A CHANCE CONSTRAINED APPROACH TO OPTIMAL SIZING OF RENEWABLE ENERGY SYSTEMS WITH PUMPED HYDRO ENERGY STORAGE

A THESIS SUBMITTED TO

THE GRADUATE SCHOOL OF ENGINEERING AND SCIENCE

OF BILKENT UNIVERSITY

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR

THE DEGREE OF

MASTER OF SCIENCE

IN

INDUSTRIAL ENGINEERING

By

Nazlı Kalkan

August 2022

A CHANCE CONSTRAINED APPROACH TO OPTIMAL SIZING OF RENEWABLE ENERGY SYSTEMS WITH PUMPED HYDRO ENERGY STORAGE

By Nazlı Kalkan

August 2022

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.

Özlem Çavuş İyigün(Advisor)

Ayşe Selin Kocaman(Co-Advisor)

Fehmi Tanrısever

Vedat Bayram

Approved for the Graduate School of Engineering and Science:

Orhan Arıkan
Director of the Graduate School

ABSTRACT

A CHANCE CONSTRAINED APPROACH TO OPTIMAL SIZING OF RENEWABLE ENERGY SYSTEMS WITH PUMPED HYDRO ENERGY STORAGE

Nazlı Kalkan
M.S. in Industrial Engineering
Advisor: Özlem Çavuş İyigün
Co-Advisor: Ayşe Selin Kocaman

August 2022

Burning fossil fuels is responsible for a large portion of the greenhouse gases released into the atmosphere. In addition to their negative impacts on the environment, fossil fuels are limited, which makes the integration of renewable energy sources into the grid inevitable. However, the intermittent nature of renewable energy sources makes it challenging to regulate energy output, resulting in low system flexibility. Adoption of an energy storage system, such as pumped hydro energy storage (PHES) and batteries, is necessary to fully utilize and integrate a larger proportion of variable renewable energy sources into the grid. On the other hand, in investment planning problems, satisfying the demand for certainty for even infrequently occurring events can lead to considerable cost increases. In this study, we propose a chance constrained two-stage stochastic program for designing a hybrid renewable energy system where the intermittent solar energy output is supported by a closed-loop PHES system. The aim of this study is to minimize the total investment cost while meeting the energy demand at a predetermined service level. For our computational study, we generate scenarios for solar radiation by using an Auto-Regressive Integrated Moving Average (ARIMA) based algorithm. In order to exactly solve our large scale problem, we utilize a Benders based branch and cut decomposition algorithm. We analize the efficiency of our proposed solution method by comparing the CPU times provided by the proposed algorithm and CPLEX. The findings indicate that the proposed algorithm solves the problem faster than CPLEX.

Keywords: Pumped hydro energy storage, Solar energy, Chance constraint, Two-stage stochastic programming, Scenario decomposition.

ÖZET

POMPAJ DEPOLAMALI HİBRİT ENERJİ SİSTEMİ BOYUTLANDIRMA PROBLEMİNE ŞANS KISITLI OPTİMİZASYON YAKLAŞIMI

Nazlı Kalkan
Endüstri Mühendisliği, Yüksek Lisans
Tez Danışmanı: Özlem Çavuş İyigün
İkinci Tez Danışmanı: Ayşe Selin Kocaman
Ağustos 2022

Atmosfere salınan sera gazlarının büyük bir kısmından fosil yakıtların yanması sorumludur. Fosil yakıtların çevre üzerindeki olumsuz etkilerinin yanı sıra sınırlı kaynaklar olmaları, yenilenebilir enerji kaynaklarının şebekeye entegrasyonunu kaçınılmaz kılmaktadır. Ancak, yenilenebilir enerji kaynaklarının aralıklı doğası, enerji çıktısını düzenlemeyi zorlaştırarak düşük sistem esnekliğine neden olur. Pompaj depolamalı hidroelektrik santraller (PHES) ve piller gibi bir enerji depolama sisteminin benimsenmesi, değişken yenilenebilir enerji kaynaklarının daha büyük bir oranını tam olarak kullanmak ve şebekeye entegre etmek için gereklidir. Öte yandan, yatırım planlama problemlerinde, nadiren meydana gelen olaylar için bile talebinin kesinlikle karşılanabilmesi koşulu ciddi maliyet artışlarına yol açabilmektedir. Bu çalışmada, aralıklı güneş enerjisi üretiminin kapalı döngü pompaj depolamalı hidroelektrik santral sistemi tarafından desteklendiği bir hibrit yenilenebilir enerji sistemi tasarlamak için şans kısıtlı iki aşamalı stokastik bir program öneriyoruz. Bu çalışmanın amacı, enerji talebini önceden belirlenmiş bir hizmet seviyesinde karşılarken toplam yatırım maliyetini minimize etmektir. Sayısal çalışmamız için, Birleştirilmiş Otoregresiv-Hareketli Ortalamalar (ARIMA) tabanlı bir algoritma kullanarak güneş ışınımı için senaryolar üretiyoruz. Büyük ölçekli problemimizi olarak çözmek için Benders tabanlı dal-sınır ayrıştırma algoritması kullanıyoruz. Kapsamlı formülasyonu CPLEX ile çözerek çözüm yöntemimizin performansını değerlendiriyoruz. Bulgular, önerilen algoritmanın problemi CPLEX'ten daha hızlı çözdüğünü göstermektedir.

Anahtar sözcükler: Pompaj depolamalı hidroelektrik santraller, Güneş enerjisi, Şans kısıtı, İki aşamalı stokastik programlama, Senaryo ayrıştırma.

Acknowledgement

I want to convey my gratitude to my advisors, Assoc. Prof. Özlem Çavuş İyigün and Assoc. Prof. Ayşe Selin Kocaman, for their support and advise throughout my studies. Their guidance, wisdom, and encouragement have enhanced my research and academic skills and inspired me to expand and apply my skills in new fields. It has been a great pleasure and privilege to work under their supervision during my master's thesis.

I also would like to thank to Assoc. Prof. Fehmi Tanrısever and Asst. Prof. Vedat Bayram for accepting to read and review my thesis, and providing invaluable comments and suggestions.

I want to thank Asst. Prof. Vedat Bayram, without whom I would not even consider pursuing this degree and would have missed out on this great opportunity, also for his endless support since my undergraduate studies. It was an honor and a pleasure to be his student.

I also want to thank my mother and my fiance Ali Demir from the bottom of my heart for their love and support. I cannot put into words how much I appreciate and value their patience and support during my studies. Lastly, I want to thank my dearest friend Merve Eser for always being supportive.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

Electricity is vital for survival since the reliance on electricity for communication, transportation, water, healthcare, and other fundamental functions continues to constantly grow. On the other hand, fossil fuels play a significant role in electricity generation. The International Energy Agency (IEA) reports that 63.1% of global electricity generation is derived from fossil fuels in 2019, with coal accounting for 36.7%, natural gas accounting for 23.6%; and oil accounting for 2.8% [1]. However, the use of fossil fuels for energy has devastating impacts on humanity and the environment because of greenhouse gas emissions. CO_2 emissions resulting from the use of fossil fuels show a rising tendency throughout the years, especially after the mid-20th century. In 2020, over 34 billion tonnes of CO_2 are emitted as a result of burning fossil fuels [2]. In addition to their detrimental environmental consequences, the finite supply of fossil fuels is a constraint which necessitates the adoption of alternative renewable sources such as wind, solar, hydropower, biomass, tidal, and geothermal to meet the energy demand. The intermittent nature of renewable energy sources, however, makes it challenging to control the energy output, causing low system flexibility. In order to incorporate a greater proportion of variable renewable energy sources into the grid and maximize their use, the adoption of an energy storage system such as PHES and batteries is essential. In 2020, the global installed capacity of PHES, utility-scale batteries, and concentrated solar power (CSP) was 159.5 GW, 9.6 GW, and 6.4

GW, respectively. The installed capacity is expected to increase by 56% by 2026 as a result of the rapid expansion in storage system utilization [3].

The intermittent nature of renewable energy resources must be considered while designing a renewable energy system since their availability is not always guaranteed when there is a need for energy. As an example, solar radiation at a given site relies on the hour of day and the clarity of the sky. Likewise, the wind speed at a particular site depends on the geographical and meteorological variables of that region. Hence, it is uncertain when renewable energy sources will be available and to what extent they may be utilized. Therefore, in order to mitigate the intermittent nature of renewable energy sources, hybrid renewable energy systems usually incorporate a storage component. [4]. In this context, the planning and sizing problem for hybrid renewable energy systems with storage should be studied by means of stochastic optimization. Depending on the sorts of renewable sources used in the system as well as the scope of the problem, demand, wind speed, stream flow and solar radiation are typically the causes of uncertainty in these problems.

It is important to take uncertainty related to different design variables into consideration while designing a hybrid energy system since many industries such as healthcare, telecommunication, and banking, are obliged to comply with strict requirements for power supply reliability. An approach based on reliability will increase consumer satisfaction and ultimately contribute to the acceptance of renewable energy technologies. Moreover, in investment planning problems, satisfying the demand under certainty even for rarely occuring events may result in significant cost increases. To address these concerns, a chance constrained optimization method is needed to prevent the undesirable results of randomness inherent in hybrid renewable energy systems and meet the demand requirements at a specified level of reliability. By employing chance constrained programming (CCP), the requirement of satisfying the demand for all random occurrences may be relaxed to prevent significant investment expenses. To the best of our knowledge, a planning problem for a renewable energy system involving PHES has not been considered from a chance constraint approach in the literature. The aim of our study is to fill this gap in the literature and provide a chance constrained planning strategy for designing a hybrid energy system where solar generation is supported by a closed-loop PHES facility.

In this thesis, we employ Value at Risk (VaR) in the constraint set of our two-stage stochastic programming (TSSP) formulation, which is also known as a chance-constraint, in order to restrict the risk of unsatisfied demand by a pre-determined threshold to ensure system reliability. For our computational study, we generate scenarios for solar radiation by using an ARIMA-based algorithm as in Yang et al. [5]. We propose a Benders based branch and cut decomposition algorithm developed by Luedtke [6] for exactly solving our problem.

The organization of this thesis is as follows: Chapter 2 is devoted to the literature review on the planning of energy storage systems under uncertainty, risk-averse approaches for hybrid energy systems, and planning of renewable energy systems supported by PHES. In Chapter 3, we give our problem definition, introduce the chance-constrained two-stage stochastic programming framework, and present our problem formulation. We propose a Benders based branch and cut decomposition algorithm as an exact solution methodology in Chapter 4. In Chapter 5, we describe an ARIMA-based algorithm for generating solar radiation scenarios, provide the data that is used to apply our proposed solution method, and then present the results. We present a summary of our findings and discuss potential directions for further research in Chapter 6.

Chapter 2

Literature Review

The main focus of most of the studies considering the optimization of energy systems involving PHES under uncertainty is on the operational planning problems ([7], [8], [9], [10], [11], [12]). Despite a vast literature on the operational planning of PHES systems, the studies considering uncertainty for infrastructure planning are rather limited. Hence, we first present the literature on the stochastic investment planning of energy storage systems (ESS) in general in Section 2.1, and in Section 2.2, we address the studies that specifically involve stochastic planning problems employing PHES as an energy storage unit. Table 2.1 provides a classification of the studies mentioned in this chapter.

2.1 Planning of Energy Storage Systems under Uncertainty

Hybrid energy systems are regularly discussed in the literature as a cost-effective means of generating electricity. In most hybrid energy systems described in the literature, renewable energy sources such as solar hydro, and wind are used together and supported with a backup dispatchable source such as diesel or a storage unit.

Kocaman et al. [13] consider a sizing problem for a hybrid energy system located in Himalaya Mountains. The hybrid system involves a solar system, hydropower stations, diesel generators, and a transmission system. In the system, uncertainty of the sources is mitigated by utilising the water storage. They propose a two-stage stochastic programming formulation where the uncertainty in the system which is arised from stream flow, solar radiation, and demand is modeled by the scenario approach. The objective is to optimally design the system components to meet the demand with minimum overall investment and penalty costs. The problem is solved using CPLEX. They show that if curtailing is allowed, running the solar power stations at less than their maximum energy output can lower the system's per-unit price.

Kocaman et al. [14] propose stochastic programming models for investigating the effects of demand response programs on the investment decisions for renewable energy systems to meet agricultural demand. They formulate the problem as a two-stage stochastic program for wind and solar cases separately. Solar radiation, wind speed, and the amount of energy used for irrigation introduce uncertainty into the problem. They also propose a model where energy storage is involved as a subsitute of demand response programs. They solve the models with CPLEX and conclude that energy storage is a key method for controlling the renewable energy integration; however, demand response programs are more cost-effective for agricultural demand.

