BI-OBJECTIVE OPTIMIZATION OF GRID-CONNECTED DECENTRALIZED ENERGY SYSTEMS

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Onur Altıntaş

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Bi-Objective Optimization of Grid-Connected Decentralized Energy Systems

By Onur Altıntaş

July 2016

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 Karsu(Advisor)

Ayşe Selin Kocaman (Co-advisor)

Oya Karaşan

Gülşah Karakaya

Approved for the Graduate School of Engineering and Science:

Levent Onural
Director of the Graduate School

ABSTRACT

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Onur Altıntaş
M.S. in Industrial Engineering
Advisor: Özlem Karsu, Ayşe Selin Kocaman (Co-advisor)
July 2016

We present a bi-objective two stage stochastic programming model for optimal sizing of a grid-connected hybrid renewable energy system. In this system, solar and wind are the main electricity generation resources. National grid is assumed to be a carbon-intense alternative to renewables and used as a backup source to ensure reliability. Storage device is included to examine its role in reducing the carbon emission and the intermittency of renewable sources. It is assumed that decision maker is sensitive to both cost and carbon emission, therefore two objectives are considered: total cost and carbon emission caused by electricity purchased from the utility grid. A simulation optimization algorithm has been developed for the problem.

Keywords: Multi-objective Optimization, Simulation, Renewable Energy Systems, CO_2 emission, Stochastic Mixed Integer Programming.

ÖZET

ŞEBEKEYE BAĞLI MERKEZİ OLMAYAN ENERJİ SİSTEMLERİNİN İKİ AMAÇLI OPTİMİZASYONU

Onur Altıntaş
Endüstri Mühendisliği, Yüksek Lisans
Tez Danışmanı: Özlem Karsu, Ayşe Selin Kocaman
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Bu çalışmada şebekeye bağlı, hibrit yenilenebilir enerji sisteminin iki amaçlı-iki aşamalı rassal modellemesi sunulmaktadır. Bu sistemde başlıca temiz enerji kaynakları güneş ve rüzgardır. Elektrik şebekesi karbon yoğunluğu fazla olan bir alternatif olarak değerlendirilmekle birlikte, sistemin güvenilirliği için gerektiğinde yedek kaynak görevini üstlenmektedir. Karbon salınımı ve yenilenebilir enerji kaynaklarının aralıklılığını azaltmadaki rolünü incelemek için batarya hücreleri sisteme dahil edilmiştir. Bahsedilen sistemde karar vericinin hem maliyet hem de karbon salınımı konusunda hassas olduğu varsayılarak iki amaç göz önüne alınmıştır: Toplam maliyet ve şebekeden satın alınan elektriğin karbon salınımı. Problemin çözümü için yeni bir benzetim en iyileme algoritması geliştirilmiştir.

Anahtar sözcükler: Çok Amaçlı Eniyileme, Benzetim, Yenilenebilir Enerji Sistemleri, CO_2 salınımı, Rassal Karma Tamsayılı Programlama.

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Chapter 1

Introduction

Global warming has become not only one of the most concerning issues of the 21st century but also will be the issue of the following centuries. It is known that the main reason of global warming is the increase in greenhouse gases emissions. The latest Intergovernmental Panel on Climate Change (IPCC) report in 2013 asserted that it is extremely likely that the human influence has been the dominant cause of the observed warming since the mid-20th century [1]. Fossil fuel use, deforestation, biomass burning, fertilizer use and land clearing are some of the human activities that emit key greenhouse gases. Among all greenhouse gases, carbon dioxide (CO_2) is the most effective driver of global warming. Even though other gases have more potent heat-trapping ability compared to CO_2, rate of increase in CO_2 emission is higher than any other human caused greenhouse gases. Also, CO_2 can last for centuries in the atmosphere, which means that even if human caused emission could be stabilized today, Earth would continue to warm for centuries because of the CO_2 residual in the atmosphere [2]. Since Industrial Revolution, human related activities, especially fossil fuel usage, have raised CO_2 levels from 280 parts per million (ppm) to 400 parts per million [3]. According to National Oceanic and Atmospheric Administration (NOAA), the rate of increase has accelerated, since first measurements on CO_2 level were taken, from 0.7 ppm to 2.1 ppm per year within last 10 years [4]. Unless immediate precuations are taken to diminish the effect of global warming, greenhouse effect will cause further warming and irreversible changes in climate system [5].

In 1992, United Nations Framework Convention on Climate Change (UNFCCC) was held in order to discuss possible ways of preventing global warming and increasing awareness on climate change. In this convention, any binding goal for stabilizing greenhouse gases emission has not been set. However, it still disclosed the necessity of intervention. Even though developed countries were opposed to any intervention that might jeopardize their economies, 196 developed countries agreed on Kyoto Protocol in 1997. With this treaty, countries had an individual cap on emission on the greenhouse gases. Each country has to cut its greenhouse gas emission by 8-10%. It was anticipated that this initiative would provide a total decrease of 5% in greenhouse gases emission [6].

