	DFW	11:22	12:52
		13	DFW	ORD	14:35	15:59
		19	ORD	BOS	17:31	19:14
N801WA	6	27	ORD	LGA	08:45	10:27
		28	LGA	ORD	11:20	13:17
		7	ORD	LGA	16:37	18:19
		43	LGA	ORD	19:44	21:41
		34	ORD	LGA	23:00	00:42
N807TR	7	40	ORD	DFW	07:45	09:15
		31	DFW	ORD	10:29	11:53
		37	ORD	DFW	13:35	15:05
		38	DFW	ORD	17:22	18:46
		39	ORD	LGA	20:20	22:02
N695UA	8	35	ORD	LGA	08:07	09:49
		1	LGA	ORD	10:41	12:39
		25	ORD	DFW	13:34	15:04
		26	DFW	ORD	15:58	17:22
		49	ORD	DEN	19:17	21:07
N422BN	9	20	ORD	DFW	09:45	11:15
		21	DFW	ORD	12:35	13:59
		22	ORD	STL	15:17	16:50
		23	STL	ORD	17:43	19:08
		9	ORD	SAN	20:01	21:39

The Aircraft Swapping Search Algorithm terminated in 3 iterations while obtaining $\mathcal{P}_2$. In each iteration, a pair of aircraft assignments to flight blocks is swapped which results in a different schedule. To show the relationship between the total operational cost F_1 and the deviation of the aircraft path variabilities F_2 of these 3 schedules, the following Pareto frontier in Figure 7.1 is provided.

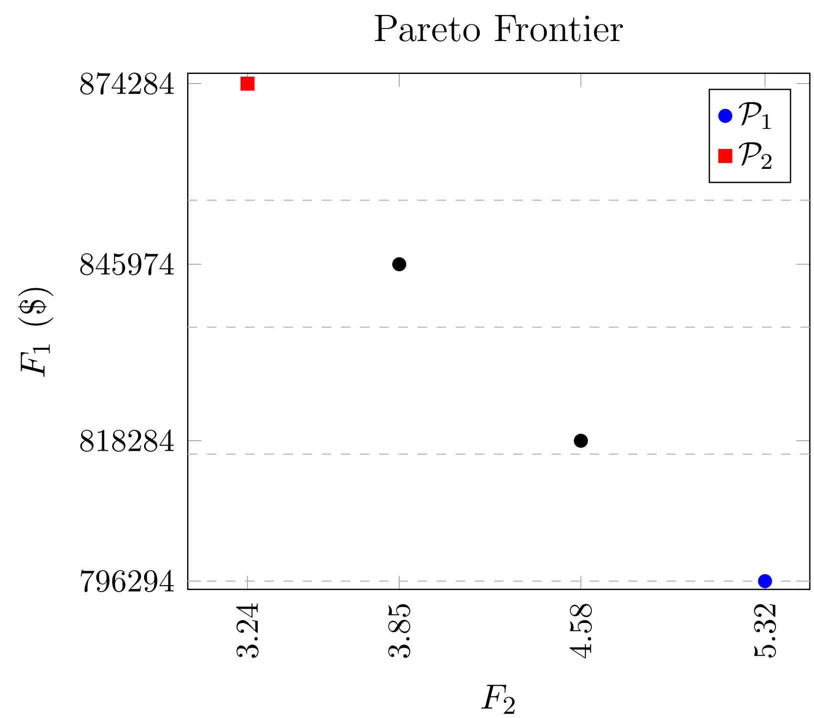

Figure 7.1: Deviation from the Average Variability vs. Total Operational Cost for 50 Flights

As it can be seen from the above figure, if we allow the cost of the schedule to deviate from the minimum by 10%, we can decrease the value of our second objective F_2 by 39% which is the deviation of aircraft path variabilities from the average.

In addition to that, each horizontal dashed line in Figure 7.1 represents a 2.5% allowance for the cost increase. By looking at the intervals in which the intermediate schedules obtained in the algorithm fall, we can observe the relationship between the allowance for the cost increase and the improvement in F_2 as shown in Figure 7.2. When the allowance is equal to 2.5%, the algorithm cannot make any swap because the additional cost of swapping the aircraft assignment of one flight block pair exceeded the allowance. Thus, it returns the same schedule as the minimum cost schedule $\mathcal{P}_1$. When the allowance is 5% and 7.5%, then the algorithm returns schedules whose F_2 values are improved by 14% and 28% compared to $\mathcal{P}_1$, respectively.

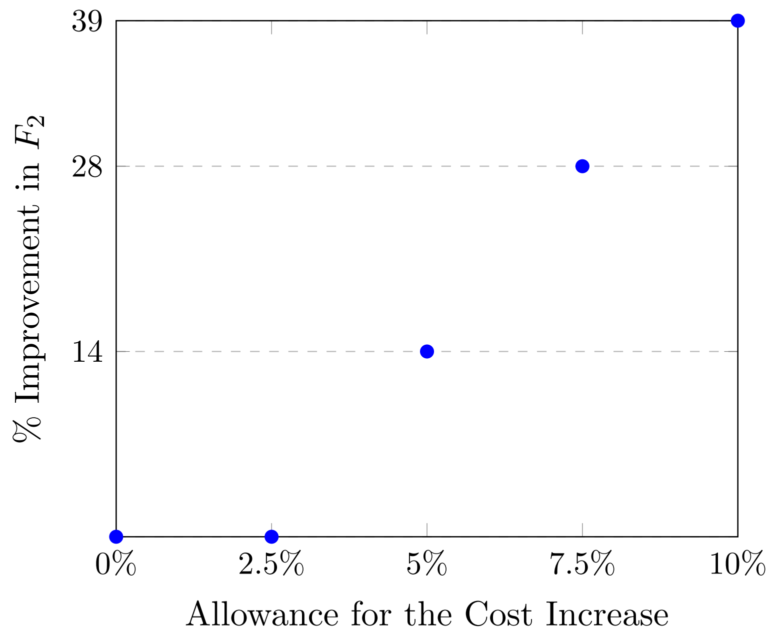

Figure 7.2: Allowance for the Cost Increase vs. Improvement in F_2 for 50 Flights

7.1.1 Posterior Analysis on Resilience

In order to measure and compare the resilience of the minimum cost schedule $\mathcal{P}_1$ and the proposed schedule $\mathcal{P}_2$, we generated disruption scenarios due to the unavailability of the aircraft. Initially, we consider the unavailability periods as equal to the whole day which means that in total, there are 10 disruption scenarios. In other words, we let ω_t denote that the aircraft $t = 0, \ldots, 9$ is unavailable for the whole day. Then, we applied the Integrated Flight and Passenger Recovery Algorithm, which is available in Chapter 6, to observe the recovery performances.

In Table 7.6, the recovery solutions against each disruption scenario ω_t is presented. For each scenario, there are multiple recovery solutions with different number of cancelled flights and different amounts of total delay. The recovery solutions which are presented in Table 7.6 are the ones with the minimum number of cancelled flights for both of the schedules. If there are multiple recovery solutions with the same number of cancelled flights for a schedule, the solutions with the shortest total delay is selected.

Table 7.6: Recovery Solutions Under Each Disruption Scenario for 50 Flights

Disruption Scenario	Min. Cost Schedule $\mathcal{P}_1$		Proposed Schedule $\mathcal{P}_2$		Change	
	# Cancelled Flights: ξ_1	Total Delay: ξ_2 (mins)	# Cancelled Flights: ξ_1	Total Delay: ξ_2 (mins)	ξ_1	ξ_2
ω_0	5	-	1	1416	-4	-
ω_1	3	891	1	1166	-2	31%
ω_2	3	990	1	1414	-2	43%
ω_3	3	905	1	925	-2	2%
ω_4	3	791	1	892	-2	13%
ω_5	3	841	1	898	-2	7%
ω_6	5	-	3	1012	-2	-
ω_7	3	847	1	1437	-2	70%
ω_8	5	-	3	1125	-2	-
ω_9	3	581	1	937	-2	61%
Average:	3.6	835	1.4	1122	-2.2	34%

Due to the bi-criteria manner that we follow to measure recovery performance of schedules, we introduce the following dominance relationship to categorize the recovery solutions. Note that these definitions are different than the standard definitions used in the multi-criteria decision making and they are specifically introduced in the scope of this problem.

Definition 7.1. *$\mathcal{P}_2$ is weakly-dominating $\mathcal{P}_1$ under disruption scenario ω iff $\xi_1(\mathcal{P}_1,\omega) = \xi_1(\mathcal{P}_2,\omega)$ and $\xi_2(\mathcal{P}_2,\omega) < \xi_2(\mathcal{P}_1,\omega)$.*

Definition 7.2. *$\mathcal{P}_2$ is strongly-dominating $\mathcal{P}_1$ under disruption scenario ω iff (I) or (II) holds:*

$$\xi_1(\mathcal{P}_2,\omega) < \xi_1(\mathcal{P}_1,\omega) \text{ and } \xi_2(\mathcal{P}_2,\omega) < \xi_2(\mathcal{P}_1,\omega) \qquad (I)$$

$$\xi_1(\mathcal{P}_1,\omega) = n(\mathcal{P}_1,\omega),\ \xi_2(\mathcal{P}_1,\omega) = 0 \text{ and } \xi_1(\mathcal{P}_2,\omega) < \xi_1(\mathcal{P}_1,\omega) \qquad (II)$$

Definition 7.3. *$\mathcal{P}_2$ is non-dominated by $\mathcal{P}_1$ under disruption scenario ω iff exactly one of (I) or (II) holds:*

$$\xi_1(\mathcal{P}_1,\omega) < \xi_1(\mathcal{P}_2,\omega) \text{ and } \xi_2(\mathcal{P}_2,\omega) > \xi_2(\mathcal{P}_1,\omega) \qquad (I)$$

$$\xi_1(\mathcal{P}_1,\omega) > \xi_1(\mathcal{P}_2,\omega) \text{ and } \xi_2(\mathcal{P}_2,\omega) < \xi_2(\mathcal{P}_1,\omega) \qquad (II)$$

Using the Definitions 7.1-7.3, we categorize the disruption scenarios depending on which type of recovery solution is yielded by the proposed schedule $\mathcal{P}_2$. Under disruption scenarios ω_0, ω_6, and ω_8, the minimum cost schedule $\mathcal{P}_1$ cancels all of the disrupted flights whereas the proposed schedule $\mathcal{P}_2$ is able to recover from the disruptions with up to 3 cancelled flights. Although cancelling all of the disrupted flights in $\mathcal{P}_1$ creates 0 delay, we classify these scenarios as yielding strongly-dominating recovery solutions by Definition 7.2. The strongly-dominating recovery solutions can be found in Figure 7.3.

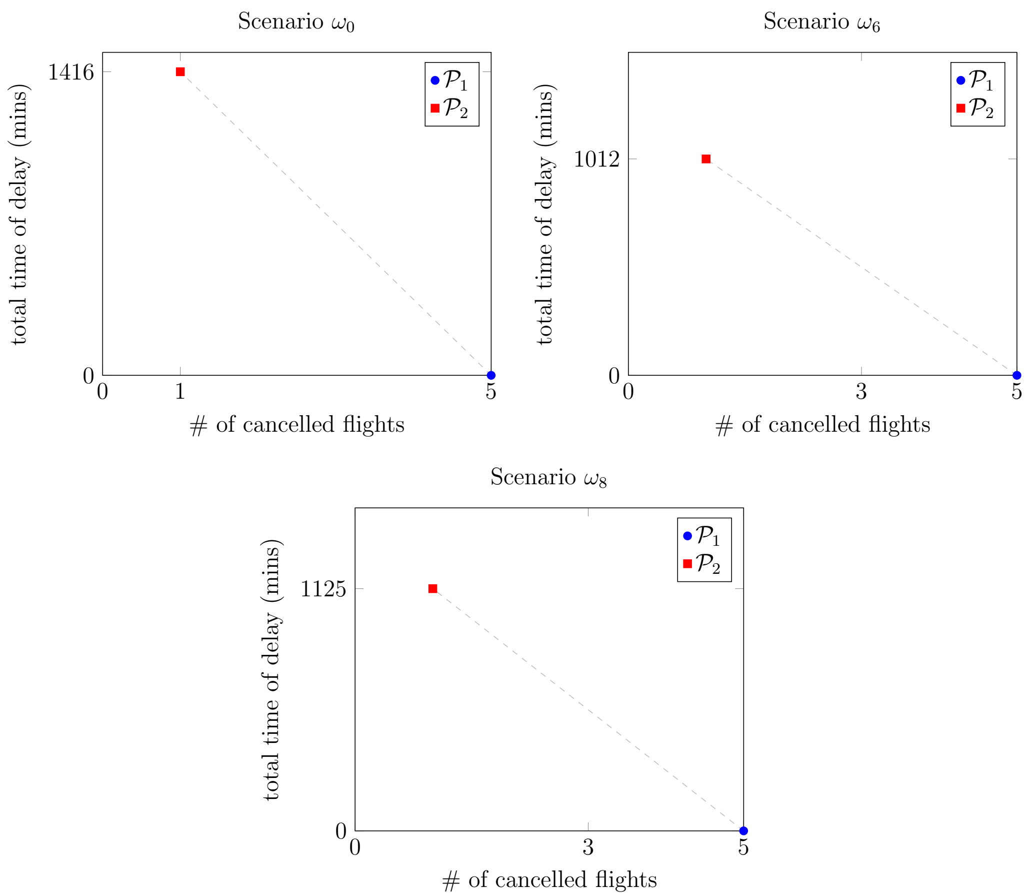

Figure 7.3: Strongly-Dominating Recovery Solutions for 50 Flights

For the disruption scenarios that yield non-dominated recovery solutions for $\mathcal{P}_2$, the difference between $\mathcal{P}_1$ and $\mathcal{P}_2$ for both of the criteria can be seen from the Figure 7.4 more clearly.

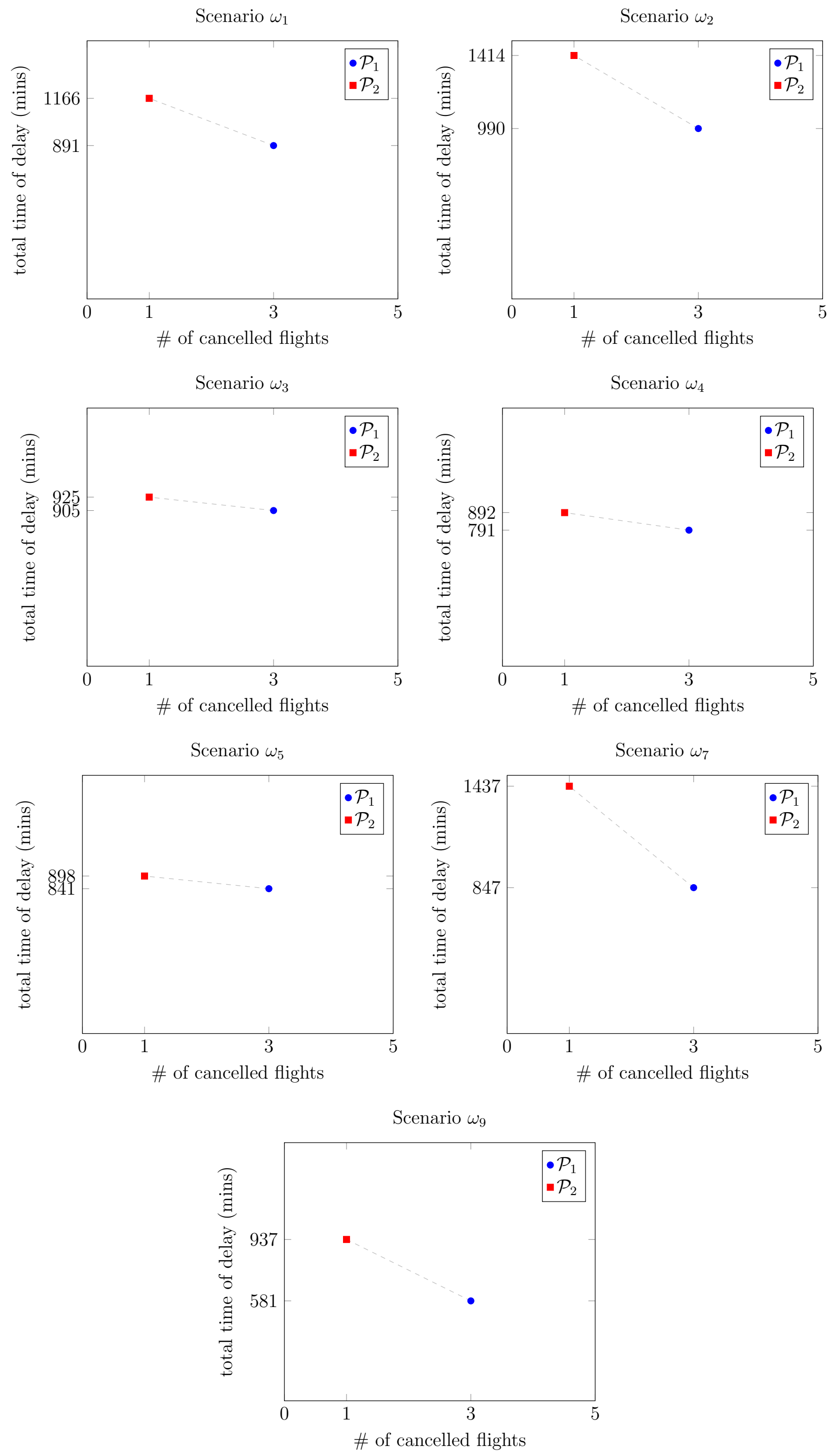

Figure 7.4: Non-Dominated Recovery Solutions for 50 Flights

As it can be seen from Figure 7.4, when the aircraft 1-5, 7, and 9 are disrupted, the proposed schedule is recovered by cancelling only 1 flight whereas the minimum cost schedule cancels 3 flights. This means that $\mathcal{P}_2$ performs 67% "better" than $\mathcal{P}_1$ in terms of the number of cancelled flights. However, in $\mathcal{P}_2$, there occurs 31% more time of delay on average and it is due to the fact that disrupted flights are recovered by accommodating them into the paths of the non-disrupted aircraft.