Aghamohamadi et al. [15] consider a residential hybrid renewable energy system planning problem with the objective of determining the optimal component sizes. They utilize a solar/battery system to meet the demand. In that study, solar generation and demand are uncertain. A two-stage adaptive robust optimization (ARO) is presented as a tri-level min–max–min problem. They employ the column-and-constraint technique to build an iterative decomposition methodology to restructure the min–max–min problem. Following that, the bi-level subproblem is linearized using the Big-M method. A post-event analysis is also conducted to find the optimal robustness level of the ARO model for preventing conservative solutions.

Ekren et al. [16] address a hybrid energy system design problem where solar panels and wind turbines are used to generate energy and a battery storage is utilized to store excess energy for later usage. The amount of electricity generated and consumed are assumed to be uncertain, and a simulation approach is employed in order to perform simulations for specified probability distributions of these variables. In order to find optimum sizes of the components, response surface methodology (RSM) is proposed. A break-even analysis is also performed to find the optimum distance at which the hybrid energy system is more cost-effective than the transmission line extension.

Ekren and Ekren [17], different from [16], apply a heuristic solution approach named Simulated Annealing (SA), where a stochastic gradient search is used to obtain an acceptable solution for the sizing problem of a solar and wind integrated hybrid energy system with battery storage. They compare the findings of the two studies, [16] and [17], and discover that the SA algorithm outperforms the Response Surface Methodology.

Kuznia et al. [18] address the planning problem for a hybrid energy system where the components of the system are wind turbines, thermal generators, a storage device, and transmission lines, and propose a two-stage stochastic MIP model for the problem. The sources of uncertainty in that study are wind speed and demand. In the objective function, total investment cost and expected operating cost are minimized. They construct a Benders based algorithm with two additional cutting planes: pareto-optimal cuts generated by a modified Magnanti-Wong (MMW) approach and cuts generated by a maximum feasible subsystem (MFS) to solve the problem exactly. They come up with that, compared to standard Benders' decomposition, utilizing MMW and MFS simultaneously can considerably decrease the solution time.

Prior research has mostly focused on the sizing problem of hybrid energy systems in a cost-effective manner. The primary objective of these studies is the expected cost minimization. However, they disregard the volatile nature of renewable energy sources.The ability of hybrid energy systems to satisfy demand can be seriously hindered by the intermittency of renewable sources, leading to decreased system reliability and, consequently, financial losses. Hence, risk-aversion should be included in the problems for planning hybrid energy systems reliably. The following studies, which are more similar to ours, consider risk in the design of hybrid systems.

Roy et al. [19] study the sizing problem for an isolated wind-battery system where the battery capacity is minimized subject to wind speed uncertainty. They propose a chance constrained programming approach for meeting the demand with a predefined degree of confidence and provide high system reliability. They reconstruct the equation that provide the energy balance in a deterministic way based on the chance constraint. They applied Monte Carlo simulation technique to obtain an approximation of the solution. Similarly, Arun et al. [20] propose a method by utilizing design space methodology involving a simulation of an isolated solar-battery system where the battery capacity is minimized subject to solar radiation uncertainty.

Kamjoo et al. [21] present a problem where the sum of the investment costs, replacement costs, and maintenance costs is minimized and system reliability is maximized. The system is comprised of wind turbines, solar panels, and storage units where the amount of generated energy is uncertain. To address the renewables' uncertainties, they employ chance constrained programming. In order to solve the problem, they propose a method that uses the Non-dominated Sorting Genetic Algorithm (NSGA-II) and chance constrained programming to find the Pareto solutions. The obtained results are compared with those produced by NSGA-II combined with Monte Carlo simulation to assess the performance of the proposed method.

Copp et al. [22] study a sizing problem for a storage system within a hybrid energy system that consists of a generator and a solar system for an islanded operation. Demand and solar generation are the sources of uncertainties. They minimize the size of the storage unit the demand is satisfied with a high service level by proposing a stochastic optimization approach based on chance constrained programming. They derive a linear inequality constraint from the chance constraint and solve the optimization problem as a linear program.

Xie et al. [23] propose a two-stage method for the sizing problem of a stand-alone renewable powered charging station considering uncertain solar power generation and demand distribution forecast errors. Charging stations consist of a battery and solar panels. The goal is to reduce the overall investment cost; while using robust chance constraints to establish reliability under uncertainty. Two risk-based formulations, a MILP model derived from VaR and an LP model constructed on CVaR (Conditional Value at Risk), are suggested to solve the proposed distributionally robust optimization planning model. They recommend using the LP model built on CVaR.

Sadeghian et al. [24] consider a siting and sizing problem for energy storage systems within virtual power plants (VPPs) under market price uncertainty. The VPP, which exchanges power with the upstream grid, is composed of wind turbines, solar systems, ESS, curtailable loads, and diesel as backup. In order to mitigate the uncertainty, a risk management technique based on CVaR is implemented. They also evaluate two reliability indices, the loss of load expectation (LOLE) and energy expected not served (ENNS), at different investment levels to determine the effect of ESS on VPP reliability. They formulate the problem as a mixed integer nonlinear program (MINLP) and solve it with the General Algebraic Modeling System commercial software package. They conclude that increasing the investment in ESS is not always the most cost-effective method for reducing the total cost of VPP. In addition, they discover that VPP's reliability indices (EENS and LOLE) are drastically reduced by the proper sizing and location of ESS in the case of limited investment.

Dolatabadi et al. [25] study a sizing problem for a hybrid energy system of a ship. Energy required to satisfy the demand is provided by a solar system, while diesel and storage units are used as backup. The objective is minimizing the total cost of the power system of the ship. The source of uncertainty in the problem is the solar radiation. A scenario reduction method is employed in order to lower the amount of computation. They suggest a two-stage stochastic optimization model based on risk to optimally design systems and employ MINLP for the solution of the problem. The CVaR methodology has been used to formulate the trade-off between minimizing the expected cost and the possibility of experiencing high costs in worse-case scenario. The obtained results demonstrate the effectiveness of the suggested risk-based stochastic method for the design of the hybrid energy system for ships.

Merzifonolu and Uzgören [26] investigate a sizing problem for a hybrid renewable energy system in a campus area that includes a solar system, a battery storage system, and a power grid. There are three sources of uncertainties in this problem: demand, solar radiation, and system performance. They first suggest two-stage stochastic programming to formulate their problem where the component sizes that satisfy the demand are determined and expected total cost is minimized. Then, they propose a risk-averse model by using CVaR in the objective function. After incorporating a payback period as a constraint, both models are rewritten as MIP problems. A sample average approximation (SAA) technique is used to approximate the expected total cost and the a heuristic and an exact solution method is employed to solve the problems. They conclude that the presented methods outperform CPLEX.

Cavus et al. [27] study a sizing problem for a hybrid energy system consisting of transmission lines, hydropower stations, solar panels and diesel generators. The stochasticity of the system arises from the stream flow, solar output, and demand. The water in the upper reservoir is used to mitigate the randomness of the resources. They propose a two-stage stochastic LP model in which CVaR is used as the risk measure. In order to solve the problem, they employ a scenario decomposition algorithm based on the L-shaped method. The problem is solved with both CPLEX and the proposed algorithm. They show that the suggested algorithm is more efficient than CPLEX.

2.2 Planning of Renewable Energy Systems supported by PHES

Nazari and Keypour [28] consider a hybrid energy storage planning problem for a microgrid that includes dispatchable sources (micro-turbines) and non-dispatchable sources (solar system and wind turbines), as well as an energy storage system. Candidates for ESS include PHES, flywheels, and lead acid batteries. The uncertainties in the system are modeled by two-stage stochastic programming in which ESS sizes are optimized. They apply the moment matching method and employ a scenario reduction technique. The objective function minimizes the total yearly cost, which is the sum of annual storage cost, cost of bilateral contracts per year, and unit commitment costs. Additionally, the demand response program is utilized as a load shifting service. They find that PHES gives the best solution.

Al-Masri et al. [29] consider a hybrid renewable energy system in order to evaluate the effect of different solar system models on the optimal system size. The system consists of a solar system and a PHES facility. They solve the problem with particle swarm optimization (PSO) and the whale optimization algorithm (WOA). Uncertainties in some of the system parameters are formulated by PSO alone, since solutions of both WOA and PSO are close to each other. They obtain the most reliable and most ecological solution by using a two-diod solar system, while the number of solar panels is the lowest when the ideal single-diode solar system is employed.

Reuter et al. [30] study a hybrid renewable energy system that combines wind power and PHES and compare the hybrid system to the one without a PHES. In the study, there are two sources of uncertainty: electricity prices and the variability of wind speed. They investigate the profitability of wind power coupled with PHES in comparison with traditional wind farms with no storage. During the planning period, the investor wants to maximize his expected profit. They solve the resulting stochastic optimization problem by recursive dynamic programming.

Amusat et al. [31] present a method for the problem of designing a hybrid renewable energy system combining different generation and storage techniques to satisfy the demand. In the system, electricity generation is provided via solar and wind generation. The goal of the study is to find the system designs that balance performance and cost while incorporating renewable variability. They solve the bi-objective problem using NSGA-II.

Liu et al. [32] consider an integrated generation system including a hydro power station, solar panels, and PHES. The sources of uncertainty in the system are solar radiation, spot price, and load. Following an analysis of the effects of the complementary index, cost of unused water, and Pearson correlation coefficient on system complementarity and economics, a method for sizing an integrated generation system is presented.

Brown et al. [33] address an optimization problem including dynamic security criteria to determine the optimal PHES capacity integrated into a small island system with an abundance of renewable energy. Hydro power and wind output data is uncertain. They employ fuzzy clustering techniques to model the uncertainties in the system such as energy output and demand. They model the problem as a linear program where the size of the system components are the primary variables. The operation and investment costs are minimized in the objective function. They conclude that using pumped storage can be a useful way to utilize the renewable energy sources.

Al-Masri et al. [34] investigate a renewable energy system that includes solar panels and PHES in consideration of the solar and PHES losses. The uncertainty in the system is caused by solar radiation, flow rate parameters and the demand, which are modeled by particle swarm optimization. The goal of the study is determining the optimum sizes of the solar system and PHES that maximize the system reliability. They discover that the investment on the solar system and PHES increases with the inclusion of the solar and PHES losses.

Anagnostopoulos and Papantonis [35] study the sizing problem of a PHES system to store the excess energy curtailed by the wind system in an isolated grid. The goal of the study is determining the optimum reservoir capacity and water pump diameter to maximize the utilized wind energy of the system. They employ an automated optimization method to solve the problem. They conclude that the financial outlook of the investment improves as the water turbine power increases; however, negative results may occur under a particular threshold. Another important result of the study is that additional energy is required to buy from the grid to maintain guaranteed energy. Thus, the recovered energy only compensates for the technical losses.

Hemmati [36] examines an isolated hybrid renewable energy system with wind, solar, and hydropower as energy sources and a PHES and hydrogen storage system (HSS) as backups. In that study, wind and solar outputs are uncertain parameters and modelled by discrete Gaussian probability distribution functions (PDF). The goal of the study is considering the optimum sizes of the reservoirs, pumps, and generators where the investment and operational costs are minimum. The problem is formulated as a stochastic MILP. Four different cases are considered according to the flow-in states of the reservoirs, and each case is examined by the change of capacity in the system components.

Islam et al. [37] address a hybrid renewable energy system that consists of solar, wind, hydro, and PHES. The uncertainties in the system arise from solar radiation, wind speed, solar capital costs, water flow rates, demand, and pipe flow losses. The aim of that study is to examine the techno-economic evaluation of hybrid systems to meet the energy demand on a community scale. They use a simulation-based optimization tool, HOMER, to find the optimal design of the solar/wind/hydro hybrid system, then compare it with a battery storage system that meets the similar load requirement. They apply a sensitivity analysis to determine the effects of uncertainty on optimum pipe design. They discover that when compared to a battery-powered system, the PHES system has a lower COE and NPC. In addition, the battery system generates an excessive amount of extra energy compared to the PHES.

Abdalla et al. [38] propose a robust long-term generation expansion planning (GEP) model considering the uncertainty of wind energy. They build a polyhedral uncertainty set for integrating the uncertainty impact into the robust model. They control the robustness of the findings by an adjustable robustness parameter. They also propose PHES and fast gas turbines for mitigating the short-term wind energy uncertainty. Size of the PHES and fast gas turbines are found and evaluated with an economic objective function for usage in centralized or distributed units. They find that using the fast gas turbines provides the most cost-effective way.

Kapsali et al. [39] consider the sizing problem of a wind/PHES system to satisfy the demand in Lesbos. They analyze the feasibility of the system working under the concurrent operation of new and existing wind systems and PHES based on an extensive sensitivity analysis. The system performance simulation is applied, and localization of the optimal solution is performed by finding a number of financial parameters like net present value. They conclude that in the most financially feasible arrangement, the renewable energy contribution rises by around 15%.