There are three main emission reduction mechanisms utilized in Kyoto Protocol, which are Carbon Pricing, the Clean Development Mechanism (CDM) and Joint Implementation. Carbon pricing is the method in which emitters are obliged to pay the price for the right of emitting one tonne of CO_2 into the atmosphere [3]. Carbon prices are determined by either commitment on price of carbon or commitment on emission limit (i.e. quota on emission).

Quota on emission mechanism, called cap-and-trade or emission trading, was constructed on an international scale in Kyoto Protocol. Afterwards, countries implemented this mechanism nationwide to satisfy their portion in the protocol. It works in a way that companies, which can stay below that quota can sell their surplus allowance to other companies, which need more allowance. In such a system, the price of unit carbon emission is variable. As a result of this, it creates a new open market for carbon emission where prices are determined accordingly. In short supply of allowance, carbon price of permits will be high. This way, companies are motivated to decrease their emission levels to benefit from selling surplus allowance.

Another commonly used mechanism is carbon tax. In this system, carbon prices are determined by authorities in advance; therefore there is no uncertainty on the price and it is directly linked to carbon emission. In principle, all sources of carbon emission are taxed depending on proportion of carbon they possess. The carbon price is a sign for economy to adjust itself to projected emission level. Hence, projected emission level can be obtained imprecisely compared to cap-and-trade policy [7]. Implementation of carbon pricing policies has a significant effect on energy sector to shift electricity production on renewable resources. In cap-and-trade system, renewable energy generators can take advantage of the high carbon prices. In carbon tax, green energy producers are promoted by tax deduction and elevated sale price for generated electricity.

Burning fossil fuels constitute about 90% of human produced CO_2 emissions [8]. In the United States, electricity and heat generation sector, which is the largest source of the U.S. greenhouse gas emission, is accounted for 30% of the total carbon dioxide emission [9]. The reason of this high carbon emission rate is that electricity generation mostly depends on centralized energy systems, which use fossil fuels as primary energy resource. Centralized energy systems are based on centralized network of electricity generation and distribution. In such a system, electricity is produced in large-scale (thermal power) plants and distributed to end user. If we consider the growth of the world population, we can foresee that need for electricity will increase rapidly. Ravindranath and Sathaye, assert that greenhouse gas mitigation can be reduced to a large extent if we make appropriate shifts towards energy efficient technologies and substitute fossil fuel with renewable energy resources [10].

In this regard, most countries promote decentralized systems, which rely on renewable resources in order to decrease carbon emission levels and their dependence to depleting fossil fuel reserves. From the end of 2004, capacity of decentralized systems grew at rates of 10-60% annually. In 2010, a third of the recently built power generation systems is constituted by decentralized systems [11]. Decentralized systems mostly have to be located in areas where renewable sources are available. Such systems can be either grid-connected or stand-alone.

Stand-alone systems are mostly located in remote places where grid network cannot penetrate. These systems have drawbacks such as low generation capacity due to intermittency of renewable resources, energy spillage due to low energy storage capacity and high storage costs. On the other hand, grid-connected decentralized systems can be built in large-scales as they are connected to the main grid network. Such systems must be close to the grid in order to be connected with the network. This connection enables system to purchase electricity from grid network when renewable energy is not sufficient enough to meet the demand. In other words, in decentralized grid-connected system, grid acts like storage device with unlimited capacity [12]. Moreover, such systems can feed electricity to grid. In this way, loss of energy due to spillage is eliminated.

There are different renewable energy resources that can be utilized to decrease carbon emission level. They include hydropower, solar energy, wind power, biomass, biofuel, tidal power, geothermal and wave power. Wind, solar and hydroelectricity are emerging renewable resources. For wind power and many other renewable technologies, the capacity growth accelerated in 2009 relative to the previous four years [13]. More wind power capacity was added during 2009 than any other renewable technology. However, grid-connected PV increased the fastest of all renewables technologies, with a 60% annual average growth rate [13]. All of these advancements demonstrate that there is a trend in investments on renewable energy systems, especially on wind and solar power systems.

One of the main obstacles of shifting to renewable energy systems is that these resources have intermittent availabilities. Due to intermittency, storage systems should be used along with the renewable energy system. In the current state of technology, these energy systems based on renewable resources have high installation costs and variable generation due to stochastic nature of availability. Therefore, the generated electricity has high costs, although it is based on clean energy production. The electricity that is supplied by the grid is often produced in large-scale thermal power plants using the advantages of economies of scale and hence is less costly to use. However, since it is generated using fossil fuels, it is associated with high levels of CO_2 emission and thus harms the environment.