7.2 Computational Analysis on the Schedule with 150 Flights

The network containing 150 flights operated by 50 different aircraft is analyzed and the corresponding minimum cost schedule $\mathcal{P}_1$ can be found in Table 7.7.

Table 7.7: Minimum Operational Cost ORD Schedule $\mathcal{P}_1$

Tail No. (Aircraft No.)	Flight No.	Origin	Dest.	Dep. Time	Arr. Time	Tail No. (Aircraft No.)	Flight No.	Origin	Dest.	Dep. Time	Arr. Time
N678UA (0)	100	ORD	BOS	07:38	09:22	N312US (5)	80	ORD	DFW	07:29	08:59
	101	BOS	ORD	10:15	12:18		136	DFW	ORD	10:29	11:53
	27	ORD	LGA	13:24	15:06		2	ORD	DFW	13:34	15:04
	58	LGA	ORD	17:16	19:13		88	DFW	ORD	17:00	18:24
	114	ORD	EWR	20:20	22:49		74	ORD	SAN	19:15	20:54
N802WA (1)	125	ORD	DFW	09:45	11:15	N681UA (6)	50	ORD	LGA	07:48	09:30
	71	DFW	ORD	12:34	13:58		1	LGA	ORD	10:23	12:20
	127	ORD	STL	15:17	16:50		102	ORD	LGA	13:15	14:57
	23	STL	ORD	17:42	19:08		133	LGA	ORD	15:56	17:53
	84	ORD	LGA	20:40	22:22		29	ORD	BOS	19:00	20:44
N805WA (2)	65	ORD	MSP	07:15	08:19	N807TR (7)	135	ORD	DFW	07:29	08:59
	66	MSP	ORD	09:15	10:16		91	DFW	ORD	10:18	11:43
	47	ORD	DFW	11:23	12:53		32	ORD	AUS	13:49	15:31
	98	DFW	ORD	14:35	15:59		83	AUS	ORD	17:21	18:58
	49	ORD	DEN	17:30	19:20		144	ORD	LGA	20:20	22:02
N309US (3)	15	ORD	MSP	07:15	08:19	N695UA (8)	85	ORD	LGA	08:10	09:52
	16	MSP	ORD	09:15	10:16		36	LGA	ORD	10:45	12:42
	12	ORD	DFW	11:23	12:53		77	ORD	LGA	13:37	15:19
	63	DFW	ORD	14:35	15:59		78	LGA	ORD	16:13	18:10
	99	ORD	DEN	17:30	19:20		19	ORD	BOS	21:30	23:14
N334NW (4)	45	ORD	MCI	07:15	08:15	N422BN (9)	20	ORD	DFW	09:45	11:15
	46	MCI	ORD	09:12	10:12		126	DFW	ORD	12:20	13:44
	97	ORD	DFW	11:22	12:52		147	ORD	ATL	14:36	15:56
	48	DFW	ORD	14:35	15:59		148	ATL	ORD	16:58	18:27
	14	ORD	DEN	17:30	19:20		94	ORD	SAN	20:00	21:39

(Cont.'d from Table 7.7)

Tail No. (Aircraft No.)	Flight No.	Origin	Dest.	Dep. Time	Arr. Time	Tail No. (Aircraft No.)	Flight No.	Origin	Dest.	Dep. Time	Arr. Time
N966UA (10)	120	ORD	MIA	08:45	10:22	N821AU (20)	110	ORD	EWR	07:24	09:53
	121	MIA	ORD	11:52	13:36		111	EWR	ORD	10:45	13:25
	7	ORD	LGA	14:32	16:14		57	ORD	LGA	14:26	16:08
	93	LGA	ORD	17:25	19:22		8	LGA	ORD	17:24	19:22
	109	ORD	LGA	21:00	22:42		69	ORD	BOS	21:30	23:14
N305FA (11)	105	ORD	MCI	06:45	07:45	N319US (21)	55	ORD	DFW	07:45	09:15
	61	MCI	ORD	09:01	10:01		41	DFW	ORD	10:23	11:47
	62	ORD	DFW	11:21	12:51		82	ORD	AUS	13:49	15:31
	13	DFW	ORD	14:35	15:59		33	AUS	ORD	17:18	18:55
	64	ORD	DEN	17:30	19:20		59	ORD	SAN	20:00	21:39
N573UA (12)	95	ORD	MCI	07:15	08:15	N240AT (22)	35	ORD	LGA	08:07	09:49
	11	MCI	ORD	09:13	10:13		141	LGA	ORD	10:41	12:39
	107	ORD	MSP	12:19	13:24		132	ORD	LGA	13:34	15:16
	108	MSP	ORD	17:06	18:07		28	LGA	ORD	16:09	18:06
	104	ORD	DFW	19:00	20:30		79	ORD	BOS	19:01	20:44
N438BN (13)	25	ORD	DFW	08:06	09:36	N164TS (23)	90	ORD	DFW	07:45	09:15
	81	DFW	ORD	10:30	11:54		131	DFW	ORD	10:47	12:11
	117	ORD	SAN	12:45	14:23		87	ORD	DFW	13:36	15:06
	68	SAN	ORD	17:06	18:29		143	DFW	ORD	17:21	18:45
	89	ORD	LGA	20:20	22:02		39	ORD	LGA	20:20	22:02
N335NW (14)	115	ORD	LAX	06:46	08:46	N656CS (24)	0	ORD	LGA	08:10	09:52
	116	LAX	ORD	09:40	11:22		86	LGA	ORD	10:45	12:42
	67	ORD	SAN	12:15	13:53		42	ORD	LGA	14:00	15:42
	118	SAN	ORD	16:51	18:14		103	LGA	ORD	16:35	18:32
	119	ORD	MIA	20:20	21:57		134	ORD	BOS	19:27	21:11
N317US (15)	40	ORD	DFW	07:45	09:15	N784CK (25)	10	ORD	MCI	07:15	08:15
	56	DFW	ORD	10:23	11:47		106	MCI	ORD	09:08	10:08
	37	ORD	DFW	13:34	15:04		142	ORD	DFW	13:34	15:04
	53	DFW	ORD	17:21	18:45		38	DFW	ORD	17:21	18:45
	44	ORD	SAN	20:00	21:39		124	ORD	ATL	22:00	23:20
N967UA (16)	140	ORD	LGA	08:10	09:52	N320US (26)	130	ORD	DFW	08:45	10:15
	51	LGA	ORD	10:45	12:42		26	DFW	ORD	11:09	12:33
	92	ORD	LGA	14:17	15:59		112	ORD	ATL	13:30	14:50
	43	LGA	ORD	17:17	19:15		113	ATL	ORD	16:51	18:20
	4	ORD	LGA	20:20	22:02		9	ORD	SAN	20:00	21:39
N801WA (17)	5	ORD	DFW	07:45	09:15	N336NW (27)	60	ORD	MCI	07:15	08:15
	76	DFW	ORD	10:49	12:13		96	MCI	ORD	09:13	10:13
	137	ORD	AUS	13:49	15:31		17	ORD	SAN	11:49	13:27
	138	AUS	ORD	17:21	18:58		18	SAN	ORD	16:46	18:10
	34	ORD	LGA	20:40	22:22		24	ORD	SAN	19:00	20:39
N969UA (18)	145	ORD	EWR	07:24	09:53	N353PA (28)	30	ORD	DFW	07:29	08:59
	146	EWR	ORD	10:45	13:25		6	DFW	ORD	10:18	11:43
	122	ORD	FLL	15:45	17:28		52	ORD	DFW	13:34	15:04
	123	FLL	ORD	18:20	20:12		3	DFW	ORD	17:00	18:24
	149	ORD	EWR	21:03	23:32		129	ORD	SAN	19:15	20:54
N727YK (19)	75	ORD	DFW	08:32	10:02	N355PA (29)	70	ORD	DFW	09:45	11:15
	31	DFW	ORD	10:55	12:19		21	DFW	ORD	12:34	13:58
	22	ORD	STL	15:17	16:50		72	ORD	STL	15:17	16:50
	128	STL	ORD	17:42	19:08		73	STL	ORD	17:42	19:08
	54	ORD	LGA	20:20	22:02		139	ORD	LGA	20:40	22:22

After the minimum cost schedule $\mathcal{P}_1$ is obtained, the Aircraft Swapping Search Algorithm is applied by allowing 10% increase in the total operational cost to obtain the proposed bi-criteria schedule $\mathcal{P}_2$ which is presented in Table 7.8.

Table 7.8: Proposed Bi-Criteria Schedule $\mathcal{P}_2$

Tail No. (Aircraft No.)	Flight No.	Origin	Dest.	Dep. Time	Arr. Time	Tail No. (Aircraft No.)	Flight No.	Origin	Dest.	Dep. Time	Arr. Time
N678UA (0)	100	ORD	BOS	07:38	09:22	N966UA (10)	120	ORD	MIA	08:45	10:22
	101	BOS	ORD	10:14	12:17		121	MIA	ORD	11:53	13:37
	27	ORD	LGA	13:23	15:05		7	ORD	LGA	14:32	16:14
	58	LGA	ORD	17:15	19:13		93	LGA	ORD	17:25	19:23
	114	ORD	EWR	20:19	22:48		49	ORD	DEN	21:01	22:51
N802WA (1)	87	ORD	DFW	09:45	11:15	N305FA (11)	105	ORD	MCI	06:45	07:46
	143	DFW	ORD	12:34	13:58		61	MCI	ORD	09:02	10:01
	127	ORD	STL	17:22	18:55		62	ORD	DFW	11:21	12:51
	23	STL	ORD	19:47	21:13		13	DFW	ORD	14:35	15:59
	84	ORD	LGA	22:46	00:28		64	ORD	DEN	17:31	19:21
N805WA (2)	65	ORD	MSP	07:15	08:20	N573UA (12)	95	ORD	MCI	07:15	08:16
	66	MSP	ORD	09:16	10:17		11	MCI	ORD	09:13	10:13
	47	ORD	DFW	11:23	12:53		107	ORD	MSP	12:19	13:24
	98	DFW	ORD	14:34	15:58		108	MSP	ORD	17:06	18:07
	109	ORD	LGA	17:29	19:11		99	ORD	DEN	19:01	20:51
N309US (3)	15	ORD	MSP	07:15	08:20	N438BN (13)	25	ORD	DFW	08:07	09:37
	16	MSP	ORD	09:16	10:17		81	DFW	ORD	10:30	11:54
	12	ORD	DFW	11:23	12:53		117	ORD	SAN	12:45	14:23
	63	DFW	ORD	14:34	15:58		68	SAN	ORD	17:07	18:30
	104	ORD	DFW	17:29	18:59		89	ORD	LGA	20:21	22:03
N334NW (4)	45	ORD	MCI	07:15	08:16	N335NW (14)	102	ORD	LGA	06:46	08:28
	46	MCI	ORD	09:12	10:11		133	LGA	ORD	09:21	11:19
	97	ORD	DFW	11:21	12:51		67	ORD	SAN	12:28	14:07
	48	DFW	ORD	14:34	15:58		118	SAN	ORD	17:05	18:28
	4	ORD	LGA	17:29	19:11		119	ORD	MIA	20:34	22:11
N312US (5)	80	ORD	DFW	07:29	08:59	N317US (15)	132	ORD	LGA	07:45	09:27
	136	DFW	ORD	10:29	11:53		28	LGA	ORD	10:35	12:32
	2	ORD	DFW	13:34	15:04		37	ORD	DFW	16:48	18:18
	88	DFW	ORD	17:01	18:25		53	DFW	ORD	20:35	21:59
	74	ORD	SAN	19:16	20:54		44	ORD	SAN	23:14	00:53
N681UA (6)	50	ORD	LGA	07:47	09:29	N967UA (16)	140	ORD	LGA	08:10	09:52
	1	LGA	ORD	10:22	12:20		51	LGA	ORD	10:44	12:42
	115	ORD	LAX	13:14	15:14		92	ORD	LGA	14:17	15:59
	116	LAX	ORD	16:14	17:56		43	LGA	ORD	17:17	19:15
	29	ORD	BOS	20:44	22:28		14	ORD	DEN	20:20	22:10
N807TR (7)	135	ORD	DFW	07:29	08:59	N801WA (17)	142	ORD	DFW	07:45	09:15
	91	DFW	ORD	10:19	11:43		38	DFW	ORD	10:49	12:13
	32	ORD	AUS	13:50	15:32		137	ORD	AUS	17:38	19:20
	83	AUS	ORD	17:22	18:59		138	AUS	ORD	21:10	22:47
	144	ORD	LGA	20:20	22:02		34	ORD	LGA	00:29	02:11
N695UA (8)	85	ORD	LGA	08:10	09:52	N969UA (18)	145	ORD	EWR	07:24	09:53
	36	LGA	ORD	10:44	12:42		146	EWR	ORD	10:45	13:25
	77	ORD	LGA	13:37	15:19		82	ORD	AUS	15:45	17:27
	78	LGA	ORD	16:13	18:10		33	AUS	ORD	18:19	19:56
	19	ORD	BOS	21:30	23:14		149	ORD	EWR	21:40	00:09
N422BN (9)	20	ORD	DFW	09:45	11:15	N727YK (19)	75	ORD	DFW	08:32	10:02
	126	DFW	ORD	12:20	13:44		31	DFW	ORD	10:55	12:19
	147	ORD	ATL	14:37	15:56		22	ORD	STL	15:17	16:50
	148	ATL	ORD	16:58	18:28		128	STL	ORD	17:42	19:08
	94	ORD	SAN	20:00	21:38		54	ORD	LGA	20:20	22:02

(Cont.'d from Table 7.8)

Tail No. (Aircraft No.)	Flight No.	Origin	Dest.	Dep. Time	Arr. Time	Tail No. (Aircraft No.)	Flight No.	Origin	Dest.	Dep. Time	Arr. Time
N821AU (20)	110	ORD	EWR	07:24	09:53	N784CK (25)	10	ORD	MCI	07:15	08:16
	111	EWR	ORD	10:45	13:25		106	MCI	ORD	09:09	10:08
	57	ORD	LGA	14:26	16:08		5	ORD	DFW	13:35	15:05
	8	LGA	ORD	17:25	19:22		76	DFW	ORD	17:23	18:47
	69	ORD	BOS	21:31	23:14		124	ORD	ATL	23:29	00:49
N319US (21)	55	ORD	DFW	07:45	09:15	N320US (26)	52	ORD	DFW	08:45	10:15
	41	DFW	ORD	10:23	11:47		3	DFW	ORD	11:09	12:33
	122	ORD	FLL	13:50	15:32		112	ORD	ATL	14:33	15:53
	123	FLL	ORD	17:20	19:12		113	ATL	ORD	17:54	19:23
	59	ORD	SAN	22:20	23:58		9	ORD	SAN	21:03	22:41
N240AT (22)	35	ORD	LGA	08:07	09:49	N336NW (27)	60	ORD	MCI	07:15	08:16
	141	LGA	ORD	10:41	12:39		96	MCI	ORD	09:13	10:13
	40	ORD	DFW	13:34	15:04		17	ORD	SAN	11:49	13:27
	56	DFW	ORD	15:57	17:21		18	SAN	ORD	16:46	18:10
	79	ORD	BOS	18:38	20:22		24	ORD	SAN	19:01	20:39
N164TS (23)	90	ORD	DFW	07:45	09:15	N353PA (28)	30	ORD	DFW	07:29	08:59
	131	DFW	ORD	10:47	12:11		6	DFW	ORD	10:19	11:43
	125	ORD	DFW	13:37	15:07		130	ORD	DFW	13:35	15:05
	71	DFW	ORD	17:22	18:46		26	DFW	ORD	17:08	18:32
	39	ORD	LGA	21:14	22:56		129	ORD	SAN	19:30	21:08
N656CS (24)	0	ORD	LGA	08:10	09:52	N355PA (29)	70	ORD	DFW	09:45	11:15
	86	LGA	ORD	10:44	12:42		21	DFW	ORD	12:34	13:58
	42	ORD	LGA	13:59	15:41		72	ORD	STL	15:17	16:50
	103	LGA	ORD	16:34	18:32		73	STL	ORD	17:42	19:08
	134	ORD	BOS	19:26	21:10		139	ORD	LGA	20:41	22:23

The Aircraft Swapping Search algorithm achieves the proposed schedule $\mathcal{P}_2$ in 9 iterations and in each iteration, the aircraft assignments of a pair of flight blocks are swapped. The relationship between the total operational cost and the deviation of aircraft path variabilities from average for the minimum cost schedule $\mathcal{P}_1$, the proposed schedule $\mathcal{P}_2$, and the schedules that are obtained in the intermediate steps of the algorithm can be seen from the Pareto frontier presented in Figure 7.5.