Kocaman [40] presents a two-stage stochastic model for the problem of designing a hybrid renewable energy system to satisfy the demand of the Mediterranean region in Turkey. The hybrid system includes a solar system supported by closed-loop and open-loop PHES systems separately. Moreover, in order to maintain system feasibility, diesel is used as an expensive resource. Uncertainty in the system arises from solar radiation and the amount of water inflow into the reservoirs, as well as electricity demand. The objective is to optimally determine the system components, minimizing the total investment and operation costs. The problems are solved by the CPLEX solver. The results indicate that 88% of demand is fulfilled by renewables when a closed-loop PHES system is employed, whereas 96% of demand is met by renewables when an open-loop PHES system is employed. Hence, the cost of produced electricity is lower when the solar system is supported by an open-loop PHES.

Kocaman and Modi [41] consider a hybrid energy system to satisfy the demand. The goal of that study is to obtain the optimum hybrid system size, which include hydro and solar energy generation as well as transmission lines, where the hydro power station is also used as a PHES and diesel is used as a backup. They propose a two-stage stochastic program to solve the problem and represent the randomness of the inflow to the upper reservoir and the solar radiation by a scenario approach. The proposed model is applied in several case studies for India. They demonstrate that PHES can reduce the diesel amount to fulfill demand to around 10% , whereas for conventional systems this percentage can exceed 50%.

In our study, we consider a similar model to that of Kocaman and Modi [41], and instead of using diesel as an expensive backup source, we develop a chance-constrained two-stage stochastic programming model and restrict the risk of unmet demand by a specified threshold to ensure system reliability. Most of the studies in the literature use diesel to ensure that the demand is satisfied for sure or incur a penalty cost for the amount of unsatisfied demand. To the best of our knowledge, our study is the first to reliably size a PHES system using a chance constraint. We employ a Benders decomposition based solution approach proposed by Luedtke [6] to exactly solve our problem. We demonstrate that our proposed algorithm is capable of solving instances that CPLEX can not solve.

Table 2.1: A classification of studies on planning of energy storage systems.

Study	Source of Uncertainty			Risk Measure		Modelling Technique			ESS Type	
	Demand	Energy Supply	Other	CVaR	VaR	TSSP	CCP	Other	PHES	Other
Kocaman et al. [13]	✓	✓				✓				✓
Kocaman et al. [14]	✓	✓				✓				✓
Kuznia et al. [18]	✓	✓				✓				✓
Aghamohamadi et al. [15]	✓	✓						✓		✓
Ekren et al. [16]	✓	✓						✓		✓
Ekren and Ekren [17]	✓	✓						✓		✓
Roy et al. [19]		✓			✓		✓			✓
Kamjoo et al. [21]		✓			✓		✓			✓
Copp et al. [22]	✓	✓			✓		✓			✓
Xie et al. [23]	✓	✓		✓	✓		✓	✓		✓
Sadeghian et al. [24]			✓	✓				✓		✓
Dolatabadi et al. [25]		✓		✓		✓				✓
Merzifonolu and Uzgören [26]	✓	✓	✓	✓		✓				✓
Cavus et al. [27]		✓		✓		✓				✓
Nazari and Keypour [28]	✓	✓	✓			✓			✓	✓
Al-Masri [29]			✓					✓	✓	
Reuter et al. [30]		✓	✓					✓	✓	
Amusat et al. [31]		✓						✓	✓	✓
Liu et al. [32]	✓	✓	✓					✓	✓	
Brown et al. [33]		✓						✓	✓	
Al-Masri et al. [34]	✓	✓						✓	✓	
Anagnostopoulos and Papantonis [35]			✓					✓	✓	
Hemmati [36]		✓						✓	✓	✓
Islam et al. [37]	✓	✓	✓					✓	✓	
Abdalla et al. [38]		✓						✓	✓	✓
Kapsali et al. [39]								✓	✓	
Kocaman [40]	✓	✓				✓			✓	
Kocaman and Modi [41]	✓	✓				✓			✓	
This Study		✓			✓	✓	✓		✓	

Chapter 3

Problem Definition and Formulation

Chapter 3 is divided into three sections. We define the problem in Section 3.1, and provide an introduction to two-stage chance constrained stochastic programming in Section 3.2. In Section 3.3, we present the formulation of the problem.

3.1 Problem Definition

Energy is a critical element for human life since it is practically impossible to manufacture, transport, or consume things without energy. However, fossil fuels, which make up the great bulk of conventional energy sources, have detrimental environmental consequences, contributing to air pollution and climate change. Moreover, fossil fuels are exhaustible. As a result, interest in renewable energy sources such as wind, solar, biomass, tidal and geothermal has grown. The intermittent nature of renewable energy sources, on the other hand, makes it difficult to govern energy production. Therefore, storing excess energy is an efficient method for preventing the negative consequences of the intermittency of renewables. According to Rehman et al. [42], PHES is the most ideal type for massive energy storage among all existing storage technologies, in terms of both technological maturity and economic compatibility. However, renewable energy generation systems including PHES, require substantial investments, which can be significantly affected by the decision makers with different risk profiles.

Kocaman and Modi [41] proposed a hybrid energy generation and allocation system for meeting the demand. The aim of their study is to determine the optimal size of the hybrid system components which include hydro and solar power stations, diesel generators as well as transmission lines connecting generation and demand points. They use the reservoirs to store water in a PHES system in which excess solar energy is stored in the form of gravitational potential energy in order to mitigate the uncertainty in the supply and demand. In the case of storage, water from the lower reservoir is pumped to the upper reservoir and released back when the energy is needed. The PHES system in [41] is an open one (i.e. there is a natural water flow into the reservoirs). Due to the high expense of producing energy with diesel generators, diesel is only employed as a backup source. Since solar panels are installed at demand points, transmission lines are used solely for the purpose of transforming energy between solar power stations and PHES.

The hybrid renewable energy generation and allocation problem in [41] is modeled as a two-stage stochastic program and a scenario approach is employed to represent the uncertainty of the water flow into the upper reservoir and the solar radiance. In the first stage, decisions are made on the size of the system components, as well as the transmission lines capacities before the realization of uncertainties. After the uncertainty has been realized, managerial decisions such as the amount of transmitted energy, the mismatch between supply and demand, and the water levels in reservoirs are made.

In the traditional two-stage stochastic programming, the objective function involves the expected value, such as maximizing the expected revenue or minimizing the expected cost as in [41]. However, in this conservative approach, meeting the entire demand in each scenario might result in substantial investment amounts. When there is uncertainty in the system, setting up different service levels for

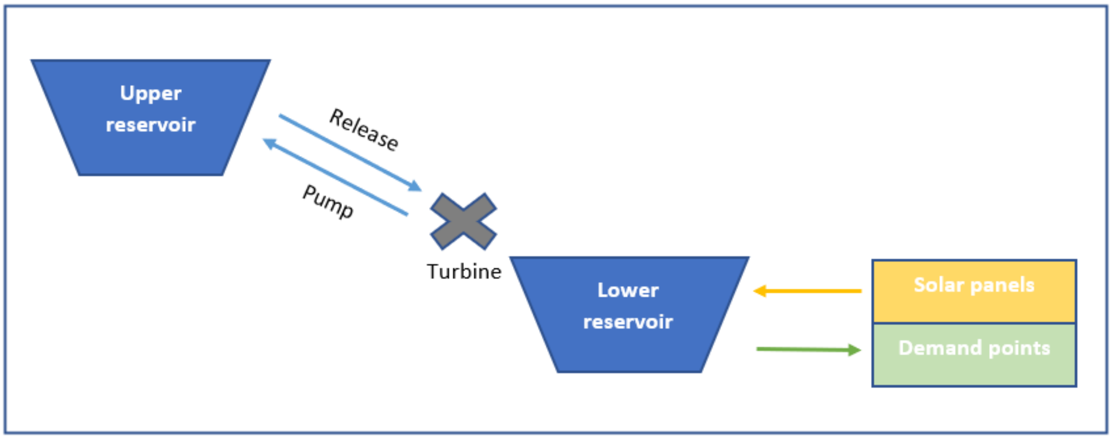


Figure 3.1: A schematic representation for hybrid energy system.

demand satisfaction (i.e. risk levels), however, can help avoiding undesirable sizing of system components. In our study, we consider a similar hybrid system to the one in [41], and build a two-stage chance constrained stochastic linear optimization model. In the first-stage, sizes of the hybrid system components such as reservoirs, hydropower generator and solar panels are determined. After the uncertainty has been realized, operational decisions such as water levels in the reservoirs, amount of generated and stored energy are decided. A chance constraint allows us to investigate the decision makers' behaviours with varying risk-aversion levels. This will enable us to determine how various risk attitudes influence investment decisions in the planning problem for hybrid renewable energy systems. Different than Kocaman and Modi [41], in our study, there is no backup source like diesel and solar generation is supported by a closed-loop PHES system i.e. there is no water inflow to the reservoirs. Hence, in our problem setting, the only uncertainty considered is solar radiation. In addition, we assume that there is already a transmission line between the generation and demand points in the system. As in [41], reservoirs are utilized to store water in a PHES system in which excess solar energy is stored in the form of gravitational potential energy. The PHES mechanism works as follows: The water that is released from the upper reservoir rotates the turbine and the power generator connected to the turbine converts the kinetic energy to electricity when there is need for energy. In the case of storage, the extra solar energy drives the power generator, which in turn spins the turbine in the opposite direction to pump water from the lower reservoir to the upper reservoir. Figure 3.1 is a representation of our hybrid energy system. In the following sections, we briefly introduce the chance-constrained two-stage (CCTS) stochastic programming framework and then give our problem formulation.

3.2 Two-Stage Chance Constrained Stochastic Programming Framework

We formulate our problem as a chance-constrained two-stage stochastic program. A chance constraint stipulates that the decision variable that is selected must fall within a region which is characterized by random variables with a high probability. ([6]). The following is a description of the generic chance-constrained stochastic problem ([43]):

$$\min_{y \in X} \; g(y) \; s.t. \quad Pr\{H(y,\xi) \; \leq 0\} \; \geq 1-\epsilon \tag{3.1}$$

where $y \in \mathbb{R}^n$ represents the vector of decisions, $g(y)$ is the objective value subject to the deterministic set of contraints $X \subset \mathbb{R}^n$, ξ is a random vector, $H : \mathbb{R}^n \times \mathbb{R}^d \rightarrow \mathbb{R}^m$ is the mapping of constraints, and $\epsilon \in (0,1)$ is a the risk tolerance, which is usually small. The interpretation is that the objective function $g(y)$ is minimized over a deterministic set X where the likelihood of $H(y,\xi) \; \geq 0$ is limited by the risk tolerance ϵ.

Chance constrained problems were first introduced to the stochastic programming literature by Charnes et al. [44]. Prékopa [45] developed the version that is considered in our study where a set of constraints are enforced with high probability. A theoretical background and a comprehensive list of references are provided in Prékopa [46]. Chance constrained problems as in (3.1) are known as difficult to solve because the feasible region of problem (3.1) can be non-convex even if both the set X and the function $H(y,\xi)$ are convex in y for all possible realizations of ξ ([43], [47]).

The two-stage stochastic program is also extensively used to deal with uncertainty. For details, see Birdge and Louveaux [48]. The following is the generic form of a two-stage stochastic program with fixed recourse:

$$\min \ c^T x + E_\xi[Q(x,\xi)] \ s.t. \quad Ax = b, x \geq 0 \tag{3.2}$$

where

$$Q(x,\xi) = \min_y \{q^T y | Wy = h - Tx, y \geq 0\} \tag{3.3}$$

Here, ξ is the random vector consisting of the components of q^T, h^T and T and E_ξ represents mathematical expectation with respect to ξ.

In this study, we concurrently employed chance constrained program and two-stage stochastic program in the formulation of our problem to address the uncertain solar radiation output. Wang et al. [49] refer to these formulations as a chance constrained two-stage program. Our aim is to optimally size the hybrid system while ensuring that the demand is satisfied with a certain threshold in order to limit the risk of unmet demand.

3.3 Mathematical Model

The following are the suggested model's sets, parameters, and decision variables:

Sets

T : set of time periods $T = \{1, 2, \ldots, T\}$,

Ω : set of scenarios.