Policy makers and energy investors will have to make decisions on how an envisaged energy system will satisfy demand; using either fossil fuel resources, which are less expensive but associated with high CO_2 emission or renewable resources with high investment cost and low carbon emission. As decentralized systems are considered, demand satisfaction can rely on partly fossil fuels and partly renewable resources depending on the scale of the system. High investment amount on renewables has potential to produce more green electricity and this mitigates the need of electricity purchased from the grid. However, the investment decision is a complex one since multiple factors should be considered such as availability of renewable resources, component types and carbon pricing. This complexity reveals the need for a decision support system that determines the scale of the energy production facilities.

Motivated by the interest in shifting from fossil fuel to renewable resources to mitigate emissions, in this thesis, we investigate optimal sizing decision of grid-connected decentralized system. The main aim of this study is to model grid-connected decentralized system in a realistic way so that decision makers can gain insight about scale of the system that they plan to build. In our setting, we assume that decision maker is both sensitive to cost and carbon emission. Therefore, we take into account the multiple criteria that the decision maker will be considering when making his decision and would allow him to see the tradeoff between cost and CO_2 emission levels.

The rest of this thesis is organized as follows: In Chapter 2, we review the literature of grid-connected and stand-alone decentralized energy systems and the solution methodologies used for infrastructure planning problems of such systems. In Chapter 3, we introduce our problem setting in detail. In Chapter 4, we present a bi-objective two-stage stochastic programming model of the system along with its single scenario and multi scenario analysis. In Chapter 5, we propose a simulation optimization algorithm and discuss its performance. The final chapter, Chapter 6, includes the concluding remarks.

Chapter 2

Literature Review

In this chapter, studies on decentralized energy systems will be reviewed. Also, solution methodologies applied on the sizing problem of such systems will be discussed.

With the awareness of global warming, the interest in decentralized energy systems which mostly work with renewable energy sources has increased in the literature. Jebaraj and Iniyan [14] and Hiremath et al. [15] have published reviews on energy models in general and decentralized energy planning models and their applications respectively. Most of the decentralized energy systems include more than one type of energy resource and these systems are called hybrid energy systems. Hybrid energy systems can consist of alternative sources such as renewables, conventional sources such as coal, natural gas or diesel generator and energy storage components such as battery bank or fuel cells. Although each of these components has some drawbacks individually, these can be alleviated by the strength of another energy source so that using both or multiple of them gives much reliable output. To illustrate, despite the unpredictable availability of alternative energy sources like solar and wind, usually, they present complementary patterns [16].

Kaundinya et al. [12] have reviewed stand-alone (SA) and grid-connected

(GC) decentralized systems and investigated their operational differences. Grid-connected decentralized systems and stand-alone decentralized systems are studied from various perspectives. Different solution approaches such as mathematical programming, optimization and simulation are commonly utilized in decentralized system modelling problems [17]. While modelling a decentralized system, there are lots of decision variables that have to be considered. This increases the computational effort to solve these problems as a result, the popularity of heuristic and metaheuristic solution approaches increases. Genetic algorithm (GA), particle swarm optimization (PSO) are the evolutionary algorithms that are mostly utilized in the literature both for single objective and multi-objective problems.

Genetic algorithm (GA) is an optimization method, which is inspired by the genetic process of biological organisms [18]. Complex real life problems can be solved by imitating this process. The main advantage of GA is that it can easily find a local optimum and is capable of finding the global optimum. This algorithm is one of the most suitable algorithms for optimal sizing problems, since it is suitable for coding almost infinite number of parameters. On the other hand, this algorithm is hard to implement due to its complexity. Also, the computation time of this algorithm increases significantly by the increase in the number of parameters.

Particle swarm optimization (PSO) is an optimization technique inspired by the social behavior of fish schooling or birds flocking. Particle swarm is the system model or social structure of basic creature which makes a group to have some purpose such as food searching. PSO has an advantage over GA, since it can be coded with few equations and it is easy to implement. Therefore, the computation time is short and it requires few memory [19]. On the other hand, only less than three objectives can easily be modeled with this technique. Also, it is more difficult to obtain global optimum solution by using PSO. It is hard to code PSO for more than three objectives. Multi-objective version of this method (MOPSO) is also commonly used.

The summary of the literature review can be found in Table 2.1.

In general, decentralized energy systems are divided into two categories based on their extent [12]. Depending on the area of interest, these systems can be either stand-alone or grid-connected. Stand-alone (SA) systems are more preferred when demand point is isolated and grid cannot penetrate. For such locations, renewable energy systems can be preferable. These systems are not connected to the grid and as a result of this, they require storage devices to store energy for future use when demand exceeds the production. Due to the intermittency of renewable resources, high storage capacities may be required. It is possible to operate such systems with relatively small storage units however, in this case, excess energy cannot be used to satisfy future demand and has to be spilled. As a result, local demand determines both the production and storage capacity of a stand-alone system. Most of the papers on hybrid renewable energy system (HRES) design and optimization are focused on stand-alone HRESs [20–36] rather than grid-connected systems [37–45]. These studies are conducted on stand-alone decentralized systems, which consist of one or more renewable energy system components such as wind turbine generators, solar panels, battery cells, diesel generators, hydro and biomass power plant and fuel cells.