As it can be seen in Figure 7.5, when we allow the total operational cost to deviate from the minimum by at most 10%, the deviation of the aircraft path variabilities from the average, i.e. F_2, decreases by 47%. Additionally, we examine different allowance values for the cost increase as in Figure 7.6 and we observed that instead of 10%, if the allowance is 2.5%, 5%, and 7.5% then F_2 decreases by 23%, 30%, and 41%, respectively.

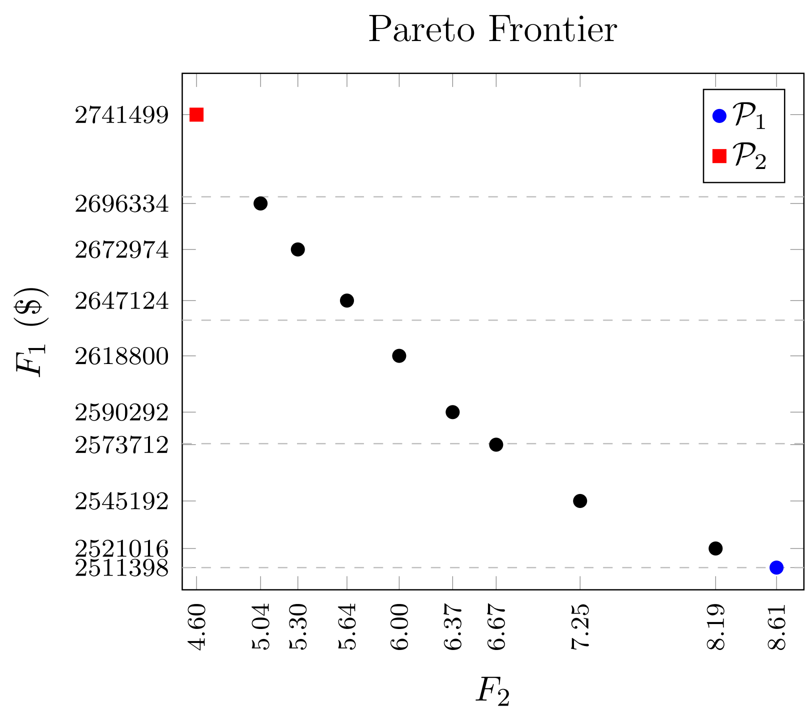

Figure 7.5: Deviation from the Average Variability vs. Total Operational Cost for 150 Flights

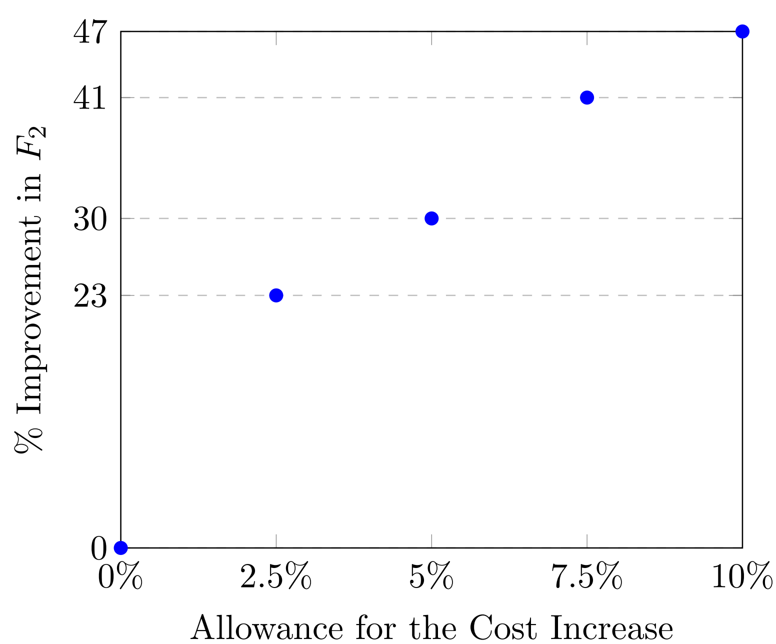

Figure 7.6: Allowance for the Cost Increase vs. Improvement in F_2 for 150 Flights

7.2.1 Posterior Analysis on Resilience

To measure the resilience of our proposed schedule by comparing the recovery performances of $\mathcal{P}_1$ and $\mathcal{P}_2$, a posterior analysis is conducted. For each aircraft, a disruption scenario caused by the unavailability of the aircraft for a whole day is generated. We let ω_t denote that the aircraft $t \in \{0, \ldots, 29\}$ is unavailable for the day. Then the Integrated Flight and Passenger Recovery Algorithm is applied. A summary of the recovery solutions for the 30 disruption scenarios is given in Table 7.9.

Table 7.9: Summary of Recovery Solutions under Each Disruption Scenario for 150 Flights

		Performance Measures					
		ξ_1			ξ_2		
Recovery Solution Type	Number of Scenarios	$\mathcal{P}_1$	$\mathcal{P}_2$	Change	$\mathcal{P}_1$	$\mathcal{P}_2$	Change
Strongly-Dominating:	22	3.8	1.2	-68%	1002	825	-18%
Non-Dominated:	8	3.1	1	-68%	751	959	28%
Overall:	30	3.6	1.1	-69%	911	861	-6%

Under 22 of the 30 disruption scenarios, the proposed schedule $\mathcal{P}_2$ yields strongly-dominating recovery solutions. On the average of these 22 scenarios, $\mathcal{P}_2$ recovers from the disruption by cancelling 2.6 less flights than $\mathcal{P}_1$ which corresponds to a 68% improvement in ξ_1. Also, $\mathcal{P}_2$ recovers with an average of 825 minutes total delay whereas $\mathcal{P}_1$ recovers with 1002 minutes which corresponds to a 18% improvement in ξ_2.

Under the remaining 8 disruption scenarios, the proposed schedule $\mathcal{P}_2$ yields non-dominated recovery solutions. On the average of these 8 scenarios, $\mathcal{P}_2$ recovers by cancelling 2.5 less flights than $\mathcal{P}_1$ but more time of delay. It corresponds to a 68% improvement in ξ_1 whereas ξ_2 increases by 28%.

Overall, the recovery performance of $\mathcal{P}_2$ is "better" than $\mathcal{P}_1$ by 69% in terms of the number of cancelled flights and 6% in terms of the total time of delay after recovery against 30 disruption scenarios. Detailed information on the recovery solutions against each of these scenarios can be found in Table 7.10.

Table 7.10: Recovery Solutions under Each Disruption Scenario for 150 Flights

Disruption Scenario	Min. Cost Schedule $\mathcal{P}_1$		Proposed Schedule $\mathcal{P}_2$		Change	
	# Cancelled Flights: ξ_1	Total Delay: ξ_2 (mins)	# Cancelled Flights: ξ_1	Total Delay: ξ_2 (mins)	ξ_1	ξ_2
ω_0	5	-	1	1168	-4	-
ω_1	3	869	1	709	-2	-18%
ω_2	3	1229	1	962	-2	-22%
ω_3	3	1186	1	720	-2	-39%
ω_4	3	733	1	786	-2	7%
ω_5	3	872	1	876	-2	0%
ω_6	5	-	1	1215	-4	-
ω_7	3	1358	1	905	-2	-33%
ω_8	4	-	1	1190	-4	-
ω_9	3	656	1	804	-2	23%
ω_{10}	3	1016	1	932	-3	-8%
ω_{11}	3	731	1	350	-2	-52%
ω_{12}	4	785	1	569	-2	-28%
ω_{13}	3	1006	1	1081	-2	7%
ω_{14}	5	439	1	922	-3	110%
ω_{15}	3	1000	1	1271	-2	27%
ω_{16}	5	-	1	1190	-4	-
ω_{17}	3	1068	1	800	-2	-25%
ω_{18}	5	-	3	231	-2	-
ω_{19}	3	600	1	975	-2	63%
ω_{20}	5	-	3	259	-2	-
ω_{21}	3	1107	1	1037	-2	-6%
ω_{22}	5	-	1	1151	-4	-
ω_{23}	3	1050	1	868	-2	-17%
ω_{24}	5	-	1	1190	-4	-
ω_{25}	3	617	1	503	-2	-18%
ω_{26}	3	1101	1	918	-2	-17%
ω_{27}	3	927	1	505	-2	-46%
ω_{28}	3	989	1	773	-2	-22%
ω_{29}	3	704	1	956	-2	36%
Average:	3.6	911	1.1	861	-2.5	-6%

7.3 Managerial Insights

The conducted computational study intrigues various questions about the behaviour and performance of our proposed schedules. In this section, some managerial insights into the problem dynamics are given. To observe the effects of the problem parameters on the generated schedules and their recovery performances, several what if analyses are conducted where the factors such as unit fuel cost, β, α, γ, and the allowance for the cost increase ϱ take different values. Schedules generated during these analyses can be found in Appendix E. In addition to the problem parameters, analyses on the recovery performance measures, number of disrupted aircraft in a scenario and the aircraft unavailability periods are also conducted. Levels for the factors unit fuel cost, β, and α are available in Table 7.11.

Table 7.11: Factor Values

		Levels		
Factor	Description	Low (L)	Medium (M)	High (H)
A	Unit fuel cost ($)	0.6	1.2	1.8
B	β	0.01	-	0.05
C	α	ln(20)	-	ln(25)

What If Analysis on Fuel Cost: Let the unit fuel cost and unit CO_2 emission cost be an experimental factor denoted by A. We set the fuel cost to 0.6, 1.2, and 1.8 $/kg for low (L), medium (M), and high (H) values. Correspondingly, we set the CO_2 emission cost to 0.01, 0.02, and 0.03 $/kg for these settings. For each case, we obtained the minimum cost schedules. Then, to obtain the proposed schedules we allowed a 10% increase in the total operational cost of the minimum cost schedule as presented in Table 7.12.

Table 7.12: Effect of Unit Fuel Cost on the Schedule Generation

Unit Fuel Cost	Min. Cost Schedule $\mathcal{P}_1$		Proposed Schedule $\mathcal{P}_2$		Improvement
	F_1 (\$)	F_2	F_1 (\$)	F_2	in F_2
L	398147	6.01	422517	5.19	14%
M	796294	5.32	874284	3.24	39%
H	1194441	5.30	1276911	3.15	39%

As expected, when the unit fuel consumption cost increases, the total operational cost of the schedule increases as well. As a result of that, when applying the Aircraft Swapping and Search Algorithm, if the percentage allowance for the cost increase is taken equal for each schedule, then the schedule with the highest unit fuel cost level has more allowance for making aircraft swaps. Therefore, the improvement in the deviation of aircraft path variabilities is higher when the unit cost value is higher. In order to find out if this has an effect on the recovery performance of the schedules, we conducted a posterior analysis whose results are shown in Table 7.13.

Table 7.13: Effect of Unit Fuel Cost on the Recovery Performance

Disruption Scenario	Unit Fuel Cost (L)				Unit Fuel Cost (M)				Unit Fuel Cost (H)			
	$\mathcal{P}_1$		$\mathcal{P}_2$		$\mathcal{P}_1$		$\mathcal{P}_2$		$\mathcal{P}_1$		$\mathcal{P}_2$	
	ξ_1	ξ_2	ξ_1	ξ_2	ξ_1	ξ_2	ξ_1	ξ_2	ξ_1	ξ_2	ξ_1	ξ_2
ω_0	5	-	1	1540	5	-	1	1416	5	-	1	606
ω_1	4	660	1	1283	3	891	1	1166	3	974	1	990
ω_2	3	986	1	1300	3	990	1	1414	4	556	1	1534
ω_3	3	987	2	573	3	905	1	925	3	886	1	1026
ω_4	3	935	1	666	3	791	1	892	3	949	1	667
ω_5	3	841	1	694	3	841	1	898	3	746	1	974
ω_6	4	631	4	414	5	-	3	1012	3	886	1	583
ω_7	3	788	1	1213	3	847	1	1437	3	1225	1	1240
ω_8	5	-	1	1420	5	-	3	1125	5	-	2	1077
ω_9	3	587	1	784	3	581	1	937	3	1184	1	954
Average:	3.4	802	1.4	989	3.6	835	1.4	1122	3.5	926	1.1	965

When the recovery solutions are generated against each disruption scenario, it is observed that the proposed schedule is able to recover from the disruption with less number of cancelled flights compared to the minimum cost schedule in each of the fuel cost settings. As a result of that, total delay occurring in the schedule may increase. In addition to that, under some scenarios such as ω_3 and ω_6, as the unit fuel cost increases, the number of cancelled flights after recovery in the proposed schedule $\mathcal{P}_2$ decreases. On the average, $\mathcal{P}_2$ recovers from the disruptions by 2, 2.2, and 2.4 less flights than the minimum cost schedule $\mathcal{P}_1$ in the settings (L), (M), and (H), respectively. Improvements observed in our recovery performance measures ξ_1 and ξ_2 can be seen from Table 7.14 as well.

Table 7.14: Minimum Cost vs. Proposed Schedule for Unit Fuel Cost Levels

	Change in the Recovery Performance	
Unit Fuel Cost	# of Cancelled Flights (ξ_1)	Total Time of Delay (ξ_2)
L	-59%	23%
M	-61%	34%
H	-69%	4%

In Table 7.14, it is shown that the improvement made in the number of cancelled flights after recovery is increased from 59% to 69% as the unit fuel cost changes from (L) to (H). Although total time of delay is higher in the proposed schedule compared to the minimum cost schedule in each of these settings, as the unit fuel cost increases, the change in the total time of delay decreases from 23% to 4% which is acceptable considering the improvement made in the number of cancelled flights.

We also consider what happens if the same allowance for the cost increase is set for each unit fuel cost setting in monetary terms instead of the percentage allowance. As shown in the example provided in Section 5.3, the largest portion of the additional cost of making an aircraft swap is caused by the inserted idle times. The effect of the fuel cost is rather insignificant compared to the idle time cost and consequently, the algorithm returns similar schedules if we set the same monetary allowance for each setting. As a result, recovery performances of those schedules are expected to be close to each other. For further insight, the results of the what if analysis on the percentage allowance for cost increase can be examined which is provided between pages 84 and 86.

What If Analysis on β*:* Values for the factor β is taken as 0.01 and 0.05 in the settings (L) and (H), respectively. Increasing the value of β significantly increases the variance values of our Log-Laplace random variables and the deviation of the path variabilities. However, as it can be seen from Table 7.15, changing β does not have a significant effect on the schedule generation since each flight leg present in the schedule is affected from the change of β very similarly due to form of the functions related to the distributions of our non-cruise time random variables.

Table 7.15: Effect of β on the Schedule Generation

Levels for β	Min. Cost Schedule $\mathcal{P}_1$		Proposed Schedule $\mathcal{P}_2$		Imp. in
	F_1 ($)	F_2	F_1 ($)	F_2	F_2
L	796294	5.32	874284	3.24	39%
H	796294	25.26	874284	15.79	37%

Table 7.16: Effect of β on the Recovery Performance

Disruption Scenario	$\beta = 0.01$ (L)				$\beta = 0.05$ (H)			
	$\mathcal{P}_1$		$\mathcal{P}_2$		$\mathcal{P}_1$		$\mathcal{P}_2$	
	ξ_1	ξ_2	ξ_1	ξ_2	ξ_1	ξ_2	ξ_1	ξ_2
ω_0	5	-	1	1416	5	-	2	1618
ω_1	3	891	1	1166	3	1121	1	1442
ω_2	3	990	1	1414	3	1003	1	1414
ω_3	3	905	1	925	3	1008	1	925
ω_4	3	791	1	892	3	879	1	1188
ω_5	3	841	1	898	3	961	1	892
ω_6	5	-	3	1012	4	600	1	1221
ω_7	3	847	1	1437	3	847	1	1470
ω_8	5	-	3	1125	5	-	1	1192
ω_9	3	581	1	937	3	959	1	1136
Average:	3.6	835	1.4	1122	3.5	922	1.1	1250

To observe whether the recovery performance of the schedules is affected by the value of β, a posterior analysis whose results are available in Table 7.16 is conducted. In each of the scenarios and levels for β, the proposed schedule $\mathcal{P}$ yields either strongly-dominating or non-dominated recovery solutions.

Average results over all scenarios are very similar to each other for $\beta = 0.01$ and $\beta = 0.05$ as shown in Table 7.17. Indeed, $\mathcal{P}_2$ is "better" by 61% and 69% in terms of the number of cancelled flights in the (L) and (H) settings respectively. However, it faces 34% and 36% more time of delay compared to $\mathcal{P}_1$.

Table 7.17: Minimum Cost vs. Proposed Schedule for β Levels

	Change in the Recovery Performance	
Levels for β	# of Cancelled Flights (ξ_1)	Total Time of Delay (ξ_2)
L	-61%	34%
H	-69%	36%

What If Analysis on α: Values for the factor α is taken as ln(20) and ln(25) in the settings low (L) and high (H) respectively. Increasing the value of α increases the average duration of the non-cruise times and as in Table 7.18, it results in less idle time insertion due to the limited time of the aircraft on a day. When $\alpha = \ln(20)$, the algorithm is able to insert a total of 555 minute idle time to the minimum cost schedule to obtain $\mathcal{P}_2$, whereas when $\alpha = \ln(25)$, the inserted idle time drops to 459 minutes.