Parameters

ℓ : length of a time period,

h : height of the upper reservoir at PHES,

g : gravitational acceleration rate,

ϵ : risk tolerance for demand satisfaction, $\epsilon \in [0, 1]$,

β : efficiency of PHES in one direction, $\beta \in [0, 1]$,

γ : efficiency of solar panels, $\gamma \in [0, 1]$,

d_{hydro} : annualization factor for PHES,

d_{solar} : annualization factor for solar power station,

c^R : unit cost of reservoir capacity at PHES,

c^G : unit cost of generator capacity at PHES,

c^S : unit cost of solar panel,

p_ω : probability of scenario $\omega \in \Omega$,

$s_{t\omega}$: amount of solar radiation at period $t \in T$ in scenario $\omega \in \Omega$,

d_t : amount of demand at period $t \in T$.

First-Stage Decision Variables

R^{max} : size of upper reservoir at PHES,

P^{max} : size of lower reservoir at PHES,

S^{max} : size of solar panels at demand point,

G^{max} : size of the generator in PHES.

Second-Stage Decision Variables

$R^U_{t\omega}$: amount of water stored in the upper reservoir at PHES in scenario $\omega\in\Omega$ at period $t \in T$,

$R^L_{t\omega}$: amount of water stored in the lower reservoir at PHES in scenario $\omega\in\Omega$ at period $t \in T$,

$N^U_{t\omega}$: amount of water released from the upper reservoir at PHES at period $t\in T$ in scenario $\omega\in\Omega$,

$O_{t\omega}$: amount of water pumped from lower reservoir to upper reservoir at period $t\in T$ in scenario $\omega\in\Omega$,

$E^S_{t\omega}$: amount of electricity sent to PHES from solar power generation station at period $t\in T$ in scenario $\omega\in\Omega$,

$V^S_{t\omega}$: solar energy directly used in demand point at period $t\in T$ in scenario $\omega\in\Omega$,

$K^S_{t\omega}$: solar energy curtailed at period $t\in T$ in scenario $\omega\in\Omega$.

We give our two-stage stochastic programming formulation below.

$$\min\,(R^{max} + P^{max})c^R d_{hydro} + G^{max} c^G d_{hydro} + S^{max} c^S d_{solar} \tag{3.4}$$

$s.t.$

$$V^S_{t\omega} + N^U_{t\omega} gh\beta - d_t \;\geqslant\; 0, \quad \forall t \in T, \omega \in \Omega \tag{3.5}$$

$$R^U_{t\omega} \;\leqslant\; R^{max}, \quad \forall t \in T, \omega \in \Omega \tag{3.6}$$

$$R^L_{t\omega} \;\leqslant\; P^{max}, \quad \forall t \in T, \omega \in \Omega \tag{3.7}$$

$$R^U_{t\omega} \;= R^U_{(t-1)\omega} + O_{t\omega} - N^U_{t\omega}, \quad \forall t \in T\backslash\{1\}, \omega \in \Omega \tag{3.8}$$

$$R^U_{1\omega} \;= R^{max}/2 + O_{1\omega} - N^U_{1\omega}, \quad \forall \omega \in \Omega \tag{3.9}$$

$$R^U_{T\omega} \;= R^{max}/2, \quad \forall \omega \in \Omega \tag{3.10}$$

$$R^L_{1\omega} \;= P^{max}/2 + N^U_{1\omega} - O_{1\omega}, \quad \forall \omega \in \Omega \tag{3.11}$$

$$R^L_{t\omega} \;= R^L_{(t-1)\omega} + N^U_{t\omega} - O_{t\omega}, \quad \forall t \in T\backslash\{1\}, \omega \in \Omega \tag{3.12}$$

$$N^U_{t\omega} gh\beta \leqslant G^{max}\ell, \quad \forall t \in T, \omega \in \Omega \tag{3.13}$$

$$O_{t\omega} g\frac{h}{\beta} \leqslant G^{max}\ell, \quad \forall t \in T, \omega \in \Omega \tag{3.14}$$

$$E^S_{t\omega} = O_{t\omega} g\frac{h}{\beta}, \quad \forall t \in T, \omega \in \Omega \tag{3.15}$$

$$V^S_{t\omega} + E^S_{t\omega} + K^S = S^{max} s_{t\omega}\gamma\ell, \quad \forall t \in T, \omega \in \Omega \tag{3.16}$$

$$R^U_{t\omega}, R^L_{t\omega}, N^U_{t\omega}, K^S_{t\omega}, E^S_{t\omega}, V^S_{t\omega}, O_{t\omega} \geqslant 0, \quad \forall t \in T, \omega \in \Omega \tag{3.17}$$

$$R^{max},\ P^{max},\ G^{max},\ S^{max} \geqslant 0 \tag{3.18}$$

The objective function of the model in (3.4) is minimizing the total annualized investment cost. It includes the annualized costs of construction of reservoirs, solar panels, and power generator used in the PHES. Constraint (3.5) ensures that the amount of energy sent to the demand point is greater than or equal to demand at all time periods and under all scenarios. Constraints (3.6) and (3.7) ensure that the amount of water in the reservoirs is restricted by the reservoir size at all time periods and under all scenarios. Constraints in (3.8)–(3.10) balance the upper reservoir level. The constraint in (3.8) connects the water levels of the upper across time periods. We define the initial and final water levels in the reservoirs based on the assumption that the reservoirs are half full at the beginning and finish in (3.9)-(3.11). Constraint (3.12) links lower reservoir levels between time periods. Constraints (3.13) and (3.14) ensure that the amount of energy generated and pumped is restricted by the generation and pumping capacity at all times and under all scenarios. Constraint (3.15) states that the amount of energy pumped must be equal to the amount that is sent from the solar power station located at the demand point at all times and under all scenarios. Constraint in (3.16) states that the summation of solar energy directly used, energy sent from the demand point to the PHES, and curtailed solar energy equals the total generated solar energy at all times and under all scenarios. Constraints (3.17) and (3.18) are added to ensure that the variables are non-negative.

In our probabilistic renewable energy system sizing problem, solar irradiance is an appropriately sized nonnegative random vector denoted by $\tilde{s}$. The sizing decisions $R^{max}, P^{max}, G^{max}, S^{max}$ are made prior to the realization of the solar irradiance amount, whereas the operational decisions consider these realizations. The demand must be met with a predetermined probability, resulting in the following chance constrained model:

$$
\begin{aligned}
&\min\,(R^{max}+P^{max})c^R d_{hydro} + G^{max}c^G d_{hydro} + S^{max}c^S d_{solar} \\
&s.t. \\
&\qquad \mathbb{P}\big\{(R^{max}, P^{max}, G^{max}, P^{max}) \in P(\tilde{s})\big\} \geq 1-\epsilon && (3.19a)\\
&\qquad R^{max},\, P^{max},\, G^{max},\, S^{max} \geqslant\, 0 && (3.19b)
\end{aligned}
$$

where

$$
\begin{aligned}
P(s) = \Big\{(R^{max}, P^{max}, G^{max}, S^{max}) \mid\ & V_t^S + N_t^U gh\beta - D_t \geq 0, \quad \forall t \in T, \\
& R_t^U \,\leqslant\, R^{max}, \quad \forall t \in T, \\
& R_t^L \,\leqslant\, P^{max}, \quad \forall t \in T, \\
& R_t^U \,= R_{(t-1)}^U + O_t - N_t^U, \quad \forall t \in T\backslash\{1\}, \\
& R_1^U \,= R^{max}/2 + O_1 - N_1^U, \\
& R_T^U \,= R^{max}/2, \\
& R_1^L \,= P^{max}/2 + N_1^U - O_1, \\
& R_t^L \,= R_{(t-1)}^L + N_t^U - O_t, \ \ \forall t \in T\backslash\{1\}, \\
& N_t^U gh\beta \leqslant\, G^{max}\ell, \quad \forall t \in T, \\
& O_t g\frac{h}{\beta} \leqslant\, G^{max}\ell, \quad \forall t \in T, \\
& E_t^S = O_t g\frac{h}{\beta}, \quad \forall t \in T, \\
& V_t^S + E_t^S + K_t^S = S^{max} s_t \gamma\ell, \quad \forall t \in T, \\
& R_t^U, R_t^L, N_t^U, O_t, E_t^S, K_t^S, V_t^S \geqslant\, 0, \ \forall t \in T \quad \Big\}.
\end{aligned}
$$

The joint chance constraint given in (3.19a) can be linearized as follows with scenario index set Ω where $M^1, M^2, ..., M^{19}$ are very big numbers :

$$-R^U_{t\omega} + R^{max} + L^1_{t\omega}M^1 \geqslant 0, \quad \forall t \in T, \omega \in \Omega \tag{3.20}$$

$$-R^L_{t\omega} + P^{max} + L^2_{t\omega}M^2 \geqslant 0, \quad \forall t \in T, \omega \in \Omega \tag{3.21}$$

$$R^U_{t\omega} - R^U_{(t-1)\omega} - O_{t\omega} + N^U_{t\omega} + L^3_{t\omega}M^3 - L^4_{t\omega}M^4 = 0, \quad \forall t \in T\backslash\{1\}, \omega \in \Omega \tag{3.22}$$

$$R^U_{1\omega} - R^{max}/2 - O_{1\omega} + N^U_{1\omega} + L^5_{t\omega}M^5 - L^6_{t\omega}M^6 = 0, \quad \forall \omega \in \Omega \tag{3.23}$$

$$R^U_{T\omega} - R^{max}/2 + L^7_{t\omega}M^7 - L^8_{t\omega}M^8 = 0, \quad \forall \omega \in \Omega \tag{3.24}$$

$$R^L_{t\omega} - R^L_{(t-1)\omega} - N^U_{t\omega} + O_{t\omega} + L^9_{t\omega}M^9 - L^{10}_{t\omega}M^{10} = 0, \quad \forall t \in T\backslash\{1\}, \omega \in \Omega \tag{3.25}$$

$$R^L_{1\omega} - P^{max}/2 - N^U_{1\omega} + O_{1\omega} + L^{11}_{t\omega}M^{11} - L^{12}_{t\omega}M^{12} = 0, \quad \forall \omega \in \Omega \tag{3.26}$$

$$-N^U_{t\omega}gh\beta + G^{max}\ell + L^{13}_{t\omega}M^{13} \geqslant 0, \quad \forall t \in T, \omega \in \Omega \tag{3.27}$$

$$-O_{t\omega}g\frac{h}{\beta} + G^{max}\ell + L^{14}_{t\omega}M^{14} \geqslant 0, \quad \forall t \in T, \omega \in \Omega \tag{3.28}$$

$$E^S_{tw} - O_{t\omega}g\frac{h}{\beta} + L^{15}_{t\omega}M^{15} - L^{16}_{t\omega}M^{16} = 0, \quad \forall t \in T, \omega \in \Omega \tag{3.29}$$

$$V^S_{t\omega} + E^S_{tw} + K^S - S^{max}s_{t\omega}\gamma\ell + L^{17}_{t\omega}M^{17} - L^{18}_{t\omega}M^{18} = 0, \quad \forall t \in T, \omega \in \Omega \tag{3.30}$$

$$V^S_{t\omega} + N^U_t gh\beta - D_{t\omega} + L^{19}_{t\omega}M^{19} \geqslant 0, \quad \forall t \in T, \omega \in \Omega \tag{3.31}$$

$$R^U_{t\omega}, R^L_{t\omega}, N^U_{t\omega}, N^L_{t\omega}, E^S_{t\omega}, V^S_{t\omega}, O_{t\omega} \geqslant 0, \quad \forall t \in T, \omega \in \Omega \tag{3.32}$$

$$\sum_{\omega \in \Omega} p_\omega T_\omega \leq \epsilon, \tag{3.33}$$

$$T_\omega \geq L^i_{t\omega}, \qquad \forall i \in \{1 \ldots 19\}, \forall t \in T, \omega \in \Omega \tag{3.34}$$

$$L^i_{t\omega} \in \{0, 1\}, \quad \forall i \in \{1 \ldots 19\}, \forall t \in T, \omega \in \Omega \tag{3.35}$$

$$T_\omega \in \{0, 1\}, \quad \forall \omega \in \Omega \tag{3.36}$$

Hence, mixed integer linear programming equivalent form of our chance constrained model (i.e. extensive formulation) is in the following form:

$$\begin{aligned} &\min\,(R^{max} + P^{max})c^R d_{hydro} + G^{max}c^G d_{hydro} + S^{max}c^S d_{solar} \\ &s.t. \\ &\qquad (3.20) - (3.36) \\ &\qquad R^{max},\ P^{max},\ G^{max},\ S^{max} \geqslant 0 \end{aligned} \tag{3.37}$$

Chapter 4

Solution Methodology

Solution of scenario-based stochastic programming models is a difficult task especially when there is a large number of scenarios. Adding a joint chance constraint makes harder solving these formulations due to the non-convexity of the probabilistic constraints in general. A chance constrained problem with finite support can be reformulated as a deterministic MIP by the big-M method, as can be seen in section 3 (3.37). However, this big-M formulation is computationally challenging because of the weak LP relaxation and its large size. The majority of studies on chance constrained programs concentrate on single-stage problems ([50], [51], [52], [53], [54], [55], [56], [57]). Despite the extensive literature on solving single-stage chance constrained mathematical programs, the studies addressing two-stage chance constrained stochastic programs are rather limited. Zhang et al. [58] study multi-stage chance constrained mathematical programs and they conclude that solving large-scale instances requires employing decomposition algorithms. Decomposition algorithms have been developed and used extensively for solving two-stage stochastic programming problems (see [48] and [59]). Van Slyke and Wet [60] suggest the use of well-known L-shaped decomposition technique by adapting the Benders decomposition ([61]) for these stochastic programming models. However, the feasibility cuts of Benders decomposition algorithm works assuming that second stage problems are feasible; hence, these methods can not be applied to two-stage chance constrained programs. Wang et al. [49] study a two-stage chance constrained programming problem and propose a combined sample average approximation method by integrating Benders decomposition. However, optimality cuts defined in this study include big-M coefficients, which causes weak lower bounds in the solution of a continuous relaxation. Zeng et al. [62] consider a two-stage chance constrained problem and suggest a decomposition algorithm which involves bilinear feasibility and optimality cuts. However, in the linearization of these cuts, big-M coefficients are introduced with additional variables, which makes the solution of the problem difficult. Luedtke [6] proposes a Benders decomposition based branch and cut decomposition algorithm for exactly solving a special case of two-stage chance constrained problems where the cost of second-stage solutions is not considered. Liu et al. [63] consider two-stage chance constrained problems with the additional cost incurred by the second stage decisions and develop strong optimality cuts in addition to the strong feasibility cuts proposed by Luedtke [6]. In our study, we utilize the strong valid inequalities suggested by Luedtke [6] for our two-stage chance constrained problem, which also does not involve additional costs for the second stage variables.