In Xu et al. [20], optimal sizing of stand-alone hybrid wind and power systems were modeled using genetic algorithms. In this model, the total capital cost was minimized while loss of power supply probability was bounded by a limit. Time horizon was taken as one year with one hour time step. Genetic algorithm (GA) was used to solve the model and their studies proved that GA converges well.

Koutroulis et al. [21] worked on designing a stand-alone hybrid system with solar panels, wind turbines and batteries with the objective of minimizing total cost. The main purpose of the model was to present the optimal system configuration among a list of commercially available system devices. The model was solved using genetic algorithm. The proposed method was applied to residential household and the result showed that using solar and wind resources together leads to lower system cost compared to exclusive usage of one energy source.

Senjyu et al. [22] presented optimal configuration fo power generating systems in isolated island with renewable energy. The system consists of solar panels, wind turbine generators, batteries and diesel generators. The proposed method was used to determine the optimum number of panels, wind turbine generators and batteries. Using this method, operational costs could be decreased by 10 percent compared to cost generated when local demand is satisfied by only diesel generators.

Yang et al. [23] studied the design of stand-alone energy systems, which consist of solar, wind and battery cells. Required loss of power supply probability (LPSP) was also taken into account while minimizing the annualized cost of the system. Genetic algorithm was used to find the optimal configuration.

Kaviani et al. [24] proposed a study which analyzes an optimal design of stand-alone hybrid renewable energy system with component outages. There were three major components of the system, which are solar panels, wind turbine generators and fuel cells. In this study, solar radiation, wind speed, and demand data were assumed to be entirely deterministic. An advanced variation of Particle Swarm Optimization algorithm is used to minimize annualized system cost. As a result of this study, it was observed that the reliability of the AC/DC converter is an upper limit for the system's reliability.

Belfkira et al. [25] presented a sizing optimization method for a stand-alone hybrid wind-solar-diesel energy system. A deterministic global optimization algorithm (DIRECT) [46] was used to minimize the total system cost while guaranteeing the availability of the energy. A comparison between the total cost of the hybrid system with and without batteries was represented. The results revealed the positive impact of battery storage on total cost.

Kaabeche and Ibtiouen [26] studied on a stand-alone system setting where local demand must be totally met. They tried to optimize the capacity sizes of stand-alone systems with different components such as solar panels, wind turbines, battery units and diesel generators. The objective of the study was to determine the optimal configuration based on minimization of cost. As a result of the study, they found out that a stand-alone system with solar/wind/diesel and battery is more economically viable compared to solar/wind/battery system or diesel generator only.

Askarzadesh and dos Santos Coelho [27] developed a model for a stand-alone system that determines three decision variables, namely, total area occupied by solar panels, total swept area of wind turbine blades and the number of batteries. Optimal values for these variables were found using PSO and some of its variants were proposed.

Ekren and Ekren [28] used simulated annealing method for optimization of a hybrid system with solar panels, wind turbines and battery storage. Simulated annealing is a heuristic approach that uses stochastic gradient search approach for optimization. The probabilistic distribution functions for solar radiation, wind speed and electricity demand were fitted for each hour of a day employing ARENA simulation software. The objective function was minimizing the total energy cost and decision variables are the solar panel area, wind turbine rotor swept area and battery capacity. A case study was presented for a campus area. Results from simulated annealing were compared with the results of their earlier study which were based on the Response Surface Methodology (RSM) [47] and it was shown that simulated annealing performs better than RSM.

Bashir and Sadeh [29] highlighted the importance of uncertainty of wind and solar resources for capacity sizing problem. They developed an algorithm to determine the capacity of the system with wind turbine, solar panel and battery while meeting a certain load. The objective was minimizing the cost while ensuring that a predetermined reliability level is satisfied. Their proposed method considered uncertainty in energy generation. The uncertainty in wind and solar power generation was assessed using the Monte Carlo simulation technique. The particle swarm optimization method was exploited to find the optimal component sizes.

One of the most commonly used methods in the field of energy planning, is Strength Pareto Evolutionary Algorithm (SPEA). This method was applied to a stand-alone hybrid system for the first time by Bernal-Agustin et al. [30]. The problem that they studied was bi-objective, in which the objectives were minimizing the total cost and the pollutant emissions respectively. The hybrid system to be designed includes photovoltaic panels, wind turbines and diesel generators. In 2008, Dufo-Lopez and Bernal-Agustin [31] used the same evolutionary algorithm along with a genetic algorithm (GA) as a solution approach. Three objectives are simultaneously minimized which are total cost, pollutant emissions and unmet load. In the study, SPEA was utilized to organize the components of the system. The secondary algorithm was a GA that determines the control strategy.

Katsigiannis et al. [32] used the NSGA-II multi-objective algorithm to design a system which consists of solar panels, wind turbines, fuel cells, diesel generators and batteries. There are two objectives considered in the study which are minimization of cost of energy and greenhouse gas (GHG) emission. The results of numerical study showed that solar-wind-battery is the most attractive combination in terms of cost and environmental standpoint.