Table 7.18: Effect of α on the Schedule Generation

Levels for α	Min. Cost Schedule $\mathcal{P}_1$		Proposed Schedule $\mathcal{P}_2$			Imp. in F_2
	F_1 (\$)	F_2	F_1 (\$)	F_2	Inserted Idle Time (mins)	
L	796294	5.32	874284	3.24	555	39%
H	796270	6.75	861300	4.25	459	37%

In order to find out whether increasing α increases the recovery performance or not, we conducted a posterior analysis and the results against each disruption scenario can be found in Table 7.19. Although the recovery performance of the schedules is expected to be improved as the idle time insertion increases, the results show that when $\alpha = \ln(25)$, the difference between the recovery performances of the proposed schedule and the minimum cost schedule is higher.

On the average, when $\alpha = \ln(25)$, $\mathcal{P}_2$ is able to recover from the schedules by cancelling 2.5 less flights than $\mathcal{P}1$,whereas this value is 2.2 if we have $\alpha = \ln(20)$. Similarly, total time of delay in $\mathcal{P}_2$ is significantly lower if $\alpha = \ln(25)$. The improvement on the performance measures can also be seen in Table 7.20.

The reason for the schedules with high setting for α performing better against disruptions might be because of where the idle times are inserted in the schedule. Indeed, the algorithm makes aircraft swaps such that the idle times are inserted after flight legs whose variability values are higher rather than the flight legs whose average duration of non-cruise times is higher which is what is affected by the change in α.

Table 7.19: Effect of α on the Recovery Performance

Disruption Scenario	$\alpha = \ln(20)$ (L)				$\alpha = \ln(25)$ (H)			
	$\mathcal{P}_1$		$\mathcal{P}_2$		$\mathcal{P}_1$		$\mathcal{P}_2$	
	ξ_1	ξ_2	ξ_1	ξ_2	ξ_1	ξ_2	ξ_1	ξ_2
ω_0	5	-	1	1416	5	-	1	1266
ω_1	3	891	1	1166	3	1163	1	785
ω_2	3	990	1	1414	3	903	1	1127
ω_3	3	905	1	925	3	702	1	739
ω_4	3	791	1	892	3	702	1	739
ω_5	3	841	1	898	3	739	1	791
ω_6	5	-	3	1012	3	905	1	867
ω_7	3	847	1	1437	4	560	1	740
ω_8	5	-	3	1125	5	-	1	1342
ω_9	3	581	1	937	3	838	1	917
Average:	3.6	835	1.4	1122	3.5	814	1	913

Table 7.20: Minimum Cost vs. Proposed Schedule for α Levels

	Change in the Recovery Performance	
Levels for α	# of Cancelled Flights (ξ_1)	Total Time of Delay (ξ_2)
L	-61%	34%
H	-71%	14%

What If Analysis on the Service Level γ: To observe the effects of the service level on the schedule generation, the parameter γ, which is the right hand side of the chance constraint (3.12) in our mathematical formulation, is set to different values ranging from 0.80 to 0.95. The relation between γ and the value of our first objective function F_1, which is the total operational cost of the schedule, can be seen in Figure 7.7.

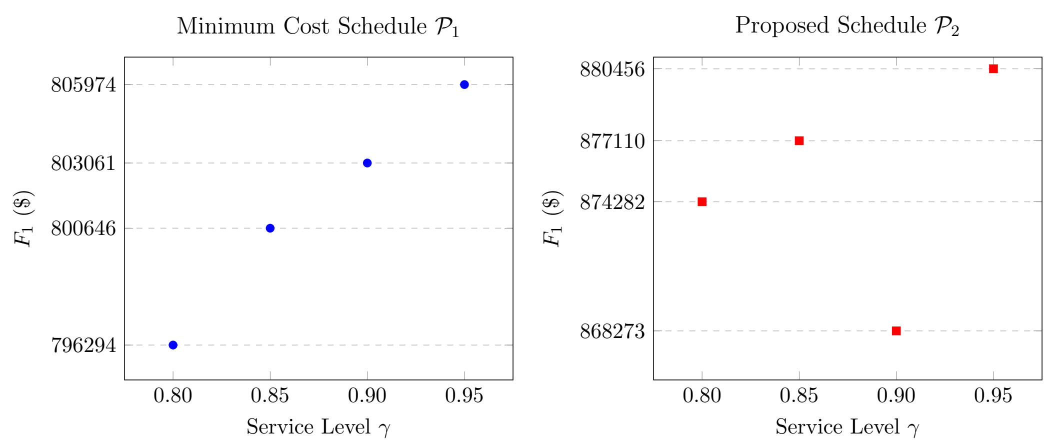

Figure 7.7: Effects of Service Level γ on the Total Operational Cost F_1

In Figure 7.7, it is shown that as the service level γ increases, the total operational cost of the minimum cost schedule $\mathcal{P}_1$ increases as well. While obtaining the proposed schedules $\mathcal{P}_2$, the allowance for the cost increase is set to 10% for each γ value and it is expected to have the total operational cost of $\mathcal{P}_2$ increasing as γ increases as well. However, at $\gamma = 0.90$, it observed that the total cost of $\mathcal{P}_2$ is less than the $\gamma = 0.95$ case. It is because the algorithm first makes the swap which yields the greatest utility and in the $\gamma = 0.90$ case, it corresponds to a 42%

improvement in F_2 with a \$65,212 increase in the total operational cost. There still remains an allowance worth of \$15,094 but the swap that yields the second most utility costs more than the remaining allowance. Therefore, when $\gamma = 0.90$, the total operational cost of $\mathcal{P}_2$ stays low compared to the other γ settings.

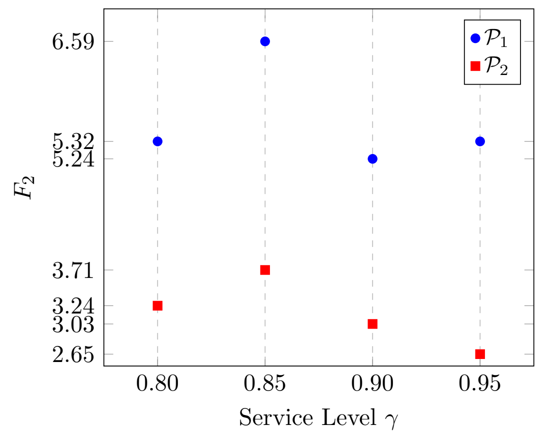

Figure 7.8: Effects of Service Level γ on the Deviation in Variability F_2

In addition, the relation between γ and F_2, which is the deviation of the aircraft path variabilities from the average, can be seen in Figure 7.8. There is not an obvious pattern on this relation as far as we observe. However, when we look at the improvement made in F_2 by the proposed schedule $\mathcal{P}_2$ in Figure 7.9, we observe that when the service level γ takes the highest value 0.95, F_2 is improved by 50% which is significantly higher compared to the case when $\gamma = 0.80$.

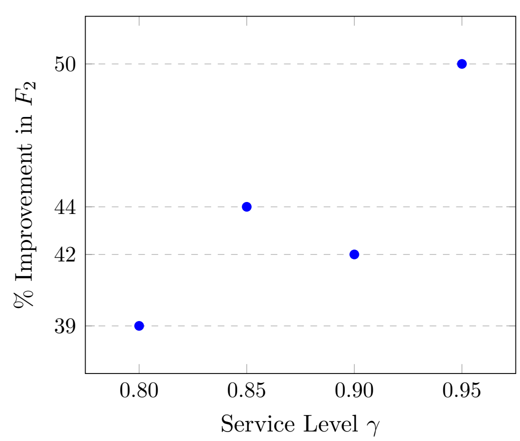

Figure 7.9: Service Level γ vs. Improvement in F_2 for 50 Flights

What If Analysis on the Allowance for Cost Increase ϱ: In the Proposed Discretized Approximation and Aircraft Swapping Algorithm, the total operational cost of the proposed schedule is allowed to deviate from the minimum cost by at most ϱ. To observe the effects of the allowance for the cost increase on the recovery performances on the proposed schedules, ϱ is set to 2.5%, 5%, 7.5%, 10%, and 15%. The total operational cost, F_1, and the deviation of aircraft path variabilities from the average, F_2, can be seen in Table 7.21 for each of the corresponding schedules.

Table 7.21: Effect of Allowance for Cost Increase on the Schedule Generation

Percentage Allowance for the Cost Increase (ϱ)	F_1 (\$)	F_2	# of Swaps Made	Inserted Idle Time (mins)
0 % (Min. Cost Schedule)	796294	5.32	-	0
2.5%	796294	5.32	0	0
5%	818284	4.58	1	155
7.5%	845912	3.85	2	355
10%	874284	3.24	3	555
15%	913564	2.50	4	832

As it is also shown in Figure 7.2, when the allowance is equal to 2.5%, the algorithm cannot make any swaps and returns exactly the minimum cost schedule. However, as the percentage allowance increases, the algorithm is able to make more swaps and to insert more idle time to the schedule. Therefore, when the allowance is equal to 15%, a total of 832 minute idle time is inserted into the schedule and the variability level is decreased to 2.50 which corresponds to a 56% improvement in F_2.

Figure 7.10 shows how the number of cancelled flights and total time of delay occurred after recovery change when the allowance for the cost increase changes on the average. As expected, the number of cancelled flights on average decreases as the allowance for the cost increase increases. When we compare the cases for 5% and 7.5% allowance, the average number of cancelled flights are reduced from 1.5 to 1.4 but this results in an increase in the total delay due to accommodating more flights in the schedule. However, when we compare the cases for 7.5% and 10% allowance, the schedules perform the same in terms of the cancellation but the total delay is significantly less in the 10% allowance case due to the more idle time insertion. Similarly, the inserted idle time worth of 832 minutes in the 15% allowance case allows the total delay to be reduced significantly.

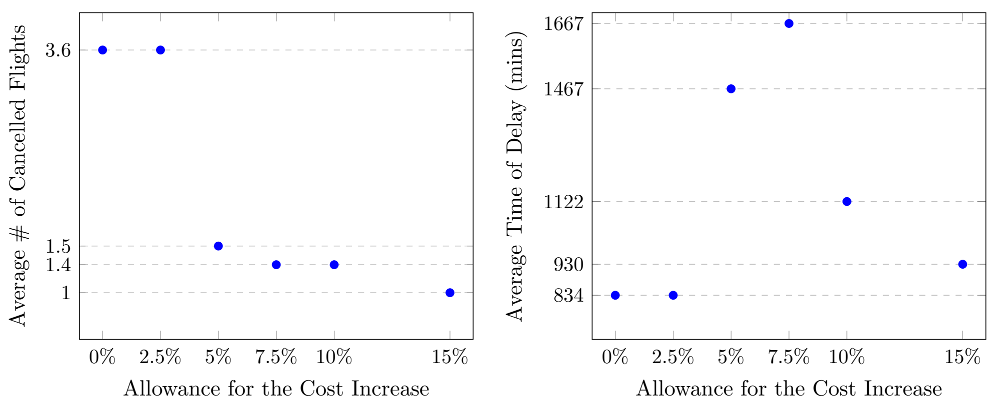

Figure 7.10: Effects of Allowance for Cost Increase on Recovery Performance

In addition to the changes in the average of the recovery performance measures, recovery solutions generated for each proposed schedule having different allowance values under each disruption scenario is presented in Tables 7.22 and 7.23.

Table 7.22: Effect of Allowance ϱ on the Number of Cancelled Flights

Disruption Scenario	Number of Cancelled Flights (ξ_1)				
	Allowance for Cost Increase (ϱ)				
	0% - 2.5%	5%	7.5%	10%	15%
ω_0	5	1	1	1	1
ω_1	3	1	1	1	1
ω_2	3	1	1	1	1
ω_3	3	1	1	1	1
ω_4	3	1	1	1	1
ω_5	3	1	1	1	1
ω_6	5	3	3	3	1
ω_7	3	1	1	1	1
ω_8	5	4	3	3	1
ω_9	3	1	1	1	1
Average:	3.6	1.5	1.4	1.4	1

In Table 7.22, under each of the disruption scenarios, the number of cancelled flights either decreases or stays the same as the percentage allowance increases which is in line with our expectations.

Similarly, in Table 7.23, under all disruption scenarios except ω_0, ω_6, and ω_8, total time of delay after recovery decreases as the allowance increases. Under scenarios ω_0, ω_6, and ω_8, since the schedules with lower allowance values cancel significantly more flights to recover, less times of delay occur in those schedules as expected.

Table 7.23: Effect of Allowance ϱ on the Total Time of Delay

Disruption Scenario	Total Time of Delay (ξ_2) (mins)				
	Allowance for Cost Increase (ϱ)				
	0% - 2.5%	5%	7.5%	10%	15%
ω_0	-	1438	1438	1416	1237
ω_1	891	1520	1441	1166	931
ω_2	990	1414	1414	1414	1261
ω_3	905	1214	925	925	925
ω_4	791	1161	892	892	715
ω_5	841	1162	892	898	715
ω_6	-	1012	1012	1012	834
ω_7	847	1436	1436	1436	1066
ω_8	-	173	1282	1125	942
ω_9	581	937	937	937	669
Average:	835	1467	1667	1122	930

What If Analysis on the Recovery Performance Measures: Although the proposed schedules are shown to perform better against disruptions in terms of the number of cancelled flights, they may have longer durations of total delay due to the higher number of flights accommodated into the existing schedule. Because of that, we also consider the maximum time of delay occurred in a single flight leg as another performance measure. Corresponding analysis for 50 flights is shown in Table 7.24.

While on the average, the proposed schedule $\mathcal{P}_2$ has 61% less number of cancelled flights with 34% more time of total delay compared to the minimum cost schedule $\mathcal{P}_1$, when we consider the maximum time of delay occurred in a single flight leg, $\mathcal{P}_2$ has only 5% more delay than $\mathcal{P}_1$.

Table 7.24: Comparison of Total Delay and Maximum Delay for 50 Flights

Disruption	# of Cancelled Flights			Total Time of Delay			Max. Delay in a Flight Leg		
Scenario	$\mathcal{P}_1$	$\mathcal{P}_2$	Change	$\mathcal{P}_1$	$\mathcal{P}_2$	Change	$\mathcal{P}_1$	$\mathcal{P}_2$	Change
ω_0	5	1	-80%	-	1416	-	-	262	-
ω_1	3	1	-67%	891	1166	31%	214	241	13%
ω_2	3	1	-67%	990	1414	43%	260	213	-18%
ω_3	3	1	-67%	905	925	2%	199	220	11%
ω_4	3	1	-67%	791	892	13%	256	212	-17%
ω_5	3	1	-67%	841	898	7%	213	213	0%
ω_6	5	3	-40%	-	1012	-	-	267	-
ω_7	3	1	-67%	847	1437	70%	214	259	21%
ω_8	5	3	-40%	-	1125	-	-	262	-
ω_9	3	1	-67%	581	937	61%	214	214	0%
Average:	3.6	1.4	-61%	835	1122	34%	224	236	5%

We also consider this performance measure for the network containing 150 flights and in Table 7.25, on the average of 30 disruption scenarios, how the recovery performance measures change in $\mathcal{P}_2$ compared to $\mathcal{P}_1$ is given.

Table 7.25: Changes in the Recovery Performance Measures for 150 Flights

	# of Cancelled Flights	Total Time of Delay	Max. Delay in a Flight Leg
Min. Cost Schedule $\mathcal{P}_1$	3.6	911	221
Proposed Schedule $\mathcal{P}_2$	1.1	861	210
Change:	-67%	-6%	-5%

While decreasing the number of cancelled flights by 67%, the proposed schedule performs 6% better in terms of the total delay in the schedule than the minimum cost schedule whereas this number is 5% for the maximum time of delay occurred in a single flight leg. Recovery solutions including these three measures under each disruption scenario can be found in Table 7.26 in detail.

Table 7.26: Comparison of Total Delay and Maximum Delay for 150 Flights

Disruption Scenario	# of Cancelled Flights			Total Time of Delay			Max. Delay in a Flight Leg		
	$\mathcal{P}_1$	$\mathcal{P}_2$	Change	$\mathcal{P}_1$	$\mathcal{P}_2$	Change	$\mathcal{P}_1$	$\mathcal{P}_2$	Change
ω_0	5	1	-80%	-	1168	-	-	212	-
ω_1	3	1	-67%	869	709	-18%	212	214	1%
ω_2	3	1	-67%	1229	962	-22%	212	149	-30%
ω_3	3	1	-67%	1186	720	-39%	253	212	-16%
ω_4	3	1	-67%	733	786	7%	213	257	21%
ω_5	3	1	-67%	872	876	0%	213	216	1%
ω_6	5	1	-80%	-	1215	-	-	248	-
ω_7	3	1	-67%	1358	905	-33%	253	216	-15%
ω_8	5	1	-80%	-	1190	-	-	263	-
ω_9	3	1	-67%	656	804	23%	213	208	-2%
ω_{10}	4	1	-75%	1016	932	-8%	291	254	-13%
ω_{11}	3	1	-67%	731	350	-52%	213	97	-54%
ω_{12}	3	1	-67%	785	569	-28%	165	165	0%
ω_{13}	3	1	-67%	1006	1081	7%	212	235	11%
ω_{14}	4	1	-75%	439	922	110%	230	246	7%
ω_{15}	3	1	-67%	1000	1271	27%	224	280	25%
ω_{16}	5	1	-80%	-	1190	-	-	263	-
ω_{17}	3	1	-67%	1068	800	-25%	245	226	-8%
ω_{18}	5	3	-40%	-	231	-	-	145	-
ω_{19}	3	1	-67%	600	975	63%	213	250	17%
ω_{20}	5	3	-40%	-	259	-	-	174	-
ω_{21}	3	1	-67%	1107	1037	-6%	252	213	-15%
ω_{22}	5	1	-80%	-	1151	-	-	235	-
ω_{23}	3	1	-67%	1050	868	-17%	234	210	-10%
ω_{24}	5	1	-80%	-	1190	-	-	263	-
ω_{25}	3	1	-67%	617	503	-18%	157	122	-22%
ω_{26}	3	1	-67%	1101	918	-17%	208	208	0%
ω_{27}	3	1	-67%	927	505	-46%	220	122	-45%
ω_{28}	3	1	-67%	989	773	-22%	212	194	-8%
ω_{29}	3	1	-67%	704	956	36%	213	214	0%
Average:	3.6	1.1	-69%	911	861	-6%	221	210	-5%

What If Analysis on the Number of Disrupted Aircraft: In order to observe the recovery performances of the minimum cost and the proposed schedules against disruptions caused by the unavailability of multiple aircraft, the number of disrupted aircraft is set to 2 and 45 disruption scenarios are generated in total. In each of these scenarios, 10 flights are disrupted and needed to be recovered. The performances of $\mathcal{P}_1$ and $\mathcal{P}_2$ can be seen in Table 7.27.