4.1 Solving Two-Stage CCMP with Branch and Cut Decomposition Algorithm

Recall the two-stage CCMP given in (3.19). To be able to apply the algorithm proposed by Luedtke [6], all problems must be well-defined. Hence, we set upper bounds for the decisions on the size of the hybrid energy system components by calculating the maximum capacities that would be needed if the demand for the whole planning horizon is met at once. Therefore, we can rewrite the problem

(3.19) as follows:

$$
\begin{aligned}
&\min \quad (R^{max} + P^{max})c^R d_{hydro} + G^{max} c^R d_{hydro} + S^{max} c^S d_{solar} \\
&s.t. \\
&\quad \mathbb{P}\big\{(R^{max}, P^{max}, G^{max}, P^{max}) \in P(\tilde{s})\big\} \geq 1 - \epsilon, && \text{(4.1a)} \\
&\quad 0 \leq R^{max} \leq R^{max}_{bound}, && \text{(4.1b)} \\
&\quad 0 \leq P^{max} \leq P^{max}_{bound}, && \text{(4.1c)} \\
&\quad 0 \leq G^{max} \leq G^{max}_{bound}, && \text{(4.1d)} \\
&\quad 0 \leq S^{max} \leq S^{max}_{bound}, && \text{(4.1e)}
\end{aligned}
$$

where

$$
P(s) = \Bigg\{(R^{max}, P^{max}, G^{max}, S^{max}) \mid
\begin{aligned}[t]
& V^S_t + N^U_t gh\beta - D_t \geq 0, \quad \forall t \in T, \\
& R^U_t \leqslant R^{max}, \quad \forall t \in T, \\
& R^L_t \leqslant P^{max}, \quad \forall t \in T, \\
& R^U_t = R^U_{(t-1)} + O_t - N^U_t, \quad \forall t \in T \backslash \{1\}, \\
& R^U_1 = R^{max}/2 + O_1 - N^U_1, \\
& R^U_T = R^{max}/2, \\
& R^L_1 = P^{max}/2 + N^U_1 - O_1, \\
& R^L_t = R^L_{(t-1)} + N^U_t - O_t, \ \forall t \in T \backslash \{1\}, \\
& N^U_t gh\beta \leqslant G^{max}\ell, \quad \forall t \in T, \\
& O_t g\frac{h}{\beta} \leqslant G^{max}\ell, \quad \forall t \in T, \\
& E^S_t = O_t g\frac{h}{\beta}, \quad \forall t \in T, \\
& V^S_t + E^S_t + K^S_t = S^{max} s_t \gamma\ell, \quad \forall t \in T, \\
& R^U_t, R^L_t, N^U_t, O_t, E^S_t, K^S_t, V^S_t \geqslant 0, \ \forall t \in T
\end{aligned}
\Bigg\}.
$$

By introducing binary variables u_r for each $r \in \mathcal{N} = \{1, \ldots, N\}$, problem (4.1) can be reformulated as follows:

$$
\begin{aligned}
\min \quad & (R^{max} + P^{max})c^R d_{hydro} + G^{max} c^R d_{hydro} + S^{max} c^S d_{solar} \\
s.t. \quad & \\
& u_r = 0 \ \Rightarrow \ (R^{max}, P^{max}, G^{max}, P^{max}) \in P_r, \quad r \in \mathcal{N}, && (4.2a) \\
& \sum_{r=1}^{N} u_r \ \leq \ h, && (4.2b) \\
& (R^{max}, P^{max}, G^{max}, P^{max}) \in X, && (4.2c) \\
& u_r \in \{0, 1\}, \ r \in \mathcal{N} && (4.2d)
\end{aligned}
$$

Here, $h = \lfloor \epsilon N \rfloor$, $X = \{(R^{max}, P^{max}, G^{max}, P^{max}) \mid (4.1b)-(4.1e)\}$ and $P_r = P(s_r)$ for $r \in \mathcal{N}$ where possible outcomes of s, s_r for $r \in \mathcal{N}$ are denoted as scenarios. The feasible region of (4.2) is $\mathcal{F} = \{(R^{max}, P^{max}, G^{max}, P^{max}, u) \mid (4.2a)-(4.2d)\}$. The single scenario optimization problem for two-stage CCMP for scenario s_r, $r \in \mathcal{N}$ is given as:

$$
\begin{aligned}
h_r(\eta) \ := \ \min \quad & \eta_1 R^{max} + \eta_2 P^{max} + \eta_3 G^{max} + \eta_4 S^{max} \\
s.t. \quad & \\
& (R^{max}, P^{max}, G^{max}, P^{max}) \in P_r \cap \bar{X} && (4.3)
\end{aligned}
$$

Here, we choose $\bar{X} = X$ since X is a compact set and require $P_r \cap \bar{X} \neq \emptyset$. Thus, problem (4.3) is well-defined. Secondly, the single scenario separation problem, is solved to detect if the obtained solution $(R^{\hat{max}}, P^{\hat{max}}, G^{\hat{max}}, P^{\hat{max}})$ violates any scenarios i.e. $\exists r \in \mathcal{N}$ where $(R^{\hat{max}}, P^{\hat{max}}, G^{\hat{max}}, P^{\hat{max}}) \notin P_r$ and get $(notin, \eta, \upsilon)$ to create the cut in the case of violation. If $(R^{\hat{max}}, P^{\hat{max}}, G^{\hat{max}}, P^{\hat{max}}) \notin P_r$, *notin* returns TRUE, otherwise it returns FALSE. Note that each P_r is defined by more than one inequality. Hence, all the inequalities must be checked to find if *notin* returns TRUE or FALSE.

The main subproblem of the algorithm is the master problem $ML(Y_0, Y_1, W)$:

$$
\begin{aligned}
ML(Y_0, Y_1, W) \;:=\; \min \;\; & (R^{max} + P^{max})c^R d_{hydro} + G^{max} c^R d_{hydro} + S^{max} c^S d_{solar} \\
s.t. \;\; & \\
& \sum_{r=1}^{N} u_r \;\leq\; h, \\
& (x, u) \in W, \quad u \in [0,1]^N, \\
& (R^{max}, P^{max}, G^{max}, P^{max}) \in X, \\
& u_r = 0, \; r \in Y_0, \quad u_r = 1, \; k \in Y_1,
\end{aligned} \tag{4.4}
$$

where W is a polyhedron characterized by the generated valid inequalities and includes the feasible region of (4.2), represented by $\mathcal{F}$ and $Y_0, Y_1 \subseteq N$ are defined such that $Y_0 \cap Y_1 = \emptyset$.

Chapter 5

Computational Study

There are three sections in this chapter. We provide the technique for scenario generation in Section 5.1, and we describe the data used in our study in Section 5.2. We present our numerical results in Section 5.3.

5.1 Scenario Generation for Solar Radiation

In stochastic programming framework, it is important to consider the uncertainty accurately. We use a scenario-based approach, that is commonly utilized in the literature [64], to model the uncertainty in our problem. We employ a scenario generation method for hourly solar radiation data because of our uncertainty assumption on the solar radiation (SR). In this section, we present this method.

The vast literature on solar radiation forecasting has various models and methodologies. Among statistical methods, the Auto-Regressive Integrated Moving Average (ARIMA) time series models have been proposed numerous times for modelling and forecasting solar radiation ([65], [66], [67]). ARIMA models are popular for modelling and predicting time series in a variety of contexts. These models belong to a broad class of linear models. See Box et al. [68] for more details.

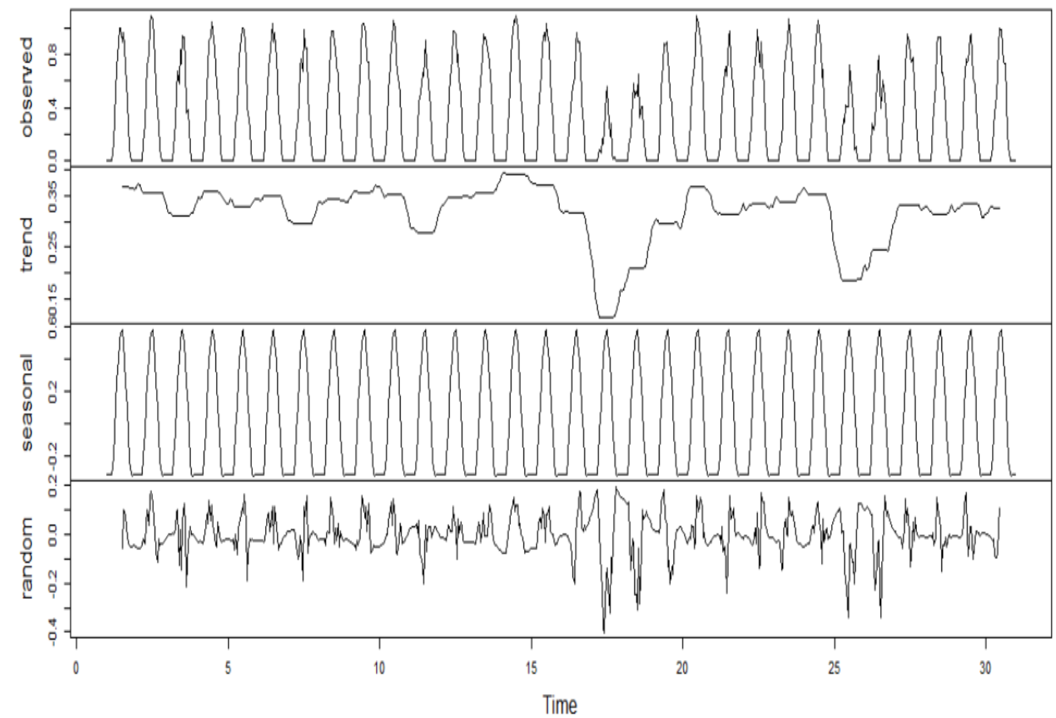


Figure 5.1: The decomposition of solar radiation data in June 2017.

As a result of the fact that the times of sunrise and sunset shift during the course of the year, Yang et al. [5] perform the data decomposition for each month. Moreno-Muñoz et al. [65] demonstrate that ARIMA is able to predict hourly solar radiation levels using the data from only a limited number of preceding hours. However, due to the existence of zero-valued night hours, solar radiation at sunrise and sunset hours cannot be accurately predicted. To overcome this problem, Yang et al. [5] propose fitting an ARIMA model for each data point in the data set by updating the training set iteratively. In this study, we employ an ARIMA based model which is adopted from Yang et al. [5]. In [5], the solar radiation data for a three-week period in each month is predicted by using the proposed method. Since the first set of training data comes from the first week of the corresponding month, the prediction for the first week's solar radiation data is not performed. Different than [5], we employ the last week of the preceding month as the first training set in order to provide a complete prediction for each month, including the first week.