Zhao et al. [33] proposed an optimal unit sizing method for stand-alone systems, which consist of solar panels, wind turbines, battery storage units and diesel generators. The proposed method is based on genetic algorithm. Three objectives are considered, which are the minimization of life-cycle cost, the maximization of renewable energy source penetration and the minimization of pollutant emissions. In this study, component sizes and operation strategy are optimized jointly.

Sharafi and ELMekkawy [34] combined a multi-objective optimization method (PSO algorithm) with a simulation tool which works like ε-constraint. This hybrid method was used to model the renewable system consisting of wind turbine, solar, diesel generator, batteries, fuel cell and hydrogen tank. The ε-constraint method has been applied to minimize the total cost of the system, unmet load and fuel emission. Also, PSO-simulation based method has been used to generate non-dominated design solutions. A sensitivity analysis was conducted to see the impact of reduced lifetime of batteries on system cost. Then, Sharafi and ELMekkawy [35] proposed a dynamic multi-objective particle swarm optimization (DMOPSO) method and compared the results of both methods.

Maheri [36] developed a multi-objective optimization method for design under uncertainty of a stand-alone wind-solar-diesel hybrid system. The probabilistic analysis was used to quantify the system reliability since there are uncertainties in the availability of renewable resources and electricity demand. The uncertainties were tackled by fitting uniform distribution functions to all random parameters. The proposed method consists of two algorithms. One of them was used to find most reliable system under cost constraint. Another one is the most cost-effective system under reliability constraint.

Grid-connected (GC) systems are more flexible compared to stand-alone systems. In GC systems the ineraction with the grid is in both directions: excess electricity can be fed to the grid, also, in case of shortage to satisfy local demand, electricity can be purchased from the grid. Correspondingly, a grid-connected decentralized system can be utilized in two different ways. A GC system can be used to meet local demand using renewable energy. In such cases, the system does not have to rely on storage units to meet the local demand. When renewable resources are unavailable, grid electricity can be purchased to meet the demand. Therefore, there might not be a motivation to use a storage unit. Another way of operating the grid-connected system is generating and feeding electricity to the grid in the same way as large electricity power plants without paying attention to local demand. Therefore, the scale of the GC decentralized system can be independent from the local demand.

Ardakani et al. [37] proposed a grid-connected hybrid solar/wind energy system with battery units. PSO algorithm was used to find the optimal sizing of system components whilst minimizing the total cost. They modeled the problem in a deterministic way and left investigation of uncertainty as future work.

A technical and economic model for the design of a grid-connected solar-battery system is proposed by Bortolini et al. [38]. The local demand is satisfied using solar energy and the national grid is utilized as backup source in the setting. The purpose of this study is to analyze the proposed model, which determines optimal rated power for solar panels along with storage capacity at minimum levelized cost of energy. Several scenarios were tested for different solar rated power and capacity of batteries. As a result of this study, with optimal configuration, levelized energy cost can be reduced about 24.5% compared to the grid electricity price.

The study by González et al. [39] focused on the optimal sizing of hybrid grid-connected solarwind power systems and genetic algorithm was used as a solution methodology. The importance of using real hourly wind and solar irradiation data and electricity demand is highlighted in the paper. They also utilized real data of a rural township in Catalonia, Spain. The results suggest that integration of HRES can save up to 40% of present cost structure throughout the next 25 years.

Kuznia et al. [40] proposed a two-stage stochastic mixed integer programming model for a hybrid power system design, with wind turbines, storage device, transmission network, and thermal generators. They used Benders' decomposition algorithm to find a set of solutions. They assume that the circulation of energy in storage device is one day. This assumption eases the problem however, causes the importance of supply shifting to be neglected.

A methodology has been proposed by Chedid and Rahman [41] which finds the optimal design of a decentralized system whose electricity generation depends on solar and wind resources. Storage devices and diesel generators are also utilized in the system as backup sources. In this study, they analyzed both stand-alone (autonomous) and grid-connected versions of the system. The proposed analysis employs linear programming techniques to minimize the average production cost of electricity and takes environmental factors into consideration both in the design and operation phases.

Wang and Singh [42] proposed a multi-criteria design setting of grid-connected hybrid renewable energy system. This system consists of solar panels, wind turbines and battery units with connection to the grid. In this setting, differently, generated excess electricity cannot be fed back to the grid rather it has to be spilled, which hinders the system to have large component sizes. Three conflicting objectives were considered in this problem, which are minimizing cost, emission and maximizing reliability (ratio of meeting demand by renewables) of the system. A multi-objective particle swarm optimization (MOPSO) algorithm has been developed and used to derive a set of non-dominated solutions.