Table 7.27: Effect of Having Two Disrupted Aircraft on the Recovery Performance

Disrupted Aircraft	# of Cancelled Flights			Total Time of Delay			Max. Delay in a Flight Leg		
	$\mathcal{P}_1$	$\mathcal{P}_2$	Change	$\mathcal{P}_1$	$\mathcal{P}_2$	Change	$\mathcal{P}_1$	$\mathcal{P}_2$	Change
0, 1	8	2	-75%	1005	2421	141%	213	262	23%
0, 2	8	2	-75%	876	3064	250%	214	262	22%
0, 3	8	2	-75%	824	2657	222%	220	262	19%
0, 4	8	2	-75%	908	2632	190%	202	302	50%
0, 5	8	2	-75%	704	2631	274%	212	302	42%
0, 6	9	2	-78%	600	2795	366%	214	280	31%
0, 7	8	2	-75%	961	2920	204%	213	262	23%
0, 8	10	2	-80%	-	3145	-	-	261	-
0, 9	8	2	-75%	695	2833	308%	213	254	19%
1, 2	6	2	-67%	2018	2992	48%	229	259	13%
1, 3	6	2	-67%	1998	2379	19%	232	259	12%
1, 4	6	2	-67%	1869	2719	45%	229	233	2%
1, 5	6	2	-67%	1869	2360	26%	229	259	13%
1, 6	7	2	-71%	1778	2863	61%	232	369	59%
1, 7	6	2	-67%	2196	2892	32%	242	232	-4%
1, 8	8	2	-75%	1005	2962	195%	213	262	23%
1, 9	6	2	-67%	1988	2514	26%	228	259	14%
2, 3	6	2	-67%	1885	2449	30%	220	257	17%
2, 4	6	2	-67%	1869	2431	30%	213	257	21%
2, 5	6	2	-67%	1860	2431	31%	213	257	21%
2, 6	7	2	-71%	1780	2879	62%	249	261	5%
2, 7	6	2	-67%	2164	2960	37%	258	213	-17%
2, 8	8	2	-75%	990	2988	202%	213	261	23%
2, 9	6	2	-67%	1993	2585	30%	260	257	-1%
3, 4	6	2	-67%	1732	2003	16%	212	220	4%
3, 5	6	2	-67%	1732	2003	16%	212	220	4%
3, 6	7	2	-71%	1643	2407	47%	203	261	29%
3, 7	6	2	-67%	1914	2304	20%	242	220	-9%
3, 8	8	2	-75%	827	2174	163%	220	262	19%
3, 9	6	2	-67%	1840	2178	18%	220	214	-3%
4, 5	6	2	-67%	1613	1950	21%	212	212	0%
4, 6	7	2	-71%	1570	2374	51%	242	261	8%
4, 7	6	2	-67%	1795	2339	30%	242	213	-12%
4, 8	8	2	-75%	707	2163	206%	212	262	24%
4, 9	6	2	-67%	1839	2158	17%	212	215	1%
5, 6	7	2	-71%	1529	2374	55%	256	261	2%
5, 7	6	2	-67%	1795	2339	30%	242	213	-12%
5, 8	8	2	-75%	707	2163	206%	212	262	24%
5, 9	6	2	-67%	1835	2158	18%	212	215	1%
6, 7	7	2	-71%	1698	2728	61%	214	262	22%
6, 8	9	2	-78%	600	2757	360%	214	280	31%
6, 9	7	2	-71%	1709	2401	40%	241	261	8%
7, 8	8	2	-75%	847	2992	253%	214	262	22%
7, 9	6	2	-67%	1914	2441	28%	242	235	-3%
8, 9	8	2	-75%	581	2510	332%	214	261	22%
Average:	7	2	-71%	1461	2543	74%	224	255	13%

Under each of the scenarios, the number of cancelled flights are significantly lower in $\mathcal{P}_2$ compared to $\mathcal{P}_1$. In addition to that, under the disruption scenario where aircraft 0 and 8 are unavailable, $\mathcal{P}_2$ is able to recover by cancelling only 2 flight while $\mathcal{P}_1$ cancels all of the 10 flights. However, since there is a significant difference between the number of cancelled filghts in $\mathcal{P}_1$ and $\mathcal{P}_2$, the corresponding total times of delay in $\mathcal{P}_2$ are significantly higher than $\mathcal{P}_1$. That is why we also look at the maximum time of delay occurred in a flight leg in the schedule as another recovery performance which is shown in Table 7.27 as well.

As a result, in the case of two disrupted aircraft, on the average, the proposed schedule $\mathcal{P}_2$ can recover from the disruption with 71% less cancellation than the minimum cost schedule $\mathcal{P}_1$ while the maximum time of delay occurred in a flight leg is increased by only 13% which corresponds to approximately 30 minutes.

In addition, the number of disrupted aircraft is set to 3 and 120 disruption scenarios are generated in total. The recovery solutions under each scenario can be found in Appendix F. On the average of 120 scenarios, number of cancelled flights in $\mathcal{P}_2$ is 5.1 whereas in $\mathcal{P}_1$, it is 10.5 and this corresponds to a 51% improvement. The time of total delay after recovery though is approximately doubled in $\mathcal{P}_2$. However, the maximum delay occurred in a single flight leg in $\mathcal{P}_2$ is only 21% higher than $\mathcal{P}_1$ as shown in Table 7.28.

Table 7.28: Summary of Recovery Solutions against 3 Disrupted Aircraft

	# of Cancelled Flights	Total Time of Delay	Max. Delay in a Flight Leg
Min. Cost Schedule $\mathcal{P}_1$	10.5	2096	234
Proposed Schedule $\mathcal{P}_2$	5.1	4022	282
Change:	-51%	101%	21%

What If Analysis on the Aircraft Unavailability Periods: Until now, we assumed that the aircraft are unavailable for the whole day to generate disruption scenarios. In order to gain an insight on how the proposed schedules perform against shorter disruptions, we conducted a what if analysis on the aircraft unavailability periods by changing the durations of the period. The description of the aircraft unavailability periods that are considered are available in Table 7.29.

Table 7.29: Description of the Aircraft Unavailability Periods

Period No.	Time Interval	Duration of Unavailability (hrs)
I	09:00 A.M. - 01:00 P.M.	4
II	09:00 A.M. - 03:00 P.M.	6
III	09:00 A.M. - 05:00 P.M.	8
IV	09:00 A.M. - 07:00 P.M.	10
V	09:00 A.M. - 09:00 P.M.	12
VI	Whole Day	24

When the aircraft unavailability period is different than the whole day, the number of disrupted flights in schedules $\mathcal{P}_1$ and $\mathcal{P}_2$ might differ. Therefore, we use the ratio of the number of cancelled flights to the number of disrupted flights as our criterion instead of using only the number of cancelled flights.

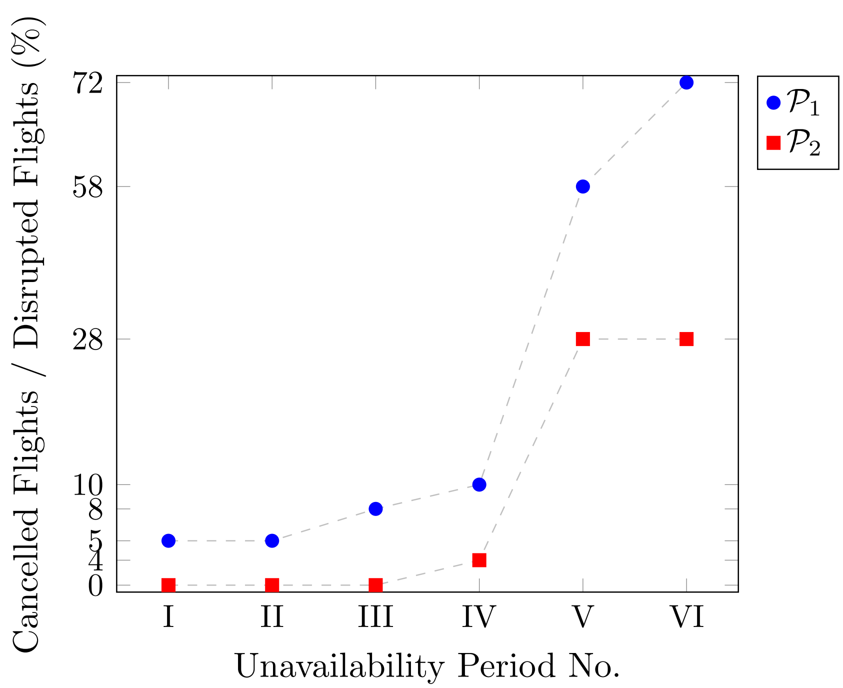

Figure 7.11: Effects of Aircraft Unavailability Periods on Recovery Performance

In Figure 7.11, the effects of the unavailability period on the recovery performances of the schedules $\mathcal{P}_1$ and $\mathcal{P}_2$ are shown. The results are for the average of the 10 disruption scenarios where each of them denotes the unavailability of one aircraft. For the unavailability periods I and II, the minimum cost schedule $\mathcal{P}_1$ cancels 5% of the disrupted flights. However, for the same unavailability periods together with the period III, the proposed schedule $\mathcal{P}_2$ is able to recover all disrupted flights. Similarly, for the remaining unavailability periods, cancellation ratio in $\mathcal{P}_2$ is significantly less than $\mathcal{P}_1$.

In addition, the number of disrupted and cancelled flights as well as the total time of delay can be seen in Table 7.30 for the average of 10 disruption scenarios for each unavailability period. As expected, the longest time of delay is occurred when the aircraft are unavailable for the whole day. For the proposed schedule $\mathcal{P}_2$, it can be concluded that the total delay after recovery increases as the unavailability period increases. However, it is not the case for the minimum cost schedule since the number of cancelled flights is not increasing as rapidly as $\mathcal{P}_2$ as the unavailability period gets longer.

Table 7.30: Average Recovery Measures for Each Unavailability Period

Unavailability	# of Disrupted Flights		# of Cancelled Flights		Total Time of Delay	
Period No.	$\mathcal{P}_1$	$\mathcal{P}_2$	$\mathcal{P}_1$	$\mathcal{P}_2$	$\mathcal{P}_1$	$\mathcal{P}_2$
I	2.6	2.6	0.2	0	761	628
II	3.8	3.6	0.2	0	1100	882
III	4	4	0.3	0	1113	941
IV	4.3	4.2	0.5	0.2	1106	1002
V	4.9	5	2.9	1.4	886	1122
VI	5	5	3.6	1.4	835	1122

Recovery solutions that the schedules $\mathcal{P}_1$ and $\mathcal{P}_2$ yield under each disruption scenario for each aircraft unavailability period can be found in Appendix G.

7.4 Summary

This chapter was devoted to the computational analysis conducted in this study. First, how the problem instances are generated is described and the selected values for the problem parameters are explained. In addition, the aircraft specific parameters, which include the fuel consumption coefficients and unit idle time costs, are provided.

Then, the results of the CPU time analysis on the Proposed Discretized Approximation and Aircraft Swapping Algorithm are briefly discussed. Afterwards, the computational study on the flight schedule with 50 flights is explained in detail. The trade-off between the operational costs and the variability objectives is examined through a Pareto frontier. Following that, a posterior analysis is conducted on the minimum cost schedule and the proposed schedule and the recovery performances of the two under disruption scenarios caused by the unavailability of the aircraft are evaluated. A similar analysis is also conducted for the flight schedule with 150 flights which is the largest problem instance that we solved in our computational experiments.

The chapter is concluded with several what if analyses which are conducted to gain some insight about the effects of problem parameters such as the unit fuel consumption cost, the desired service level for the chance constraint and the allowance for the cost increase in our proposed algorithm. Besides the problem parameters, what if analyses on the type of recovery performance measures, the number of disrupted aircraft and the duration of the aircraft unavailability periods are done as well.

Chapter 8

Conclusion and Future Works

In the introduction, a background information on the resilient airline scheduling is provided, the motivation behind this study and its contributions are explained. In this chapter, a summary of this thesis is given and its contributions to the resilient airline scheduling literature along with the potential future research directions arising from this study are discussed.

8.1 Summary and Contributions

In this study, we aim to create resilient schedules which are adaptable to uncertain challenges while continuing to stay operational. Unlike the traditional objective of the airlines which is the minimization of the operational costs, as a significant contribution, we also incorporate the variability into our formulation as a surrogate measure to the resilience. To this end, we define a bi-objective problem which aims to minimize the deviation of the aircraft path variabilities from the average without causing the total operational cost to deviate from the minimum too much.

We formulate the problem as a bi-criteria nonlinear mixed-integer mathematical model with chance constraints. To handle the nonlinearity, we utilize second order cone programming and to handle the chance constraints, we use value-at-risk measure. To solve the problem via commercial solvers, we implement the ε-constraint approach. We also develop a novel math-heuristic algorithm which first generates a near minimum cost schedule and then converts it to a more balanced schedule in terms of the aircraft path variabilities by making necessary swaps between the aircraft and flight block assignments.

As an important contribution, we propose a data-driven methodology to estimate departure and arrival delay probabilities of flights and turnaround times of the aircraft. Through the empirical techniques that we introduce, we are able to capture the trends in the historical data in our parameter calculations which were previously done in the existing literature in more traditional ways.

We devise an integrated flight and passenger recovery algorithm to evaluate the performance of our proposed schedules under disruption scenarios in a posterior analysis. Another important contribution is that in case of disruptions caused by the unavailability of the aircraft, we provide the decision maker with flexible recovery strategies having different characteristics due to the bi-criteria nature of our recovery performance evaluation.

We observe that the schedules that we propose can recover from the disruptions with less number of flight cancellations compared to the minimum cost schedules. This is another crucial contribution of this study since airlines avoid cancelling flights since the opportunity costs of flight cancellation are high and also the passenger convenience and satisfaction are of great importance to them. We show that by allowing a small deviation from the minimum cost schedule at the schedule generation phase, the potential recovery costs in the future can be reduced significantly. This is a result of the trade-off between the total operational costs and the deviation of the aircraft path variabilities which is what initially motivated this study.

8.2 Future Works

The contributions of this study can be extended with several possible future research directions. In this study, not all the subproblems of an airline scheduling problem such as aircraft maintenance routing is considered since including them would increase the complexity of the problem even further. The results show that our proposed algorithm can come up with schedules for large-sized problems in reasonable CPU times. Therefore, maintenance routing can be added to the problem and linked with the disruption scenarios as well to create an integrated approach in the future.

We assume that the non-cruise time random variables follow a Log-laplace distribution. One possible research idea would be considering other probability distributions which have closed form representations for the non-cruise time random variables. Then, this study can be extended to include an analysis on the performance of schedules generated under different probability distributions.

To capture the uncertainty in the non-cruise times, we follow a data-driven manner and estimate the flight delay probabilities via logistic regression. In a possible future study, different generalized models to estimate those problem parameters can be applied and the results can be compared to our results in order to show which procedure is capturing the uncertainty better.

We use value-at-risk risk function in the chance constraint of the proposed model. In a potential research, a coherent risk measure can be used and results can be compared in terms of capturing the behaviour of the random variables.

Another direction would be to follow a stochastic programming framework instead of using chance constraints to deal with the variability in the non-cruise times. The disruption scenarios that we generate for our posterior analyses might be considered as scenarios for the stochastic model to create an integrated approach. However, we expect the computation times of this approach to be significantly high since the numerous disruption scenarios may increase the size of the problem rapidly.