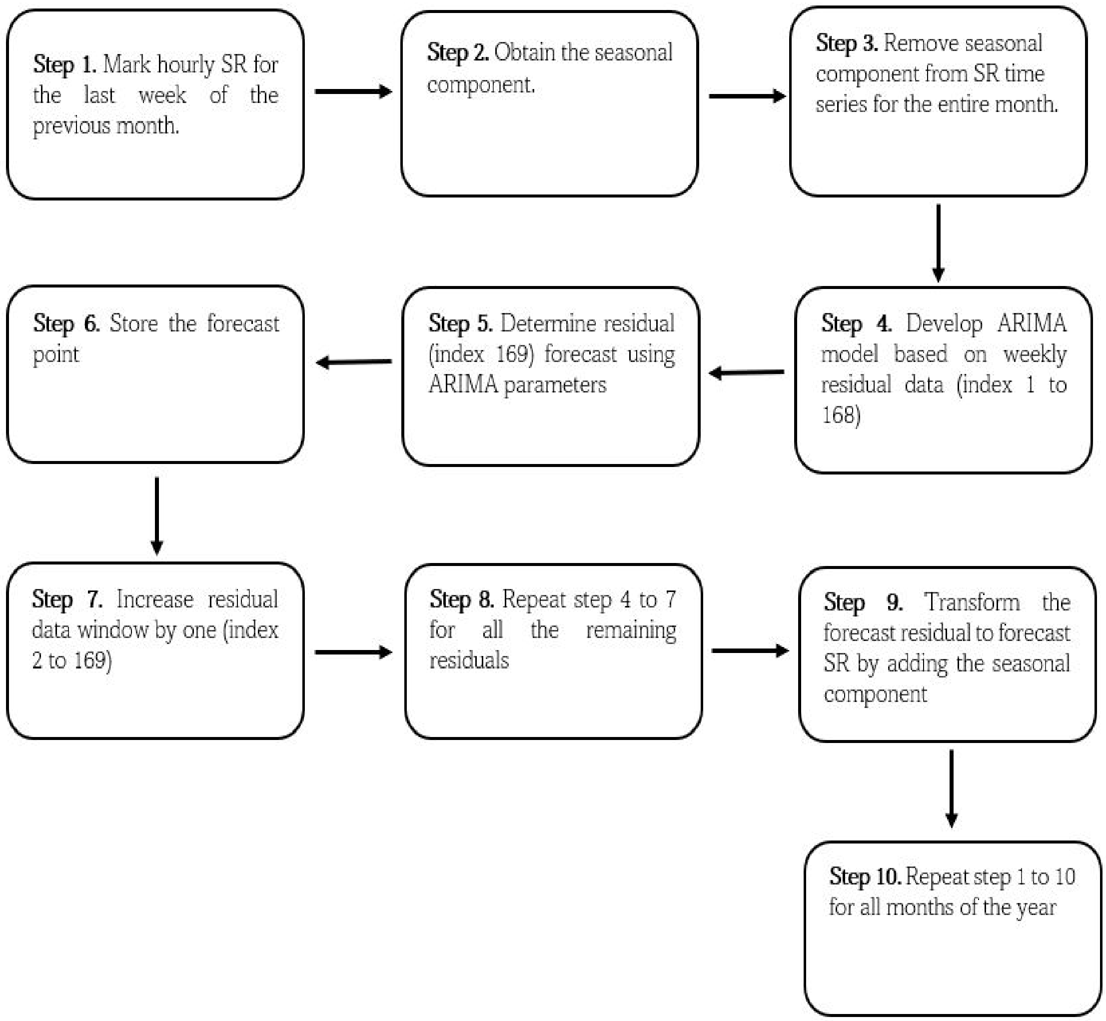


Figure 5.2: Scenario generation flow diagram.

First, the solar radiation data is decomposed into seasonal, trend, and irregular components for each month. Figure 5.1 illustrates the decomposed components of solar radiation data that belongs to June of 2017. Then, the seasonal component is eliminated from the solar radiation measurement. By using the remainder, next hour's residual is forecasted the using ARIMA. The residuals from previous month's last week are used as training data for ARIMA model, which is then used to forecast the next hour's residual, that is added to the training set. The training set's data window is then expanded by one, and an ARIMA model is fitted once more to forecast the next hour's residual. This procedure is repeated until all of the residuals for the month have been processed. After that, the seasonal component is added to provide a solar radiation forecast. For each month of the year, this procedure is repeated. Figure 5.2 shows the flow diagram of scenario generation process.

Table 5.1: Forecast RMSE and MAE for hourly SR data

Time Period	Mean observed SR	RMSE	MAE
January	0.105085	0.050224	0.025805
February	0.142500	0.065517	0.034884
March	0.191549	0.083138	0.044695
April	0.237064	0.087646	0.050133
May	0.282644	0.088071	0.052589
June	0.318079	0.087896	0.054113
July	0.317602	0.086150	0.050413
August	0.286959	0.079453	0.0473286
September	0.243383	0.074763	0.040329
October	0.178096	0.059745	0.030497
November	0.117692	0.061573	0.031496
December	0.094537	0.046990	0.024097

The accuracy of the solar radiation estimates is determined by calculating the root mean square error (RMSE) and the mean absolute error (MAE). These terms are defined as follows:

$$RMSE = \sqrt{\frac{1}{n}.\sum_{i=1}^{n}(x_{pred,i} - x_{obs,i})^2} \tag{5.1}$$

$$MAE = \frac{1}{n}.\sum_{i=1}^{n}|x_{pred,i} - x_{obs,i}| \tag{5.2}$$

where n is the number of evaluated data pairs, and $x_{pred,i}$ and $x_{obs,i}$ are the i^{th} valid forecast and observation values, respectively. Table 5.1 shows RMSE and MAE values for the procedure that we followed in our study.

5.2 Experimental Setup

In this study, we use the same efficiency and cost parameters as in Kocaman and Modi [41]. Table 5.2 shows the adapted parameters from [41]. We set the planning horizon to one year, and each time period is one hour long. The lifespans of the PHES and the solar power plant are considered to be 60 and 30 years, respectively. Considering that each system has a different usable lifetime, we derive a cost parameter representing the annual cost of building for each system. This parameter is calculated using the formula $d = e/(1-(e+1)^{-j}$, where e and j refer to the discount rate and the component's lifespan, respectively.

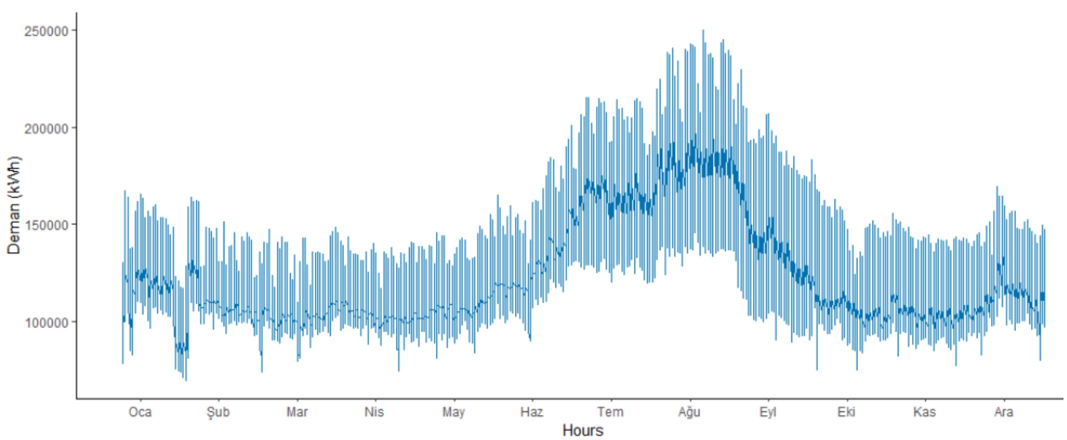


Figure 5.3: Hourly demand data.

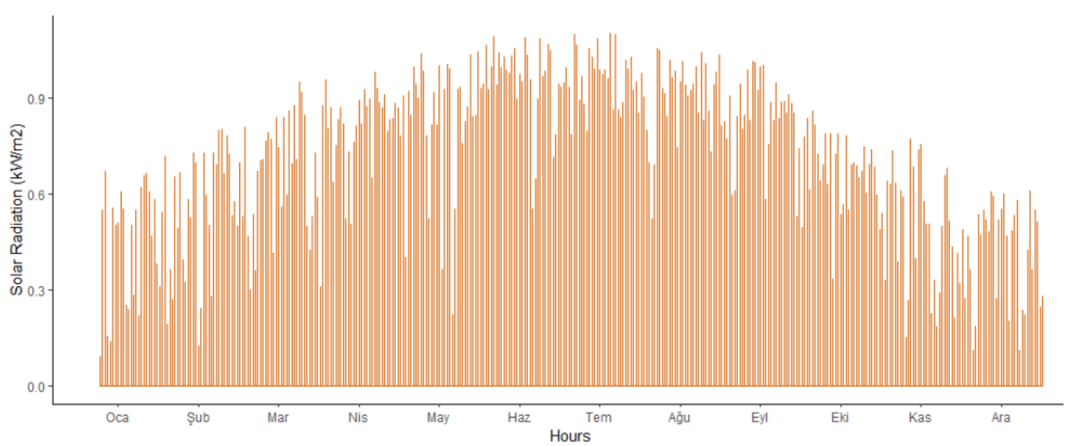


Figure 5.4: Hourly solar radiation data.

Table 5.2: Problem parameters

Parameter	Value
c^R	3 $\$/m^3$
c^G	500 $\$/kW$
c^S	200 $\$/m^2$
β	0.88
γ	0.12
j_{hydro}	60 years
j_{solar}	30 years
e	0.05
g	9.8
h	100

The same demand and solar data used in [27] is employed here, which comes from the Energy Market Regulatory Authority of Turkey [69] and Homer Energy [70], respectively. The hourly solar radiation and demand data are shown in Figure 5.3 and Figure 5.4. Solar radiation is assumed to be uncertain while demand is considered to be deterministic.

5.3 Numerical Results

This section is devoted to the results of our computational study. All computational experiments are conducted on a server with 64GB RAM and a 2.4 GHz Intel Xeon E5-2630 v3 CPU. We solve the extensive formulation of our model with CPLEX version 20.1.0.0. The proposed Benders based branch and cut decomposition algorithm is coded in Python 3.8 and the optimization problems that are developed in Python are solved by CPLEX 20.1.0.0 in parallel mode using up to 16 threads. We utilize the lazy constraint callback feature of CPLEX. We evaluate the CPU time-based performances of the extensive formulation and branch and cut decomposition algorithm. Different risk tolerance (ϵ) values are considered to detect the effects of the diverse risk attitudes of the decision maker. Hence, we can detect the changes in the results as decision maker becomes more risk-averse. We work with a variety of scenarios ranging from 20 to 65 to see the effects of number of scenarios on the results. To compare the performance of the proposed decomposition algorithm, the problem is solved using the proposed algorithm and the CPU timings are computed. Then, we solve the extensive formulation using CPLEX by setting the algorithm's solution time as the CPLEX time limit. We solve the problem with 20, 50, and 65 scenarios and different risk tolerances. We receive an internal CPLEX callback error when we use 100 scenarios in the algorithm. Here, the risk tolerance is determined by the parameter ϵ. For example, as ϵ decreases, the decision maker becomes more risk-averse. Later in this section, the impact of this parameter on the optimal solution will be discussed. We calculate the gap in the objective function and share the results in Table 5.3.

Table 5.3: Comparison of performances of the scenario decomposition algorithm and CPLEX

$\|\Omega\|$	ϵ	Total Cost		% Gap	CPU time (s)
		Scenario Decomp. Algorithm	CPLEX		
20	0.05	193,637,822	193,637,822	0	82,026
20	0.1	193,418,698	4,256,886,085,899	2,200,766	137,555
50	0.05	194,354,738	195,102,696	0.3848	417,439
50	0.1	193,979,174	-	-	188,749
65	0.05	194,394,177	-	-	513,765
65	0.1	194,093,782	-	-	433,456

Table 5.4: CPU times of the scenario decomposition algorithm and CPLEX.

ϵ	CPLEX CPU time (s)	Scenario Decomp. Algorithm CPU time (s)
0.05	192,541	81,990
0.1	-	137,555

Table 5.3 displays the CPU times and the total costs that are provided by the proposed algorithm and CPLEX under the time limit. It is seen that CPLEX could not find an incumbent solution within the time limit for three instances. When the problem is solved with 20 scenarios and 10% risk tolerance, the gap in total cost is 2,200,766% which is a significant amount. With the same number of scenarios but 5% risk tolerance, CPLEX solves the problem with 0% gap.