Perera et al. [43] proposed a multi-objective optimization technique to determine the optimal design of grid-connected hybrid solar-wind energy system with storage. Steady state ε-Multi objective optimization [48] was used as the multi-objective optimization technique which is based ε-dominance method [49]. This technique was utilized to find optimal component sizes with minimum levelized energy cost and level of grid integration. Sensitivity analysis was conducted for cost of component and cost of grid electricity. Results obtained from the multi-objective optimization shows that levelized energy cost decreases when moving from stand-alone mode to grid-connected mode.

Sharafi et al. [44] proposed a simulation based DMOPSO model for optimal sizing of a grid-connected hybrid renewable energy system for residential buildings. Three objective functions, which are minimizing total net present cost and CO_2 emission, were utilized. The system consists of a heat pump, a biomass boiler, wind turbines, solar heat collectors, solar panels and a heat storage tank. Also, plug-in electric vehicles were included in the system so that vehicles could be charged using renewable energy. Proposed model was applied on an existing residential apartment in Canada and results are compared against two multi-objective optimization algorithms, which are multi-objective GA and MOPSO. Quality of Pareto front was analyzed and sensitivity analysis on parameters was performed to investigate their impact on net present cost. In this work, uncertainty in renewable resource availability was not taken into account.

Sharafi and ElMekkawy [45] included stochasticity of renewable resources and variability in demand to the system which they proposed in [44]. Simulation module, DMOPSO algorithm and sampling average technique were utilized to approximate a Pareto front. Three objectives were utilized which are maximizing renewable energy ratio, minimizing total net present cost and fuel emission. Also, loss of load probability was taken into consideration. Randomness was incorporated in parameters were generated using synthetic data generation techniques.

Stochastic and deterministic Pareto fronts were compared and sensitivity analysis was conducted.

Decentralized system design projects involve multi-objectives that are conflicting with each other such as cost and pollution minimization. There are some studies which consider these trade-offs and use multi-objective metaheuristics such as MOPSO, SPEA and GA to solve their problems [30–35, 41, 42].

In recent years, there is a growing interest in the field of renewable energy systems. Due to the variability and intermittency of renewable resources, modelling systems with renewable resources is a challenging task. Therefore, in most of the optimal design of decentralized energy system model, intermittent resources like wind and solar are modeled using hourly average values for their availabilities [20, 21, 24–26, 30–35, 41–44]. Representing intermittent sources with their average availabilities cause to overstate their value and they are considered as if they are incredibly productive [50, 51]. Also, the variability and trend in their availabilities cannot be captured by averages. Therefore, there is no way to gain valuable and realistic insights from models that use average values for intermittent sources.

Some studies in literature do not include uncertainty of these resources. These studies mostly use one year of hourly data to capture seasonality and trends in resource availabilities [22, 23, 27, 33, 37–39, 45].

Additionally, Bashir and Sadeh stated [29] that considering uncertainty in renewable energy generation will create a more realistic view of reliability and cost. Powell et al. highlights the importance of modelling uncertainty of renewable resources and clarifies the problems that are commonly encountered while modelling uncertainty by giving examples [50]. Bashir and Sadeh determined the best probability density function for wind and solar resource availabilities every two-hour data. Also, Ekren and Ekren [28] fitted random distribution to availabilities for each hour of the months. They both utilized these probability distributions to sample random parameters and used them in their simulation models. When simulation is run several times, they were able to analyze the outputs statistically. Each data point in resource availability data is correlated with an another one. This kind of approach, however, causes each data point in time series to be independent from each other.

In Kuznia et al. [40], the optimal design problem was modeled using two-stage stochastic mixed integer programming. Due to the complexity of the problem, one year of wind speed data was decomposed into a set of seasons where wind speed can be considered constant. Then, the problem was solved using the variant of Benders' decomposition method. Even in this case, real life decision making process cannot be captured because mathematical model was able to see future within a spesific scenario [50].

In Sharafi and ElMekkawy [45], multi-objective nature of the problem and stochasticity of renewable resources were considered in their setting. Additionally, they utilized simulation module to mimic real-life decisions. Optimal design decisions were made using a meta-heuristic algorithm (DMOPSO). The stochasticity of renewables were handled using sampling average method.

To sum up, the two aspects that make these optimal design problem complex (multi-objective nature and stochastic nature) should be considered in order to obtain more realistic results. Yet, to the best of our knowledge, there is only one study [45] in the literature that consider a multi-objective design problem of a grid-connected decentralied energy system while handling uncertainty related to renewable resources. This thesis aims to contribute the literature by focusing on bi-objective optimization of grid-connected decentralized energy systems where renewable resource availabilities are assumed to be uncertain.