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Appendix A

Integrated Flight and Passenger Recovery Algorithm

Algorithm 2 Integrated Flight and Passenger Recovery Algorithm (IAPRA)

INITIALIZATION:
Define the set of problems as $\mathcal{P} := \emptyset$ and the set of solutions as $\mathcal{S} := \emptyset$.
Take E_D, E_N and F_i as input. Calculate the matrices $[a]_i^t$ and $[b]_{ij}$.
Denote the problem with these matrices as P_0 and let the problem set $\mathcal{P} \leftarrow \{P_0\}$.
STEP 1: Solve (FRM) for problem$P_k \in \mathcal{P}$. Update $\mathcal{P} \leftarrow \mathcal{P} \backslash P_k$.
Let S represent the solution. Update $\mathcal{S} \leftarrow \mathcal{S} \cup S$.
In the solution S:
for each $i \in E_D$ **do**
    for each $t \in T$ **do**
        if $accom_i^t = 1$ **then**
            Create problem P by updating $a_i^t \leftarrow 0$ and let $\mathcal{P} \leftarrow \mathcal{P} \cup \{P\}$.
        else if $swap_{ij} = 1$ **then**
            Create problem P by updating $b_{ij} \leftarrow 0$ and let $\mathcal{P} \leftarrow \mathcal{P} \cup \{P\}$.
        end if
    end for
end for
Go to Step 2.
STEP 2: Solve (RRM) for solution S. Report the solution.
if $\mathcal{S} \neq \emptyset$ **then**
    Go to Step 1.
else
    Stop. Report $\mathcal{S}$ as the set of recovery solutions.
end if

Appendix B

Algorithms to Check Eligibility

Algorithm 3 Algorithm to Check Eligibility for Swapping Disrupted and Existing Flight Blocks

for each $i \in E$ **do**
    Let $block^i := \sum_{k \in F_i} f_k^l$ denote the block time of flight block i.
    Let $cruise^i := \sum_{k \in F_i} f_k$ denote the total cruise time of flight block i.
    Let $idle^i := \sum_{k \in F_i} s_k$ denote the total idle time in flight block i.
    if $c^i = 1$ **then**
        Let $slack^i$ denote the time until midnight after flight block i.
    end if
end for
for each $i \in E$ **do**
    for each $i \in E$ **do**
        if $t^i = t^j$ **then**
            $b_{ij} \leftarrow 0$
        else if $c^j = 2$ **and** $block^i \leq cruise^j + idle^j$ **then**
            $b_{ij} \leftarrow 1$
        else if $c^j = 1$ **and** $block^i \leq cruise^j + idle^j + slack^j$ **then**
            $b_{ij} \leftarrow 1$
        else
            $b_{ij} \leftarrow 0$
        end if
    end for
end for

Algorithm 4 Algorithm to Check Eligibility for Accommodating a Disrupted Flight Block into an Existing Path

for each $i \in E$ **do**
    Let $block^i := \sum_{k \in F_i} f_k^l$ denote the block time of flight block i.
    Let $cruise^i := \sum_{k \in F_i} f_k$ denote the total cruise time of flight block i.
    Let $idle^i := \sum_{k \in F_i} s_k$ denote the total idle time in flight block i.
    if $c^i = 1$ **then**
        Let $slack^i$ denote the time until midnight after flight block i.
    end if
end for
for each $t \in T$ **do**
    Let $slackInPath^t$ denote the slack time that can be created in the path of aircraft t.
    $slackInPath^t \leftarrow 0$
    for each $i \in E$ **do**
        if $t^i = t$ **then**
            if $c^i = 2$ **then**
                $slackInPath^t \leftarrow slackInPath^t + idle^i + cruise^i - block^i$
            else if $c^i = 1$ **then**
                $slackInPath^t \leftarrow slackInPath^t + idle^i + slack^i + cruise^i - block^i$
            end if
        end if
    end for
end for
for each $i \in E$ **do**
    for each $t \in T$ **do**
        if $t^i = t$ **then**
            $a_i^t \leftarrow 0$
        else if $c^j = 2$ **and** $block^i + turnTime \leq slackInPath^t$ **then**
            $a_i^t \leftarrow 1$
        else
            $a_i^t \leftarrow 0$
        end if
    end for
end for

Appendix C

Air Times

Table C.1: Air Times of Flights Operating Between 21 Major U.S. Airports

	ATL	**AUS**	**BOS**	**DCA**	**DEN**	**DFW**	**EWR**	**FLL**	**LAS**	**LAX**	**LGA**
ATL	-	99	100	77	109	84	153	99	85	120	98
AUS	80	-	109	86	117	93	161	108	93	128	107
BOS	111	138	-	116	147	123	192	138	124	159	137
DCA	73	100	101	-	109	86	154	101	86	121	99
DEN	82	109	109	86	-	94	163	109	94	130	108
DFW	66	93	94	71	102	-	147	93	79	114	92
EWR	154	181	182	159	191	166	-	181	167	202	180
FLL	99	126	127	104	135	111	180	-	111	146	125
LAS	53	79	80	57	89	65	134	80	-	101	79
LAX	87	114	115	93	124	100	169	115	100	-	113
LGA	104	131	132	109	140	116	185	131	116	152	-
MCI	37	64	64	41	73	49	117	64	49	84	63
MIA	88	115	116	93	124	100	169	115	101	136	114
MSP	39	65	66	43	75	50	120	65	51	86	64
ORD	94	120	122	99	130	106	175	121	106	141	120
PHL	116	142	143	120	152	127	197	142	128	163	141
PHX	73	100	101	78	109	86	154	101	86	121	99
SAN	64	91	92	69	101	77	146	92	77	112	90
SFO	109	136	137	114	146	121	190	136	121	156	135
SLC	61	87	88	65	97	72	141	87	73	109	86
STL	68	94	95	72	104	79	149	94	80	116	94

Table C.2: Air Times of Flights Operating Between 21 Major U.S. Airports - Cont.'d from Table C.1

	MCI	**MIA**	**MSP**	**ORD**	**PHL**	**PHX**	**SAN**	**SFO**	**SLC**	**STL**
ATL	49	92	54	105	110	105	95	146	109	86
AUS	57	101	63	114	119	114	104	154	118	95
BOS	88	131	93	145	150	144	134	185	148	125
DCA	50	93	55	107	112	106	96	147	110	88
DEN	59	101	64	116	121	115	105	156	119	97
DFW	43	86	48	99	104	99	89	139	103	80
EWR	131	174	136	188	193	187	177	229	191	169
FLL	76	119	81	132	138	132	122	173	137	114
LAS	30	72	34	86	92	86	76	127	90	68
LAX	64	107	69	121	126	121	110	161	125	102
LGA	81	124	86	138	143	138	127	178	142	119
MCI	-	56	19	70	75	70	60	110	74	51
MIA	65	-	70	122	127	121	111	162	125	102
MSP	16	58	-	72	78	71	62	113	76	53
ORD	71	114	76	-	132	127	116	168	131	109
PHL	93	135	97	149	-	148	139	190	153	130
PHX	50	93	55	107	112	-	96	147	110	88
SAN	41	84	46	98	103	97	-	139	101	79
SFO	86	129	91	142	147	142	131	-	146	124
SLC	38	80	42	94	99	94	84	134	-	75
STL	45	87	49	101	107	101	91	142	105	-

Appendix D

Available Aircraft and Their Types

Table D.1: List of Available Aircraft and Their Types

Tail Number	Type	Tail Number	Type
N240AT	B737 500	N312US	A320 111
N656CS	B737 500	N317US	A320 111
N678UA	B737 500	N319US	A320 111
N681UA	B737 500	N320US	A320 111
N695UA	B737 500	N334NW	A320 212
N821AU	B737 500	N335NW	A320 212
N966UA	B737 500	N336NW	A320 212
N967UA	B737 500	N573UA	B767 300
N969UA	B737 500	N784CK	B767 300
N305FA	MD 83	N164TS	B727 228
N801WA	MD 83	N353PA	B727 228
N802WA	MD 83	N355PA	B727 228
N805WA	MD 83	N422BN	B727 228
N807TR	MD 83	N438BN	B727 228
N309US	A320 111	N727YK	B727 228

Appendix E

Schedules Generated for What If Analyses

Table E.1: 50 Flights Minimum Cost Schedule for Low Unit Fuel Cost Setting

Tail No.	Aircraft No.	Flight No.	Origin	Dest.	Departure Time	Arrival Time
N678UA	0	0	ORD	LGA	08:06	09:48
		36	LGA	ORD	10:41	12:39
		27	ORD	LGA	13:34	15:16
		28	LGA	ORD	16:08	18:06
		29	ORD	BOS	19:01	20:44
N802WA	1	30	ORD	DFW	07:29	08:59
		6	DFW	ORD	10:19	11:43
		7	ORD	LGA	14:17	15:59
		43	LGA	ORD	17:19	19:16
		39	ORD	LGA	20:20	22:02
N805WA	2	5	ORD	DFW	07:45	09:15
		41	DFW	ORD	10:23	11:47
		2	ORD	DFW	13:35	15:05
		38	DFW	ORD	17:22	18:46
		44	ORD	SAN	20:00	21:39
N309US	3	10	ORD	MCI	07:15	08:15
		46	MCI	ORD	09:13	10:12
		17	ORD	SAN	11:49	13:28
		18	SAN	ORD	16:47	18:10
		24	ORD	SAN	19:00	20:39
N334NW	4	45	ORD	MCI	07:15	08:15
		11	MCI	ORD	09:12	10:11
		47	ORD	DFW	11:22	12:52
		48	DFW	ORD	14:35	15:59
		14	ORD	DEN	17:30	19:20

Table E.2: Cont.'d from Table E.1

Tail No.	Aircraft No.	Flight No.	Origin	Dest.	Departure Time	Arrival Time
N312US	5	15	ORD	MSP	07:15	08:19
		16	MSP	ORD	09:15	10:16
		12	ORD	DFW	11:23	12:53
		13	DFW	ORD	14:35	15:59
		49	ORD	DEN	17:30	19:20
N801WA	6	40	ORD	DFW	07:45	09:15
		31	DFW	ORD	10:29	11:53
		32	ORD	AUS	13:50	15:32
		33	AUS	ORD	17:22	18:59
		34	ORD	LGA	20:40	22:22
N807TR	7	25	ORD	DFW	08:45	10:15
		26	DFW	ORD	11:09	12:33
		37	ORD	DFW	13:39	15:09
		3	DFW	ORD	17:22	18:46
		4	ORD	LGA	20:20	22:02
N695UA	8	35	ORD	LGA	08:10	09:52
		1	LGA	ORD	10:45	12:42
		42	ORD	LGA	14:18	16:00
		8	LGA	ORD	17:24	19:21
		19	ORD	BOS	21:30	23:14
N422BN	9	20	ORD	DFW	09:45	11:15
		21	DFW	ORD	12:34	13:58
		22	ORD	STL	15:17	16:49
		23	STL	ORD	17:42	19:08
		9	ORD	SAN	20:00	21:39

Table E.3: 50 Flights Proposed Schedule for Low Unit Fuel Cost Setting

Tail No.	Aircraft No.	Flight No.	Origin	Dest.	Departure Time	Arrival Time
N678UA	0	0	ORD	LGA	08:06	09:48
		36	LGA	ORD	10:41	12:39
		5	ORD	DFW	13:34	15:04
		41	DFW	ORD	16:08	17:33
		29	ORD	BOS	19:01	20:44
N802WA	1	30	ORD	DFW	07:29	08:59
		6	DFW	ORD	10:19	11:43
		7	ORD	LGA	14:17	15:59
		43	LGA	ORD	17:19	19:16
		39	ORD	LGA	20:20	22:02
N805WA	2	27	ORD	LGA	07:45	09:27
		28	LGA	ORD	10:23	12:20
		2	ORD	DFW	13:35	15:05
		38	DFW	ORD	17:22	18:46
		44	ORD	SAN	20:00	21:39
N309US	3	10	ORD	MCI	07:15	08:15
		46	MCI	ORD	09:13	10:12
		17	ORD	SAN	11:49	13:28
		18	SAN	ORD	16:47	18:10
		24	ORD	SAN	19:00	20:39
N334NW	4	45	ORD	MCI	07:15	08:15
		11	MCI	ORD	09:12	10:11
		47	ORD	DFW	11:22	12:52
		48	DFW	ORD	14:35	15:59
		14	ORD	DEN	17:30	19:20
N312US	5	15	ORD	MSP	07:15	08:19
		16	MSP	ORD	09:15	10:16
		12	ORD	DFW	11:23	12:53
		13	DFW	ORD	14:35	15:59
		49	ORD	DEN	17:30	19:20
N801WA	6	40	ORD	DFW	07:45	09:15
		31	DFW	ORD	10:29	11:53
		32	ORD	AUS	13:50	15:32
		33	AUS	ORD	17:22	18:59
		34	ORD	LGA	20:40	22:22
N807TR	7	25	ORD	DFW	08:45	10:15
		26	DFW	ORD	11:09	12:33
		37	ORD	DFW	13:39	15:09
		3	DFW	ORD	17:22	18:46
		4	ORD	LGA	20:20	22:02
N695UA	8	35	ORD	LGA	08:10	09:52
		1	LGA	ORD	10:45	12:42
		42	ORD	LGA	14:18	16:00
		8	LGA	ORD	17:24	19:21
		19	ORD	BOS	21:30	23:14
N422BN	9	20	ORD	DFW	09:45	11:15
		21	DFW	ORD	12:34	13:58
		22	ORD	STL	15:17	16:49
		23	STL	ORD	17:42	19:08
		9	ORD	SAN	20:00	21:39

Table E.4: 50 Flights Minimum Cost Schedule for High Unit Fuel Cost Setting

Tail No.	Aircraft No.	Flight No.	Origin	Dest.	Departure Time	Arrival Time
N678UA	0	35	ORD	LGA	08:10	09:52
		36	LGA	ORD	10:45	12:42
		42	ORD	LGA	14:18	16:00
		8	LGA	ORD	17:24	19:21
		19	ORD	BOS	21:30	23:14
N802WA	1	5	ORD	DFW	07:45	09:15
		41	DFW	ORD	10:23	11:47
		32	ORD	AUS	13:50	15:32
		33	AUS	ORD	17:22	18:59
		39	ORD	LGA	20:20	22:02
N805WA	2	30	ORD	DFW	07:29	08:59
		6	DFW	ORD	10:19	11:43
		7	ORD	LGA	14:16	15:58
		43	LGA	ORD	17:07	19:04
		44	ORD	SAN	20:00	21:39
N309US	3	15	ORD	MSP	07:15	08:19
		16	MSP	ORD	09:16	10:17
		17	ORD	SAN	11:49	13:28
		18	SAN	ORD	16:46	18:10
		24	ORD	SAN	19:00	20:39
N334NW	4	45	ORD	MCI	07:15	08:15
		46	MCI	ORD	09:12	10:11
		47	ORD	DFW	11:22	12:52
		48	DFW	ORD	14:35	15:59
		14	ORD	DEN	17:30	19:20
N312US	5	10	ORD	MCI	07:15	08:15
		11	MCI	ORD	09:12	10:11
		12	ORD	DFW	11:22	12:52
		13	DFW	ORD	14:35	15:59
		49	ORD	DEN	17:30	19:20
N801WA	6	25	ORD	DFW	08:45	10:15
		26	DFW	ORD	11:09	12:33
		37	ORD	DFW	13:39	15:09
		3	DFW	ORD	17:22	18:46
		4	ORD	LGA	20:20	22:02
N807TR	7	40	ORD	DFW	07:45	09:15
		31	DFW	ORD	10:29	11:53
		2	ORD	DFW	13:35	15:05
		38	DFW	ORD	17:22	18:46
		34	ORD	LGA	20:40	22:22
N695UA	8	0	ORD	LGA	08:06	09:48
		1	LGA	ORD	10:41	12:39
		27	ORD	LGA	13:34	15:16
		28	LGA	ORD	16:08	18:06
		29	ORD	BOS	19:01	20:44
N422BN	9	20	ORD	DFW	09:45	11:15
		21	DFW	ORD	12:34	13:58
		22	ORD	STL	15:17	16:49
		23	STL	ORD	17:42	19:08
		9	ORD	SAN	20:00	21:39

Table E.5: 50 Flights Proposed Schedule for High Unit Fuel Cost Setting

Tail No.	Aircraft No.	Flight No.	Origin	Dest.	Departure Time	Arrival Time
N678UA	0	35	ORD	LGA	08:10	09:52
		36	LGA	ORD	10:45	12:42
		42	ORD	LGA	14:18	15:59
		49	ORD	DEN	17:24	19:14
		8	LGA	ORD	21:30	23:27
N802WA	1	27	ORD	LGA	07:45	09:27
		28	LGA	ORD	10:23	12:20
		32	ORD	AUS	13:50	15:32
		33	AUS	ORD	17:22	18:59
		39	ORD	LGA	20:20	22:02
N805WA	2	30	ORD	DFW	07:29	08:59
		6	DFW	ORD	10:19	11:43
		7	ORD	LGA	14:16	15:58
		43	LGA	ORD	17:07	19:04
		44	ORD	SAN	20:00	21:38
N309US	3	15	ORD	MSP	07:15	08:19
		16	MSP	ORD	09:16	10:17
		17	ORD	SAN	11:49	13:28
		18	SAN	ORD	16:46	18:10
		24	ORD	SAN	19:00	20:38
N334NW	4	45	ORD	MCI	07:15	08:15
		46	MCI	ORD	09:12	10:11
		47	ORD	DFW	11:22	12:52
		48	DFW	ORD	14:35	15:59
		29	ORD	BOS	17:30	19:14
N312US	5	10	ORD	MCI	07:15	08:15
		11	MCI	ORD	09:12	10:11
		12	ORD	DFW	11:22	12:52
		13	DFW	ORD	14:35	15:59
		19	ORD	BOS	17:30	19:14
N801WA	6	25	ORD	DFW	08:45	10:15
		26	DFW	ORD	11:09	12:33
		37	ORD	DFW	13:39	15:09
		3	DFW	ORD	17:22	18:46
		4	ORD	LGA	20:20	22:02
N807TR	7	40	ORD	DFW	07:45	09:15
		31	DFW	ORD	10:29	11:53
		2	ORD	DFW	13:35	15:05
		38	DFW	ORD	17:22	18:46
		34	ORD	LGA	20:40	22:22
N695UA	8	0	ORD	LGA	08:06	09:49
		1	LGA	ORD	10:41	12:38
		14	ORD	DEN	13:34	15:24
		5	ORD	DFW	16:08	17:38
		41	DFW	ORD	19:01	20:25
N422BN	9	20	ORD	DFW	09:45	11:15
		21	DFW	ORD	12:34	13:58
		22	ORD	STL	15:17	16:49
		23	STL	ORD	17:42	19:08
		9	ORD	SAN	20:00	21:38