However, the solution that CPLEX provides is not guaranteed as the optimal solution. There were still open nodes in the search tree when the time limit was reached. With 50 scenarios at 5% risk tolerance, the gap is relatively small. In addition, Table 5.4 shows the CPU times in seconds for 20 scenarios and for $\epsilon \in \{0.05, 0.1\}$ provided by both CPLEX and the proposed algorithm. The proposed algorithm solves the problem almost 2.4 times faster than CPLEX for $\epsilon = 0.05$. Moreover, CPLEX is unable to solve the problem when ϵ is increased to 0.1 after 100+ hours (wallclock time). The results show that the proposed decomposition algorithm is able to solve instances that can not be solved by CPLEX.

Table 5.5: Total costs of the system in annual basis for 20 and 50 scenarios.

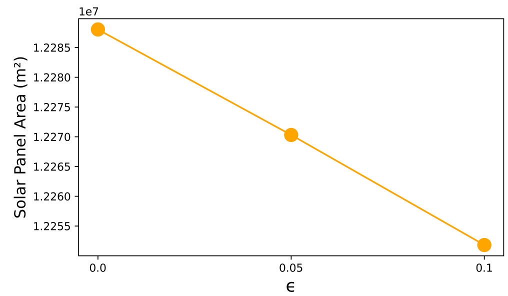
ϵ	Total Cost for 20 scenarios ($)	Total Cost for 50 scenarios ($)	Difference	% Deviation
0.1	193,418,698	193,979,174	560,475	0.2889
0.05	193,637,822	194,354,738	716,916	0.3689

Table 5.6: Total costs of the system in annual basis for 50 and 65 scenarios.

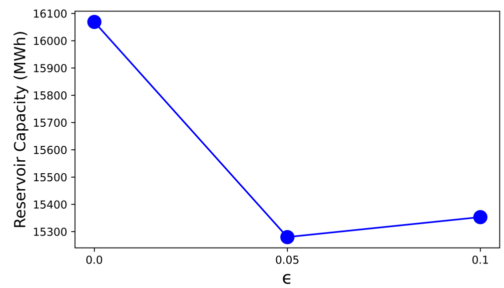
ϵ	Total Cost for 50 scenarios ($)	Total Cost for 65 scenarios ($)	Difference	% Deviation
0.1	193,979,174	194,093,782	114,609	0.0591
0.05	194,354,738	194,394,177	39,439	0.0203

We compare the optimal overall cost for 20 and 50 scenarios, as well as for 50 and 65 scenarios. As it is seen in Table 5.6, the deviation is too small when the number of scenarios is increased from 50 to 65 which suggests that increasing the number of scenarios further may not significantly chance the solution of the problem.

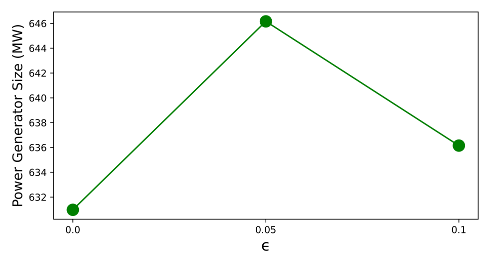
We consider different ϵ values to examine the effect of risk levels in the first stage decision variables for 50 scenarios. Figures 5.5a, 5.5b and 5.5c display the optimal sizes for solar panels, reservoirs, and power generators for various risk levels, respectively. Figure 5.5a demonstrates that as ϵ increases, the size of the solar panel decreases. To put it differently, when the decision maker becomes less risk-averse, less investment is made in solar energy. The decision maker's aversion to risk related to unmet demand decreases as the value of ϵ increases. As a result,



(a) Solar Panel Area



(b) Reservoir Size



(c) Power Generator Size

Figure 5.5: Size of hybrid system components

less money is invested in energy generation to meet demand. In Figures 5.5b and 5.5c, it is seen that there is a reverse relationship between reservoir capacity and the power generator capacity. The reservoir size decreases initially when ϵ changes from 0 to 0.05 , then increases slightly as ϵ increases. When the value of ϵ increases from 0 to 0.1, on the other hand, the power generator's capacity first goes up at $\epsilon = 0.05$, then goes down.

Table 5.7: Annualized costs (\$) for solar and storage systems for 50 scenarios for $\epsilon \in \{0, 0.05, 0.1\}$. % Deviation (3rd and 5th columns) represents the difference with no-risk case.

ϵ	Annualized Cost of Storage (\$)	% Deviation	Annualized Cost of Solar System (\$)	% Deviation
0.1	34,705,565	-1.85	159,273,609	-0.29
0.05	34,840,671	-1.46	159,514,067	-0.14
0	35,358,216	-	159,744,480	-

In Table 5.7, we show the deviation in the system cost for the two resource types that are employed in the system for 50 scenarios. It is clearly seen in Table

5.7 that the cost of solar and PHES systems increases with decreasing risk level. Because the decision maker wants to meet demand more likely, she increases the investment in both the storage and solar systems. Table 5.7 also shows that the percentage deviation of the storage cost from no-risk solution (i.e. $\epsilon = 0$) is more than solar for both risk levels 0.05 and 0.1. Solar is system's primary energy source, thus the decision maker decreases the investment in storage more.

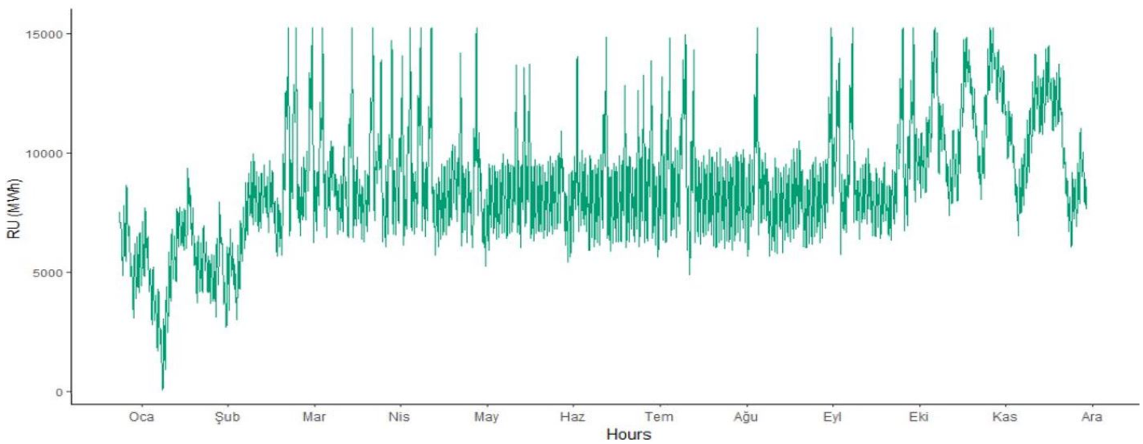


Figure 5.6: Amount of energy stored in the upper reservoir for a typical scenario.

Figure 5.6 illustrates the stored energy in the upper reservoir for each hour of one year. It is clear that there is a daily cycle in the stored energy, similar to solar radiation. The system supplies the energy need by releasing water from the upper reservoir when solar radiation is low. Also, the system pumps water from the lower reservoir to the upper reservoir when the solar radiation is high. Figure 5.6 also shows that in the first two months, the energy storage is utilized a lot, mostly because the radiation in these motnhs is too low compared to the next months. Between March and October, the amount of energy stored in the upper reservoir shows a stable trend. Since the amount of solar radiation is relatively high in these months, there is a balance in the system. Starting from October, solar radiation levels again decrease, causing the stored energy to fluctuate as in the first two months. Moreover, although there is a daily cycle in the operation of PHES, it is clear that the PHES supports the system for seasonal changes, which shows the necessity of annual planning horizon [71].

Chapter 6

Conclusion

In this thesis, we study an investment planning problem for a hybrid energy system that combines a PHES system with a solar system under solar radiation uncertainty. We formulate the sizing problem of this hybrid energy system as a chance constrained two-stage stochastic program where the system's reliability in satisfying demand is modeled by a joint chance constraint. The aim of this study is to minimize the total annualized investment cost while meeting the energy demand with a predefined service level.

In investment planning problems, supplying the demand for certainty for even infrequently occurring events can lead to considerable cost increases. A chance constrained optimization strategy can be used to relax the necessity of satisfying the demand for all random events in order to tackle this issue. In this way, the undesirable consequences of the inherent randomness in hybrid renewable energy systems are avoided. In this context, we develop a chance constrained approach for designing a hybrid renewable energy system where solar generation is supported by a PHES system.

Stochastic programming is a scenario-driven method; hence, a sufficient number of scenarios must be used to ensure the quality of the solution. However, adopting a large number of scenarios significantly enlarges the problem. In this context, the decomposition algorithm that we suggested enables us to use a large scenario set while reducing the solution time by a significant amount. We propose a branch and cut decomposition algorithm based on the Benders decomposition technique in order to exactly solve our large scale problem. By decomposing a large problem into multiple smaller problems, the solution method that we present decreases the solution time by an important amount.

We generate scenarios for solar radiation by using an ARIMA based algorithm of Yang et al. [5]. We investigate the variations in decision-making process based on a variety of persfectives. Our findings demonstrate that, as expected, as the decision maker increases the reliability of the system, storage and solar component investments increase as well. We solve our chance constrained two-stage problem for several instances by considering different number of scenarios. We solve the extensive formulation with CPLEX by setting the algorithm's solution time as the CPLEX time limit to evaluate the performance of our solution method. The results indicate that compared to CPLEX, the algorithm that we present needs less CPU time to solve the problem.

For potential future work, we can consider an open-loop PHES system in order to incorporate the uncertainties relevant to the water flow into the reservoirs. In this way, we can analyze the effects of different types of uncertainties on the decisions. We can design systems with different renewable energy sources such as wind, biomass and geothermal. Considering wind, for example, requires different scenario generation techniques and may require higher number of scenarios to accurately take uncertainty into account. Resulting large-scale problems may need alternative decomposition techniques.

Bibliography

[1] "Global share of electricity generation, 2019." https://www.iea.org/data-and-statistics/charts/global-share-of-electricity-generation-2019. Accessed: July 2022.

[2] H. Ritchie, M. Roser, and P. Rosado, "Co_2 and greenhouse gas emissions," *Our World in Data*, 2020. https://ourworldindata.org/co2-and-other-greenhouse-gas-emissions.

[3] "How rapidly will the global electricity storage market grow by 2026?." https://www.iea.org/articles/how-rapidly-will-the-global-electricity-storage-market-grow-by-2026. Accessed: July 2022.

[4] G. Bolukbasi and A. S. Kocaman, "A prize collecting steiner tree approach to least cost evaluation of grid and off-grid electrification systems," *Energy*, vol. 160, pp. 536–543, 2018.

[5] D. Yang, P. Jirutitijaroen, and W. M. Walsh, "Hourly solar irradiance time series forecasting using cloud cover index," *Solar Energy*, vol. 86, no. 12, pp. 3531–3543, 2012.

[6] J. Luedtke, "A branch-and-cut decomposition algorithm for solving chance-constrained mathematical programs with finite support," *Math. Program.*, vol. 146, p. 219–244, 2014.

[7] P. Toufani, E. Nadar, and A. S. Kocaman, "Operational benefit of transforming cascade hydropower stations into pumped hydro energy storage systems," *Journal of Energy Storage*, vol. 51, p. 104444, 2022.

[8] H. Avci, E. Cigdem Karakoyun, A. Kocaman, E. Nadar, and P. Toufani, "Integration of pumped hydro energy storage and wind energy generation: Structural analysis and algorithms," 2021.

[9] B. S. Pali and S. Vadhera, "An innovative continuous power generation system comprising of wind energy along with pumped-hydro storage and open well," *IEEE Transactions on Sustainable Energy*, vol. 11, no. 1, pp. 145–153, 2020.

[10] J.-F. Toubeau, Z. De Grève, P. Goderniaux, F. Vallée, and K. Bruninx, "Chance-constrained scheduling of underground pumped hydro energy storage in presence of model uncertainties," *IEEE Transactions on Sustainable Energy*, vol. 11, no. 3, pp. 1516–1527, 2020.

[11] M. Ak, E. Kentel, and S. Savasaneril, "Quantifying the revenue gain of operating a cascade hydropower plant system as a pumped-storage hydropower system," *Renewable Energy*, vol. 139, pp. 739–752, 2019.

[12] I. Wilson, E. Barbour, T. Ketelaer, and W. Kuckshinrichs, "An analysis of storage revenues from the time-shifting of electrical energy in germany and great britain from 2010 to 2016," *Journal of Energy Storage*, vol. 17, pp. 446–456, 2018.

[13] A. Selin Kocaman, C. Abad, T. J. Troy, W. Tim Huh, and V. Modi, "A stochastic model for a macroscale hybrid renewable energy system," *Renewable and Sustainable Energy Reviews*, vol. 54, pp. 688–703, 2016.