Table 2.1: Summary of Literature Review

Authors	System Components: Solar Panel	Wind Turbine	Fuel Cell	Biomass	Storage	Diesel Generator	SA/GC	Stoch	MOP	Objective Function	Method
Xu et al. [20]	•	•			•		SA	No	No	Min. Total cost	GA
Koutroulis et al. [21]	•	•					SA	No	No	Min. Total cost	GA
Senjyu et al. [22]	•	•			•	•	SA	No	No	Min. Total cost	GA
Yang et al. [23]	•	•			•		SA	No	No	Min. Annualized system cost	GA
Kaviani et al. [24]	•	•	•				SA	No	No	Min. Annualized system cost	PSO
Belfkira et al. [25]	•	•				•	SA	No	No	Min. Total cost	DIRECT algorithm
Kaabeche and Ibtiouen [26]	•	•			•	•	SA	No	No	Min. Total cost	PSO
Askarzadeh and dos Santos Coelho [27]	•	•			•		SA	No	No	Min. Life-cycle cost	Weight-based PSO
Bashir and Sadeh [29]	•	•			•		SA	Yes	No	Min. Annualized system cost	Simulation
Ekren and Ekren [28, 47]	•	•			•		SA	Yes	No	Min. Total cost	RSM, Simulated annealing
Bernal-Agustin et al. [30]	•	•				•	SA	No	Yes	Min. Total cost Min. Pollutant emission	SPEA
Dufo-Lopez and Bernal-Agustin [31]	•	•			•	•	SA	No	Yes	Min. Total cost Min. Pollutant emission Min. Unmet load	SPEA & GA
Katsigiannis et al. [32]	•	•	•		•	•	SA	No	Yes	Min. Cost of energy Min. Pollutant emission	NSGA-II
Zhao et al. [33]	•	•			•	•	SA	No	Yes	Min. Life-cycle cost Max. Renewable penetration Min. Pollutant emission	GA
Sharafi and ELMekkawy [34, 35]	•	•			•	•	SA	No	Yes	Min. Total cost Min. Unmet load Min. Fuel emission	MOPSO, DMOPSO
Maheri [36]	•	•				•	SA	Yes	Yes	Min. Levelized cost of energy Max. Reliability	Multi-objective opt.
Ardakani et al. [37]	•	•			•		GC	No	No	Min. Total cost	PSO
González et al. [39]	•	•					GC	No	No	Min. Life-cycle cost	GA
Bortolini et al. [38]	•				•		GC	No	No	Min. Levelized energy cost	Simulation
Kuznia et al. [40]		•			•	•	GC	Yes	No	Min. Total cost	SMIP
Chedid and Rahman [41]	•	•			•	•	SA/GC	No	Yes	Min. Average production cost Min. Pollutant emission	LP based algorithm
Wang and Singh [42]	•	•			•		GC	No	Yes	Min. Cost Max. Reliability Min. Pollutant emission	MOPSO
Perera et al. [43]	•	•			•		GC	No	Yes	Min. Levelized energy cost Min. Level of grid integration	Steady state ε-multi objective optimization
Sharafi et al. [44]	•	•		•	•	•	GC	No	Yes	Min. Total net present cost Max. Renewable energy ratio Min. CO_2 emission	DMOPSO
Sharafi and ELMekkawy [45]	•	•		•	•	•	GC	Yes	Yes	Min. Total net present cost Max. Renewable energy ratio Min. Fuel emission	DMOPSO, Sampling average

Chapter 3

Problem Definition

There is a global trend of shifting electricity generation from fossil fuel dependent systems to renewable systems. However, the investment decisions on renewable systems are complex decisions due to challenges such as high costs of generating renewable energy and intermittency of renewables. For a carbon sensitive decision maker, this investment decision is even harder since the scale of the renewable system not only affects cost but also affects the level of carbon emission.

On one hand, there is the option of relying fully on fossil fuel based energy, i.e. electricity from the grid, which incurs less cost but results in high emission. On the other hand, there is another option of making high investment in renewables, which is ideal for emission minimization. It is acknowledged that there will be intermediate solutions between these two extreme solutions. In these intermediate solutions, demand satisfaction will rely partly on renewables and partly on the grid. Depending on the scale of the decentralized system, the same demand level can be satisfied with different amount of carbon emissions at different system costs. Therefore, this problem requires a decision support system which is based on optimization model to determine investment amount. Also, this model should incorporate multiple criteria that a carbon-sensitive investor will be considering when making his decisions, namely cost and emission.

In this study, we consider a framework in which a decision maker plans to invest in a decentralized system where the demand point (such as a village, a campus) is already connected to the grid network, which is assumed to supply carbon-intense energy at a low price. The projected decentralized system is a hybrid renewable energy system which consists of solar and wind power systems and a storage device. Combination of renewable energy resources and a storage device reduces the effect of intermittency while increasing the reliability of the system. For wind power generation, three different wind turbine types are available for investment in our problem. These turbines have different costs and rated powers, and investors can either invest in one or multiple types. For solar power generation and storage systems, we do not explicitly specify the technology used, rather we simply model them as generic units. In this way, our setting can be utilized along with any type of technology. We assume linear cost functions for the solar power generation and storage devices (i.e. the cost of unit size of these components is constant).