Table E.6: 50 Flights Minimum Cost Schedule for $\beta = 0.05$

Tail No.	Aircraft No.	Flight No.	Origin	Dest.	Departure Time	Arrival Time
N678UA	0	0	ORD	LGA	08:10	09:52
		36	LGA	ORD	10:45	12:42
		42	ORD	LGA	14:18	16:00
		8	LGA	ORD	17:24	19:21
		19	ORD	BOS	21:30	23:14
N802WA	1	30	ORD	DFW	07:29	08:59
		6	DFW	ORD	10:19	11:43
		32	ORD	AUS	13:50	15:32
		33	AUS	ORD	17:22	18:59
		4	ORD	LGA	20:20	22:02
N805WA	2	5	ORD	DFW	07:45	09:15
		41	DFW	ORD	10:23	11:47
		2	ORD	DFW	13:35	15:05
		3	DFW	ORD	17:22	18:46
		44	ORD	SAN	20:00	21:39
N309US	3	15	ORD	MSP	07:15	08:19
		16	MSP	ORD	09:15	10:17
		17	ORD	SAN	11:49	13:28
		18	SAN	ORD	16:47	18:10
		24	ORD	SAN	19:00	20:39
N334NW	4	45	ORD	MCI	07:15	08:15
		11	MCI	ORD	09:12	10:11
		47	ORD	DFW	11:22	12:52
		48	DFW	ORD	14:35	15:59
		49	ORD	DEN	17:30	19:20
N312US	5	10	ORD	MCI	07:15	08:15
		46	MCI	ORD	09:12	10:11
		12	ORD	DFW	11:22	12:52
		13	DFW	ORD	14:35	15:59
		14	ORD	DEN	17:30	19:20
N801WA	6	25	ORD	DFW	08:45	10:15
		26	DFW	ORD	11:09	12:33
		7	ORD	LGA	14:18	17:00
		43	LGA	ORD	17:24	19:21
		34	ORD	LGA	20:40	22:22
N807TR	7	40	ORD	DFW	07:45	09:15
		31	DFW	ORD	10:29	11:53
		37	ORD	DFW	13:35	15:05
		38	DFW	ORD	17:22	18:46
		39	ORD	LGA	20:20	22:02
N695UA	8	35	ORD	LGA	08:06	09:48
		1	LGA	ORD	10:41	12:39
		27	ORD	LGA	13:33	15:15
		28	LGA	ORD	16:08	18:06
		29	ORD	BOS	19:01	20:44
N422BN	9	20	ORD	DFW	09:45	11:15
		21	DFW	ORD	12:34	13:58
		22	ORD	STL	15:17	16:49
		23	STL	ORD	17:42	19:08
		9	ORD	SAN	20:00	21:39

Table E.7: 50 Flights Proposed Schedule for $\beta = 0.05$

Tail No.	Aircraft No.	Flight No.	Origin	Dest.	Departure Time	Arrival Time
N678UA	0	0	ORD	LGA	08:10	09:52
		36	LGA	ORD	10:45	12:42
		42	ORD	LGA	14:18	16:00
		8	LGA	ORD	17:24	19:21
		49	ORD	DEN	21:30	23:20
N802WA	1	30	ORD	DFW	07:29	08:59
		6	DFW	ORD	10:19	11:43
		32	ORD	AUS	13:50	15:32
		33	AUS	ORD	17:22	18:59
		4	ORD	LGA	20:20	22:02
N805WA	2	5	ORD	DFW	07:45	09:15
		41	DFW	ORD	10:23	11:47
		2	ORD	DFW	13:35	15:05
		3	DFW	ORD	17:22	18:46
		44	ORD	SAN	20:00	21:39
N309US	3	15	ORD	MSP	07:15	08:19
		16	MSP	ORD	09:15	10:17
		17	ORD	SAN	11:49	13:28
		18	SAN	ORD	16:47	18:10
		24	ORD	SAN	19:00	20:39
N334NW	4	45	ORD	MCI	07:15	08:15
		11	MCI	ORD	09:12	10:11
		47	ORD	DFW	11:22	12:52
		48	DFW	ORD	14:35	15:59
		19	ORD	BOS	17:30	19:14
N312US	5	10	ORD	MCI	07:15	08:15
		46	MCI	ORD	09:12	10:11
		12	ORD	DFW	11:22	12:52
		13	DFW	ORD	14:35	15:59
		29	ORD	BOS	17:30	19:14
N801WA	6	27	ORD	LGA	08:45	10:27
		28	LGA	ORD	11:09	13:06
		7	ORD	LGA	14:18	16:00
		43	LGA	ORD	17:24	19:21
		34	ORD	LGA	20:40	22:22
N807TR	7	40	ORD	DFW	07:45	09:15
		31	DFW	ORD	10:29	11:53
		37	ORD	DFW	13:35	15:05
		38	DFW	ORD	17:22	18:46
		39	ORD	LGA	20:20	22:02
N695UA	8	35	ORD	LGA	08:06	09:48
		1	LGA	ORD	10:41	12:39
		25	ORD	DFW	13:33	15:04
		26	DFW	ORD	16:08	17:33
		14	ORD	DEN	19:01	20:51
N422BN	9	20	ORD	DFW	09:45	11:15
		21	DFW	ORD	12:34	13:58
		22	ORD	STL	15:17	16:49
		23	STL	ORD	17:42	19:08
		9	ORD	SAN	20:00	21:39

Table E.8: 50 Flights Minimum Cost Schedule for $\alpha = \ln(25)$

Tail No.	Aircraft No.	Flight No.	Origin	Dest.	Departure Time	Arrival Time
N678UA	0	35	ORD	LGA	07:48	09:30
		36	LGA	ORD	10:29	12:26
		27	ORD	LGA	13:26	15:08
		28	LGA	ORD	16:06	18:04
		29	ORD	BOS	19:04	20:48
N802WA	1	20	ORD	DFW	09:45	11:15
		21	DFW	ORD	12:31	13:56
		22	ORD	STL	15:15	16:48
		23	STL	ORD	17:45	19:11
		4	ORD	LGA	20:20	22:02
N805WA	2	30	ORD	DFW	07:29	08:59
		6	DFW	ORD	10:19	11:43
		32	ORD	AUS	13:50	15:32
		33	AUS	ORD	17:21	18:58
		34	ORD	LGA	20:40	22:22
N309US	3	45	ORD	MCI	07:15	08:15
		46	MCI	ORD	09:16	10:15
		12	ORD	DFW	11:24	12:54
		13	DFW	ORD	14:35	15:59
		14	ORD	DEN	17:30	19:20
N334NW	4	10	ORD	MCI	07:15	08:15
		11	MCI	ORD	09:16	10:15
		47	ORD	DFW	11:24	12:54
		48	DFW	ORD	14:35	15:59
		49	ORD	DEN	17:30	19:20
N312US	5	15	ORD	MSP	07:15	08:19
		16	MSP	ORD	09:20	10:21
		17	ORD	SAN	11:49	13:28
		18	SAN	ORD	16:45	18:08
		24	ORD	SAN	19:03	20:42
N801WA	6	5	ORD	DFW	07:45	09:15
		31	DFW	ORD	10:31	11:56
		37	ORD	DFW	13:36	15:06
		38	DFW	ORD	17:18	18:42
		9	ORD	SAN	20:00	21:39
N807TR	7	40	ORD	DFW	07:45	09:15
		41	DFW	ORD	10:25	11:49
		7	ORD	LGA	14:16	15:58
		8	LGA	ORD	17:15	19:13
		39	ORD	LGA	20:20	22:02
N695UA	8	0	ORD	LGA	08:04	09:46
		1	LGA	ORD	10:45	12:42
		42	ORD	LGA	14:17	15:59
		43	LGA	ORD	17:24	19:21
		19	ORD	BOS	21:30	23:14
N422BN	9	25	ORD	DFW	08:45	10:15
		26	DFW	ORD	11:14	12:38
		2	ORD	DFW	13:42	15:13
		3	DFW	ORD	17:18	18:42
		44	ORD	SAN	20:00	21:39

Table E.9: 50 Flights Proposed Schedule for $\alpha = \ln(25)$

Tail No.	Aircraft No.	Flight No.	Origin	Dest.	Departure Time	Arrival Time
N678UA	0	35	ORD	LGA	07:48	09:30
		36	LGA	ORD	10:29	12:26
		5	ORD	DFW	13:26	14:56
		6	DFW	ORD	16:06	17:31
		29	ORD	BOS	19:04	20:48
N802WA	1	2	ORD	DFW	09:45	11:15
		3	DFW	ORD	12:31	13:56
		22	ORD	STL	15:15	16:48
		23	STL	ORD	17:45	19:11
		4	ORD	LGA	20:20	22:02
N805WA	2	27	ORD	LGA	07:29	09:11
		28	LGA	ORD	10:19	12:16
		32	ORD	AUS	13:50	15:32
		33	AUS	ORD	17:21	18:58
		34	ORD	LGA	20:40	22:22
N309US	3	45	ORD	MCI	07:15	08:15
		46	MCI	ORD	09:16	10:15
		30	ORD	DFW	11:24	12:54
		31	DFW	ORD	14:35	15:59
		14	ORD	DEN	17:30	19:20
N334NW	4	10	ORD	MCI	07:15	08:15
		11	MCI	ORD	09:16	10:15
		47	ORD	DFW	11:24	12:54
		48	DFW	ORD	14:35	15:59
		49	ORD	DEN	17:30	19:20
N312US	5	15	ORD	MSP	07:15	08:19
		16	MSP	ORD	09:20	10:21
		17	ORD	SAN	11:49	13:28
		18	SAN	ORD	16:45	18:08
		24	ORD	SAN	19:03	20:42
N801WA	6	12	ORD	DFW	07:45	09:15
		13	DFW	ORD	10:31	11:56
		37	ORD	DFW	13:36	15:06
		38	DFW	ORD	17:18	18:42
		9	ORD	SAN	20:00	21:39
N807TR	7	40	ORD	DFW	07:45	09:15
		41	DFW	ORD	10:25	11:49
		7	ORD	LGA	14:16	15:58
		8	LGA	ORD	17:15	19:13
		39	ORD	LGA	20:20	22:02
N695UA	8	0	ORD	LGA	08:04	09:46
		1	LGA	ORD	10:45	12:42
		42	ORD	LGA	14:17	15:59
		43	LGA	ORD	17:24	19:21
		19	ORD	BOS	21:30	23:14
N422BN	9	25	ORD	DFW	08:45	10:15
		26	DFW	ORD	11:14	12:38
		20	ORD	DFW	13:42	15:13
		21	DFW	ORD	17:18	18:42
		44	ORD	SAN	20:00	21:39

Table E.10: 50 Flights Proposed Schedule with Allowance = 5%

Tail No.	Aircraft No.	Flight No.	Origin	Dest.	Departure Time	Arrival Time
N678UA	0	0	ORD	LGA	08:10	09:52
		36	LGA	ORD	10:45	12:42
		42	ORD	LGA	14:18	15:59
		8	LGA	ORD	17:24	19:21
		19	ORD	BOS	21:30	23:14
N802WA	1	30	ORD	DFW	07:29	08:59
		6	DFW	ORD	10:19	11:43
		32	ORD	AUS	13:50	15:32
		33	AUS	ORD	17:22	18:59
		4	ORD	LGA	20:20	22:02
N805WA	2	5	ORD	DFW	07:45	09:15
		41	DFW	ORD	10:23	11:47
		2	ORD	DFW	13:35	15:05
		3	DFW	ORD	17:22	18:46
		44	ORD	SAN	20:00	21:38
N309US	3	15	ORD	MSP	07:15	08:19
		16	MSP	ORD	09:15	10:17
		17	ORD	SAN	11:49	13:28
		18	SAN	ORD	16:47	18:10
		24	ORD	SAN	19:00	20:38
N334NW	4	45	ORD	MCI	07:15	08:15
		11	MCI	ORD	09:12	10:11
		47	ORD	DFW	11:22	12:52
		48	DFW	ORD	14:35	15:59
		49	ORD	DEN	17:30	19:20
N312US	5	10	ORD	MCI	07:15	08:15
		46	MCI	ORD	09:12	10:11
		12	ORD	DFW	11:22	12:52
		13	DFW	ORD	14:35	15:59
		14	ORD	DEN	17:30	19:20
N801WA	6	27	ORD	LGA	08:45	10:27
		28	LGA	ORD	11:09	13:07
		7	ORD	LGA	14:18	15:59
		43	LGA	ORD	17:24	19:21
		34	ORD	LGA	20:40	22:22
N807TR	7	40	ORD	DFW	07:45	09:15
		31	DFW	ORD	10:29	11:53
		37	ORD	DFW	13:35	15:05
		38	DFW	ORD	17:22	18:46
		39	ORD	LGA	20:20	22:02
N695UA	8	35	ORD	LGA	08:06	09:49
		1	LGA	ORD	10:41	12:38
		25	ORD	DFW	13:33	15:04
		26	DFW	ORD	16:08	17:32
		29	ORD	BOS	19:01	20:44
N422BN	9	20	ORD	DFW	09:45	11:15
		21	DFW	ORD	12:34	13:58
		22	ORD	STL	15:17	16:49
		23	STL	ORD	17:42	19:08
		9	ORD	SAN	20:00	21:38

Table E.11: 50 Flights Proposed Schedule with Allowance = 7.5%

Tail No.	Aircraft No.	Flight No.	Origin	Dest.	Departure Time	Arrival Time
N678UA	0	0	ORD	LGA	08:10	09:52
		36	LGA	ORD	10:45	12:42
		42	ORD	LGA	14:18	15:59
		8	LGA	ORD	17:24	19:21
		14	ORD	DEN	21:30	23:20
N802WA	1	30	ORD	DFW	07:29	08:59
		6	DFW	ORD	10:19	11:43
		32	ORD	AUS	13:50	15:32
		33	AUS	ORD	17:22	18:59
		4	ORD	LGA	20:20	22:02
N805WA	2	5	ORD	DFW	07:45	09:15
		41	DFW	ORD	10:23	11:47
		2	ORD	DFW	13:35	15:05
		3	DFW	ORD	17:22	18:46
		44	ORD	SAN	20:00	21:38
N309US	3	15	ORD	MSP	07:15	08:19
		16	MSP	ORD	09:15	10:17
		17	ORD	SAN	11:49	13:28
		18	SAN	ORD	16:47	18:10
		24	ORD	SAN	19:00	20:38
N334NW	4	45	ORD	MCI	07:15	08:15
		11	MCI	ORD	09:12	10:11
		47	ORD	DFW	11:22	12:52
		48	DFW	ORD	14:35	15:59
		49	ORD	DEN	17:30	19:20
N312US	5	10	ORD	MCI	07:15	08:15
		46	MCI	ORD	09:12	10:11
		12	ORD	DFW	11:22	12:52
		13	DFW	ORD	14:35	15:59
		19	ORD	BOS	17:30	19:14
N801WA	6	27	ORD	LGA	08:45	10:27
		28	LGA	ORD	11:09	13:07
		7	ORD	LGA	14:18	15:59
		43	LGA	ORD	17:24	19:21
		34	ORD	LGA	20:40	22:22
N807TR	7	40	ORD	DFW	07:45	09:15
		31	DFW	ORD	10:29	11:53
		37	ORD	DFW	13:35	15:05
		38	DFW	ORD	17:22	18:46
		39	ORD	LGA	20:20	22:02
N695UA	8	35	ORD	LGA	08:06	09:49
		1	LGA	ORD	10:41	12:38
		25	ORD	DFW	13:33	15:04
		26	DFW	ORD	16:08	17:32
		29	ORD	BOS	19:01	20:44
N422BN	9	20	ORD	DFW	09:45	11:15
		21	DFW	ORD	12:34	13:58
		22	ORD	STL	15:17	16:49
		23	STL	ORD	17:42	19:08
		9	ORD	SAN	20:00	21:38