[14] A. S. Kocaman, E. Ozyoruk, S. Taneja, and V. Modi, "A stochastic framework to evaluate the impact of agricultural load flexibility on the sizing of renewable energy systems," *Renewable Energy*, vol. 152, pp. 1067–1078, 2020.

[15] M. Aghamohamadi, A. Mahmoudi, and M. H. Haque, "Two-stage robust sizing and operation co-optimization for residential pv–battery systems considering the uncertainty of pv generation and load," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 2, pp. 1005–1017, 2021.

[16] O. Ekren, B. Y. Ekren, and B. Ozerdem, "Break-even analysis and size optimization of a pv/wind hybrid energy conversion system with battery storage – a case study," *Applied Energy*, vol. 86, no. 7, pp. 1043–1054, 2009.

[17] O. Ekren and B. Y. Ekren, "Size optimization of a pv/wind hybrid energy conversion system with battery storage using simulated annealing," *Applied Energy*, vol. 87, no. 2, pp. 592–598, 2010.

[18] L. Kuznia, B. Zeng, G. Centeno, and Z. Miao, "Stochastic optimization for power system configuration with renewable energy in remote areas," *Annals of Operations Research*, vol. 210, p. 411–432, 2013.

[19] A. Roy, S. B. Kedare, and S. Bandyopadhyay, "Optimum sizing of wind-battery systems incorporating resource uncertainty," *Applied Energy*, vol. 87, no. 8, pp. 2712–2727, 2010.

[20] P. Arun, R. Banerjee, and S. Bandyopadhyay, "Optimum sizing of photovoltaic battery systems incorporating uncertainty through design space approach," *Solar Energy*, vol. 83, no. 7, pp. 1013–1025, 2009.

[21] A. Kamjoo, A. Maheri, A. M. Dizqah, and G. A. Putrus, "Multi-objective design under uncertainties of hybrid renewable energy system using nsga-ii and chance constrained programming," *International Journal of Electrical Power Energy Systems*, vol. 74, pp. 187–194, 2016.

[22] D. A. Copp, T. A. Nguyen, and R. H. Byrne, "Optimal sizing of behind-the-meter energy storage with stochastic load and pv generation for islanded operation," in *2018 IEEE Power Energy Society General Meeting (PESGM)*, pp. 1–5, 2018.

[23] R. Xie, W. Wei, M. E. Khodayar, J. Wang, and S. Mei, "Planning fully renewable powered charging stations on highways: A data-driven robust optimization approach," *IEEE Transactions on Transportation Electrification*, vol. 4, no. 3, pp. 817–830, 2018.

[24] O. Sadeghian, A. Oshnoei, R. Khezri, and S. Muyeen, "Risk-constrained stochastic optimal allocation of energy storage system in virtual power plants," *Journal of Energy Storage*, vol. 31, p. 101732, 2020.

[25] A. Dolatabadi and B. Mohammadi-Ivatloo, “Stochastic risk-constrained optimal sizing for hybrid power system of merchant marine vessels,” *IEEE Transactions on Industrial Informatics*, vol. 14, no. 12, pp. 5509–5517, 2018.

[26] Y. Merzifonluoglu and E. Uzgoren, “Photovoltaic power plant design considering multiple uncertainties and risk,” *Annals of Operations Research*, vol. 262, pp. 153–184, 2018.

[27] O. Cavus, A. S. Kocaman, and O. Yilmaz, “A risk-averse approach for the planning of a hybrid energy system with conventional hydropower,” *Computers Operations Research*, vol. 126, p. 105092, 2021.

[28] A. Nazari and R. Keypour, “A two-stage stochastic model for energy storage planning in a microgrid incorporating bilateral contracts and demand response program,” *Journal of Energy Storage*, vol. 21, pp. 281–294, 2019.

[29] H. M. K. Al-Masri, S. K. Magableh, A. Abuelrub, O. Saadeh, and M. Ehsani, “Impact of different photovoltaic models on the design of a combined solar array and pumped hydro storage system,” *Applied Sciences*, vol. 10, no. 10, 2020.

[30] W. H. Reuter, S. Fuss, J. Szolgayová, and M. Obersteiner, “Investment in wind power and pumped storage in a real options model,” *Renewable and Sustainable Energy Reviews*, vol. 16, no. 4, pp. 2242–2248, 2012.

[31] O. O. Amusat, P. R. Shearing, and E. S. Fraga, “Optimal design of hybrid energy systems incorporating stochastic renewable resources fluctuations,” *Journal of Energy Storage*, vol. 15, pp. 379–399, 2018.

[32] J. Liu, J. Li, Y. Xiang, and S. Hu, “Optimal sizing of hydro-pv-pumped storage integrated generation system considering uncertainty of pv, load and price,” *Energies*, vol. 12, no. 15, 2019.

[33] P. D. Brown, J. A. PeÇas Lopes, and M. A. Matos, “Optimization of pumped storage capacity in an isolated power system with large renewable penetration,” *IEEE Transactions on Power Systems*, vol. 23, no. 2, pp. 523–531, 2008.

[34] H. M. K. Al-Masri, S. K. Magableh, A. Abuelrub, and K. Alzaareer, "Realistic coordination and sizing of a solar array combined with pumped hydro storage system," *Journal of Energy Storage*, vol. 41, p. 102915, 2021.

[35] J. Anagnostopoulos and D. Papantonis, "Simulation and size optimization of a pumped–storage power plant for the recovery of wind-farms rejected energy," *Renewable Energy*, vol. 33, no. 7, pp. 1685–1694, 2008.

[36] R. Hemmati, "Stochastic energy investment in off-gridrenewable energy hub for autonomousbuilding," *IET Renewable Power Generation*, vol. 13, pp. 2232–2239, 2019.

[37] M. Islam, B. K. Das, P. Das, and M. H. Rahaman, "Techno-economic optimization of a zero emission energy system for a coastal community in newfoundland, canada," *Energy*, vol. 220, p. 119709, 2021.

[38] O. H. Abdalla, L. SMIEEE, M. A. A. Adma, and A. S. Ahmed, "Two-stage robust generation expansion planning considering long- and short-term uncertainties of high share wind energy," *Electric Power Systems Research*, vol. 189, p. 106618, 2020.

[39] M. Kapsali, J. Anagnostopoulos, and J. Kaldellis, "Wind powered pumped-hydro storage systems for remote islands: A complete sensitivity analysis based on economic perspectives," *Applied Energy*, vol. 99, pp. 430–444, 2012.

[40] A. S. Kocaman, "Pompaj depolamalı hibrid enerji sistemi optimizasyonu - türkiye için vaka analizi," *Gazi Üniversitesi Mühendislik Mimarlık Fakültesi Dergisi*, vol. 34, no. 1, pp. 53 – 68, 2019.

[41] A. S. Kocaman and V. Modi, "Value of pumped hydro storage in a hybrid energy generation and allocation system," *Applied Energy*, vol. 205, pp. 1202–1215, 2017.

[42] S. Rehman, L. M. Al-Hadhrami, and M. M. Alam, "Pumped hydro energy storage system: A technological review," *Renewable and Sustainable Energy Reviews*, vol. 44, pp. 586–598, 2015.

[43] S. Ahmed and A. Shapiro, "Solving chance-constrained stochastic programs via sampling and integer programming," *INFORMS TutORials in Operations Research*, pp. 261–269, 2014.

[44] A. Charnes, W. W. Cooper, and G. H. Symonds, "Cost horizons and certainty equivalents: An approach to stochastic programming of heating oil," *Management Science*, vol. 4, no. 3, pp. 235–263, 1958.

[45] A. Prékopa, "On probabilistic constrained programming," in *Proceedings of the Princeton symposium on mathematical programming*, vol. 113, p. 138, Citeseer, 1970.

[46] A. Prékopa, "Stochastic programming," *Kluwer Academic Publishers*, 1995.

[47] B. K. Pagnoncelli, S. Ahmed, and A. Shapiro, "Sample average approximation method for chance constrained programming: theory and applications," *Journal of optimization theory and applications*, vol. 142, no. 2, pp. 399–416, 2009.

[48] J. R. Birge and F. Louveaux, *Introduction to stochastic programming.* Springer Science & Business Media, 2011.

[49] Q. Wang, Y. Guan, and J. Wang, "A chance-constrained two-stage stochastic program for unit commitment with uncertain wind power output," *IEEE transactions on power systems*, vol. 27, no. 1, pp. 206–215, 2011.

[50] J. Luedtke and S. Ahmed, "A sample approximation approach for optimization with probabilistic constraints," *SIAM Journal on Optimization*, vol. 19, no. 2, pp. 674–699, 2008.

[51] J. Luedtke, S. Ahmed, and G. L. Nemhauser, "An integer programming approach for linear programs with probabilistic constraints," *Mathematical programming*, vol. 122, no. 2, pp. 247–272, 2010.

[52] S. Küçükyavuz, "On mixing sets arising in chance-constrained programming," *Mathematical programming*, vol. 132, no. 1, pp. 31–56, 2012.

[53] S. Sen, "Relaxations for probabilistically constrained programs with discrete random variables," *Operations Research Letters*, vol. 11, no. 2, pp. 81–86, 1992.

[54] D. Dentcheva, A. Prékopa, and A. Ruszczynski, "Concavity and efficient points of discrete distributions in probabilistic programming," *Mathematical programming*, vol. 89, no. 1, pp. 55–77, 2000.

[55] P. Beraldi and A. Ruszczyński, "A branch and bound method for stochastic integer problems under probabilistic constraints," *Optimization Methods and Software*, vol. 17, no. 3, pp. 359–382, 2002.

[56] P. Beraldi and A. Ruszczyński, "The probabilistic set-covering problem," *Operations Research*, vol. 50, no. 6, pp. 956–967, 2002.

[57] Y. Song and J. R. Luedtke, "Branch-and-cut approaches for chance-constrained formulations of reliable network design problems," *Mathematical Programming Computation*, vol. 5, no. 4, pp. 397–432, 2013.

[58] M. Zhang, S. Küçükyavuz, and S. Goel, "A branch-and-cut method for dynamic decision making under joint chance constraints," *Management Science*, vol. 60, no. 5, pp. 1317–1333, 2014.

[59] A. Shapiro, D. Dentcheva, and A. Ruszczynski, *Lectures on stochastic programming: modeling and theory*. SIAM, 2021.

[60] R. M. Van Slyke and R. Wets, "L-shaped linear programs with applications to optimal control and stochastic programming," *SIAM journal on applied mathematics*, vol. 17, no. 4, pp. 638–663, 1969.

[61] J. F. Benders, "Partitioning procedures for solving mixed-variables programming problems," *Computational Management Science*, vol. 2, no. 1, pp. 3–19, 2005.

[62] B. Zeng, Y. An, and L. Kuznia, "Chance constrained mixed integer program: Bilinear and linear formulations, and benders decomposition," *arXiv preprint arXiv:1403.7875*, 2014.

[63] X. Liu, S. Küçükyavuz, and J. Luedtke, "Decomposition algorithms for two-stage chance-constrained programs," *Mathematical Programming*, vol. 157, no. 1, pp. 219–243, 2016.

[64] J. Garcia-Gonzalez, R. M. R. de la Muela, L. M. Santos, and A. M. Gonzalez, "Stochastic joint optimization of wind generation and pumped-storage units in an electricity market," *IEEE Transactions on Power Systems*, vol. 23, no. 2, pp. 460–468, 2008.

[65] A. Moreno-Munoz, J. De La Rosa, R. Posadillo, and V. Pallares, "Short term forecasting of solar radiation," in *2008 IEEE International Symposium on Industrial Electronics*, pp. 1537–1541, IEEE, 2008.

[66] G. Reikard, "Predicting solar radiation at high resolutions: A comparison of time series forecasts," *Solar energy*, vol. 83, no. 3, pp. 342–349, 2009.

[67] L. Martín, L. F. Zarzalejo, J. Polo, A. Navarro, R. Marchante, and M. Cony, "Prediction of global solar irradiance based on time series analysis: Application to solar thermal power plants energy production planning," *Solar Energy*, vol. 84, no. 10, pp. 1772–1781, 2010.

[68] G. E. Box, G. M. Jenkins, G. C. Reinsel, and G. M. Ljung, *Time series analysis: forecasting and control*. John Wiley & Sons, 2015.

[69] "Republic of turkey energy market regulatory." https://www.epdk.gov.tr/. Accessed: July 2022.

[70] "Homer energy." " http://www.homerenergy.com/. Accessed: July 2022.

[71] A. S. Kocaman, *Essays on infrastructure design and planning for clean energy systems*. Columbia University, 2014.