Table E.12: 50 Flights Proposed Schedule with Allowance = 15%

Tail No.	Aircraft No.	Flight No.	Origin	Dest.	Departure Time	Arrival Time
N678UA	0	0	ORD	LGA	08:10	09:52
		36	LGA	ORD	10:45	12:42
		5	ORD	DFW	14:18	15:48
		41	DFW	ORD	17:24	18:48
		14	ORD	DEN	21:30	23:20
N802WA	1	30	ORD	DFW	07:29	08:59
		6	DFW	ORD	10:19	11:43
		32	ORD	AUS	13:50	15:32
		33	AUS	ORD	17:22	18:59
		4	ORD	LGA	20:20	22:02
N805WA	2	42	ORD	LGA	07:45	09:27
		8	LGA	ORD	10:23	12:20
		2	ORD	DFW	13:35	15:05
		3	DFW	ORD	17:22	18:46
		44	ORD	SAN	20:00	21:38
N309US	3	15	ORD	MSP	07:15	08:19
		16	MSP	ORD	09:15	10:17
		17	ORD	SAN	11:49	13:28
		18	SAN	ORD	16:47	18:10
		24	ORD	SAN	19:00	20:38
N334NW	4	45	ORD	MCI	07:15	08:15
		11	MCI	ORD	09:12	10:11
		47	ORD	DFW	11:22	12:52
		48	DFW	ORD	14:35	15:59
		29	ORD	BOS	17:30	19:14
N312US	5	10	ORD	MCI	07:15	08:15
		46	MCI	ORD	09:12	10:11
		12	ORD	DFW	11:22	12:52
		13	DFW	ORD	14:35	15:59
		19	ORD	BOS	17:30	19:14
N801WA	6	27	ORD	LGA	08:45	10:27
		28	LGA	ORD	11:09	13:07
		7	ORD	LGA	14:18	15:59
		43	LGA	ORD	17:24	19:21
		34	ORD	LGA	20:40	22:22
N807TR	7	40	ORD	DFW	07:45	09:15
		31	DFW	ORD	10:29	11:53
		37	ORD	DFW	13:35	15:05
		38	DFW	ORD	17:22	18:46
		39	ORD	LGA	20:20	22:02
N695UA	8	35	ORD	LGA	08:06	09:49
		1	LGA	ORD	10:41	12:38
		25	ORD	DFW	13:33	15:04
		26	DFW	ORD	16:08	17:32
		49	ORD	DEN	19:01	20:51
N422BN	9	20	ORD	DFW	09:45	11:15
		21	DFW	ORD	12:34	13:58
		22	ORD	STL	15:17	16:49
		23	STL	ORD	17:42	19:08
		9	ORD	SAN	20:00	21:38

Appendix F

What If Analysis on the Number of Disrupted Aircraft

Table F.1: Recovery Solutions for Three Disrupted Aircraft

Disrupted	# of Cancelled Flights			Total Time of Delay			Max. Delay in a Flight Leg		
Aircraft	$\mathcal{P}_1$	$\mathcal{P}_2$	Change	$\mathcal{P}_1$	$\mathcal{P}_2$	Change	$\mathcal{P}_1$	$\mathcal{P}_2$	Change
0, 1, 2	11	6	-45%	2095	4244	103%	235	257	9%
0, 1, 3	11	5	-55%	2013	4190	108%	220	302	37%
0, 1, 4	11	5	-55%	2048	4092	100%	264	261	-1%
0, 1, 5	11	5	-55%	2048	4189	105%	264	302	14%
0, 1, 6	12	5	-58%	1757	4457	154%	242	280	16%
0, 1, 7	11	6	-45%	2082	4348	109%	253	261	3%
0, 1, 8	13	6	-54%	891	4620	419%	214	261	22%
0, 1, 9	11	5	-55%	1816	4181	130%	253	261	3%
0, 2, 3	11	5	-55%	2046	4079	99%	260	302	16%
0, 2, 4	11	5	-55%	1946	4079	110%	235	302	29%
0, 2, 5	11	5	-55%	1946	4079	110%	235	302	29%
0, 2, 6	12	5	-58%	1590	4303	171%	214	280	31%
0, 2, 7	11	6	-45%	2096	4218	101%	246	261	6%
0, 2, 8	13	6	-54%	876	4316	393%	214	261	22%
0, 2, 9	11	5	-55%	1830	4180	128%	260	261	0%
0, 3, 4	11	5	-55%	1878	3816	103%	212	262	24%
0, 3, 5	11	5	-55%	1878	3975	112%	212	302	42%
0, 3, 6	12	5	-58%	1689	4035	139%	241	279	16%
0, 3, 7	11	5	-55%	1949	4290	120%	220	302	37%
0, 3, 8	13	5	-62%	969	4092	322%	199	261	31%
0, 3, 9	11	5	-55%	1683	3917	133%	220	261	19%
0, 4, 5	11	5	-55%	1729	3686	113%	213	261	23%
0, 4, 6	12	5	-58%	1570	3853	145%	241	302	25%
0, 4, 7	11	6	-45%	1947	4166	114%	214	263	23%
0, 4, 8	13	5	-62%	908	4139	356%	212	263	24%
0, 4, 9	11	5	-55%	1681	3920	133%	214	263	23%
0, 5, 6	12	5	-58%	1570	3853	145%	241	302	25%
0, 5, 7	11	5	-55%	1947	4247	118%	214	302	41%
0, 5, 8	13	5	-62%	908	4139	356%	212	263	24%
0, 5, 9	11	5	-55%	1688	3920	132%	213	263	23%
0, 6, 7	12	5	-58%	1709	4265	150%	241	280	16%
0, 6, 8	14	5	-64%	600	4372	629%	214	280	31%

Table F.2: Cont.'d from Table F.1

Disrupted Aircraft	# of Cancelled Flights $\mathcal{P}_1$	$\mathcal{P}_2$	Change	Total Time of Delay $\mathcal{P}_1$	$\mathcal{P}_2$	Change	Max. Delay in a Flight Leg $\mathcal{P}_1$	$\mathcal{P}_2$	Change
0, 6, 9	12	5	-58%	1551	3898	151%	214	280	31%
0, 7, 8	13	6	-54%	961	4325	350%	213	262	23%
0, 7, 9	11	5	-55%	2043	4180	105%	249	262	5%
0, 8, 9	13	5	-62%	695	4250	512%	213	261	23%
1, 2, 3	9	5	-44%	3208	3934	23%	235	259	10%
1, 2, 4	9	5	-44%	3150	3934	25%	266	259	-3%
1, 2, 5	9	5	-44%	3150	3934	25%	266	259	-3%
1, 2, 6	10	5	-50%	2884	4328	50%	242	280	16%
1, 2, 7	9	6	-33%	3356	4114	23%	266	232	-13%
1, 2, 8	11	6	-45%	2018	4497	123%	229	262	14%
1, 2, 9	9	5	-44%	2812	4097	46%	233	232	0%
1, 3, 4	9	5	-44%	3139	3830	22%	229	259	13%
1, 3, 5	9	5	-44%	3139	3830	22%	229	259	13%
1, 3, 6	10	5	-50%	2768	3837	39%	241	369	53%
1, 3, 7	9	5	-44%	3258	3960	22%	255	257	1%
1, 3, 8	11	5	-55%	1998	4218	111%	232	302	30%
1, 3, 9	9	5	-44%	3164	4038	28%	229	232	1%
1, 4, 5	9	5	-44%	3068	3787	23%	229	259	13%
1, 4, 6	10	5	-50%	2735	3951	44%	242	354	46%
1, 4, 7	9	5	-44%	3202	3916	22%	258	257	0%
1, 4, 8	11	5	-55%	1869	4174	123%	229	302	32%
1, 4, 9	9	5	-44%	3015	4013	33%	229	232	1%
1, 5, 6	10	5	-50%	2735	3804	39%	229	354	55%
1, 5, 7	9	5	-44%	3202	3916	22%	258	257	0%
1, 5, 8	11	5	-55%	1869	4174	123%	229	302	32%
1, 5, 9	9	5	-44%	3015	4013	33%	229	232	1%
1, 6, 7	10	5	-50%	2840	4145	46%	235	280	19%
1, 6, 8	12	5	-58%	1879	4174	122%	235	280	19%
1, 6, 9	10	5	-50%	2574	4000	55%	235	369	57%
1, 7, 8	11	6	-45%	2224	4441	100%	250	262	5%
1, 7, 9	9	5	-44%	3183	4097	29%	250	257	3%
1, 8, 9	11	5	-55%	1988	4129	108%	229	261	14%
2, 3, 4	9	5	-44%	3262	3763	15%	235	220	-6%
2, 3, 5	9	5	-44%	3262	3763	15%	235	220	-6%
2, 3, 6	10	5	-50%	2567	3881	51%	220	369	68%
2, 3, 7	9	5	-44%	2933	3959	35%	251	247	-2%
2, 3, 8	11	5	-55%	1885	4249	125%	220	302	37%
2, 3, 9	9	5	-44%	1970	4074	107%	262	259	-1%
2, 4, 5	9	5	-44%	3071	3733	22%	251	213	-15%
2, 4, 6	10	5	-50%	2552	3848	51%	213	354	66%
2, 4, 7	9	5	-44%	2918	3915	34%	251	247	-2%
2, 4, 8	11	5	-55%	18869	4205	-78%	213	302	42%
2, 4, 9	9	5	-44%	2955	4033	36%	262	241	-8%
2, 5, 6	10	5	-50%	2552	3848	51%	213	354	66%
2, 5, 7	9	5	-44%	2918	3915	34%	251	247	-2%
2, 5, 8	11	5	-55%	1869	4205	125%	213	302	42%
2, 5, 9	9	5	-44%	1955	4085	109%	262	213	-19%
2, 6, 7	10	5	-50%	2859	4234	48%	260	279	7%
2, 6, 8	12	5	-58%	1697	4315	154%	242	279	15%
2, 6, 9	10	5	-50%	2593	4077	57%	269	369	37%
2, 7, 8	11	6	-45%	2259	4450	97%	269	302	12%
2, 7, 9	9	5	-44%	3217	4106	28%	253	241	-5%
2, 8, 9	11	5	-55%	1993	4171	109%	260	261	0%
3, 4, 5	9	5	-44%	2724	3428	26%	220	220	0%
3, 4, 6	10	5	-50%	2552	3435	35%	212	369	74%
3, 4, 7	9	5	-44%	2801	3694	32%	249	257	3%
3, 4, 8	11	5	-55%	1869	3974	113%	212	261	23%
3, 4, 9	9	5	-44%	3007	3864	29%	229	220	-4%
3, 5, 6	10	5	-50%	2552	3435	35%	212	369	74%
3, 5, 7	9	5	-44%	2801	3694	32%	249	257	3%
3, 5, 8	11	5	-55%	1869	3524	89%	212	261	23%

Table F.3: Cont.'d from Table F.2

Disrupted Aircraft	# of Cancelled Flights			Total Time of Delay			Max. Delay in a Flight Leg		
	$\mathcal{P}_1$	$\mathcal{P}_2$	Change	$\mathcal{P}_1$	$\mathcal{P}_2$	Change	$\mathcal{P}_1$	$\mathcal{P}_2$	Change
3, 5, 9	9	5	-44%	3007	4070	35%	229	220	-4%
3, 6, 7	10	5	-50%	2706	3949	46%	235	369	57%
3, 6, 8	12	5	-58%	1560	3952	153%	242	369	52%
3, 6, 9	10	5	-50%	2440	3820	57%	235	369	57%
3, 7, 8	11	5	-55%	2106	4249	102%	249	302	21%
3, 7, 9	9	5	-44%	3211	3843	20%	220	241	10%
3, 8, 9	11	5	-55%	1840	3909	112%	220	261	19%
4, 5, 6	10	5	-50%	2403	3367	40%	213	354	66%
4, 5, 7	9	5	-44%	2809	3664	30%	249	257	3%
4, 5, 8	11	5	-55%	1720	3911	127%	213	261	23%
4, 5, 9	9	5	-44%	2866	3844	34%	212	215	1%
4, 6, 7	10	5	-50%	2691	3938	46%	235	369	57%
4, 6, 8	12	5	-58%	1456	3856	165%	256	354	38%
4, 6, 9	10	5	-50%	2425	3789	56%	235	369	57%
4, 7, 8	11	5	-55%	2104	4264	103%	249	302	21%
4, 7, 9	9	5	-44%	3083	3824	24%	214	241	13%
4, 8, 9	11	5	-55%	1839	3889	111%	212	261	23%
5, 6, 7	10	5	-50%	2691	3938	46%	235	369	57%
5, 6, 8	12	5	-58%	1725	3904	126%	254	354	39%
5, 6, 9	10	5	-50%	2425	3789	56%	235	369	57%
5, 7, 8	11	5	-55%	2104	4264	103%	249	302	21%
5, 7, 9	9	5	-44%	2082	3824	84%	214	241	13%
5, 8, 9	11	5	-55%	1838	3889	112%	212	261	23%
6, 7, 8	12	5	-58%	1446	4472	209%	214	354	65%
6, 7, 9	10	5	-50%	2853	4021	41%	240	262	9%
6, 8, 9	12	5	-58%	1446	4104	184%	242	280	16%
7, 8, 9	11	5	-55%	2291	4212	84%	246	262	7%
Average:	10.5	5.1	-51%	2396	4022	101%	234	282	21%

Appendix G

What If Analysis on the Aircraft Unavailability Periods

Table G.1: Recovery Solutions for Different Aircraft Unavailability Periods

Period	Disrupted Aircraft	Min. Cost Schedule $\mathcal{P}_1$				Proposed Schedule $\mathcal{P}_2$			
		# of Disrupted Flights	# of Cancelled Flights	Cancelled / Disrupted	Total Delay (mins)	# of Disrupted Flights	# of Cancelled Flights	Cancelled / Disrupted	Total Delay (mins)
I	0	2	0	0%	789	2	0	0%	629
	1	2	0	0%	697	2	0	0%	411
	2	2	0	0%	700	2	0	0%	424
	3	4	0	0%	1146	4	0	0%	849
	4	4	1	25%	1198	4	0	0%	882
	5	4	1	25%	1271	4	0	0%	882
	6	2	0	0%	594	2	0	0%	718
	7	2	0	0%	671	2	0	0%	442
	8	2	0	0%	96	2	0	0%	614
	9	2	0	0%	448	2	0	0%	424
	Average:	2.6	0.2	5%	761	2.6	0	0%	628
II	0	4	0	0%	1218	4	0	0%	1198
	1	4	0	0%	1156	4	0	0%	983
	2	4	0	0%	1113	4	0	0%	980
	3	4	0	0%	1146	4	0	0%	849
	4	4	1	25%	1198	4	0	0%	882
	5	4	1	25%	1271	4	0	0%	882
	6	4	0	0%	994	2	0	0%	718
	7	4	0	0%	1108	4	0	0%	998
	8	4	0	0%	1345	4	0	0%	906
	9	2	0	0%	448	2	0	0%	424
	Average:	3.8	0.2	5%	1100	3.6	0	0%	882

Table G.2: Cont.'d from Table G.1

Period	Disrupted Aircraft	Min. Cost Schedule $\mathcal{P}_1$				Proposed Schedule $\mathcal{P}_2$			
		# of Disrupted Flights	# of Cancelled Flights	Cancelled / Disrupted	Total Delay (mins)	# of Disrupted Flights	# of Cancelled Flights	Cancelled / Disrupted	Total Delay (mins)
III	0	4	0	0%	1241	4	0	0%	1198
	1	4	0	0%	1156	4	0	0%	983
	2	4	0	0%	1113	4	0	0%	980
	3	4	0	0%	1146	4	0	0%	849
	4	4	2	50%	989	4	0	0%	882
	5	4	1	25%	1271	4	0	0%	882
	6	4	0	0%	994	4	0	0%	1010
	7	4	0	0%	1108	4	0	0%	998
	8	4	0	0%	1368	4	0	0%	906
	9	4	0	0%	744	4	0	0%	718
	Average:	4	0.3	8%	1113	4	0	0%	941
IV	0	4	0	0%	1241	4	0	0%	1198
	1	4	0	0%	1156	4	0	0%	983
	2	4	0	0%	1113	4	0	0%	980
	3	5	1	20%	1130	4	0	0%	849
	4	5	2	40%	932	5	1	20%	1188
	5	5	2	40%	1271	5	1	20%	1188
	6	4	0	0%	994	4	0	0%	1010
	7	4	0	0%	1108	4	0	0%	998
	8	4	0	0%	1368	4	0	0%	906
	9	4	0	0%	744	4	0	0%	718
	Average:	4.3	0.5	10%	1106	4.2	0.2	4%	1002
V	0	4	0	0%	1241	5	1	20%	1416
	1	5	1	20%	1156	5	1	20%	1166
	2	5	3	60%	725	5	1	20%	1414
	3	5	3	60%	905	5	1	20%	925
	4	5	3	60%	791	5	1	20%	892
	5	5	3	60%	841	5	1	20%	898
	6	5	5	100%	-	5	3	60%	1012
	7	5	3	60%	847	5	1	20%	1437
	8	5	5	100%	-	5	3	60%	1125
	9	5	3	60%	581	5	1	20%	937
	Average:	4.9	2.9	58%	886	5	1.4	28%	1122
VI	0	5	5	100%	-	5	1	20%	1416
	1	5	3	60%	891	5	1	20%	1166
	2	5	3	60%	990	5	1	20%	1414
	3	5	3	60%	905	5	1	20%	925
	4	5	3	60%	791	5	1	20%	892
	5	5	3	60%	841	5	1	20%	898
	6	5	5	100%	-	5	3	60%	1012
	7	5	3	60%	847	5	1	20%	1437
	8	5	5	100%	-	5	3	60%	1125
	9	5	3	60%	581	5	1	20%	937
	Average:	5	3.6	72%	835	5	1.4	28%	1122