Hybrid renewable energy system (HRES) can be used either to satisfy local demand or to make profit by selling green energy to the grid at elevated prices. In this study we assume that the decision maker is carbon sensitive; hence the priority of the decentralized system is to satisfy local demand using green energy rather than feeding energy to the grid to make profit. Therefore, in this framework, primary use of generated renewable energy is to satisfy local demand. If there is a surplus of renewable energy, it can be either stored in storage device or/and fed to the grid. We assume that storage device can only store green energy and this energy can only be used to satisfy the demand, i.e. renewable energy cannot be sold to the grid through the storage device so that we can prioritize renewable energy to be used for local demand. Fossil fuel based electricity from the grid will be used as a backup source only when renewable energy is not sufficient to meet the demand. Schematic description of the decentralized system can be found in Figure 3.1.

Governments impose different incentive policies, such as feed-in tariff programs, tax deduction, investment and operating subsidies, to promote renewable energy investments and mitigate CO_2 emission [52]. We consider a setting in

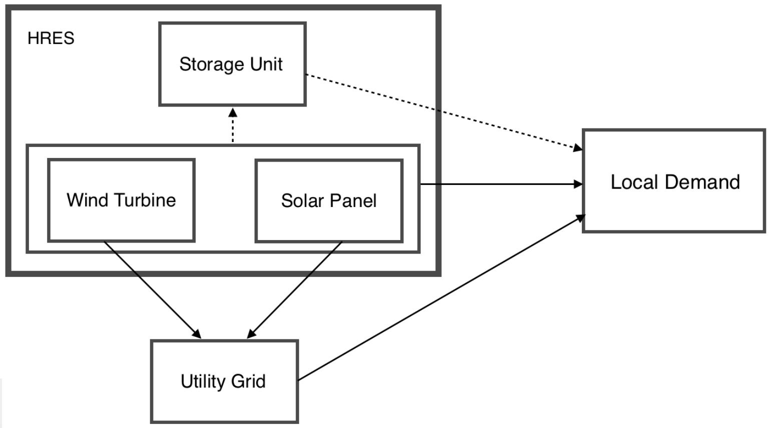

Figure 3.1: The Decentralized System

which a feed-in tariff program is available to investors. A feed-in tariff program is an incentive policy which aims to promote renewable energy investments by offering higher selling prices for each renewable energy. Green energy can be sold to the grid for higher prices for a limited time [52]. It is expected that feed-in tariff programs will increase the ratio of clean energy fed to the grid in the long run. This will decrease the carbon emission rate of the electricity purchased from the grid. However, in this study it is assumed that this improvement is negligible. In other words, clean energy that is fed to the grid will not have a diminishing effect on carbon emission of electricity purchased from the grid.

To handle the two conflicting objectives considered (cost and CO_2 emission) we propose a solution framework, in which we determine optimal sizing of the components and their relations and present a set of solutions rather than single solution. The framework that we present is generic, i.e. independent of the system scale. Thus, it is can be used for demand points of different sizes at different locations.

The decisions to be made in such systems are of two types: investment decisions and operational decisions. Investment decisions include the sizing decisions for the components (solar panel area, number of wind turbines and storage size) and are of a one-time decisions. Operational decisions, on the other hand, are made in each time unit, such as deciding on the amount of energy to be sent to the storage, to be purchased and/or to be sold. The decision support system we propose helps the decision maker to make investment decisions for such systems. All these decisions are to be made considering both cost and emission criteria. Note that, in addition to being bi-objective, the problem is a stochastic problem due to the uncertainty in the availability of renewable resources. The decision support system we propose helps the decision maker to make investment decisions for such systems.

Chapter 4

Bi-objective Two Stage Stochastic Mixed Integer Programming Model

In this chapter, first, the nature of stochastic programming methodologies will be introduced briefly and a bi-objective two stage stochastic programming model of our problem will be explained in detail. Then, the data used for numerical study and analysis of the output will be introduced.

In two stage stochastic programs, decision making process is divided into two stages. There are two different types of decision variables namely first and second stage variables. First stage variables are decided upon before the realization of random parameters. After uncertain events unfold, further adjustments, i.e. operational decisions can be made. The general form of the two stage stochastic linear program is given below:

$$
\begin{aligned}
\text{Min} \quad & c^T X + \mathbb{E}\big[Q(X, \xi(\theta))\big] \\
s.t \quad & AX = b \\
& X \geq 0
\end{aligned}
$$

$$
\begin{aligned}
\text{where} \quad & Q(X,\xi(\theta)) = \text{Min} \ \ q^T Y \\
s.t \quad & tX + wY = h \\
& Y \geq 0
\end{aligned}
$$

where X and Y are first and second stage variables, respectively. The second stage problem depends on the data (q, t, w, h) where any or all elements can be random. Expectation of Q is taken with regards to probability of ξ. Probability of ξ can be implemented in two ways. The first one is using a continuous probability distribution. This approach keeps the problem size steady but it may cause nonlinearities and computational difficulties [53]. The second one is a scenario-based approach. In this approach, uncertainty is modeled as union of random discrete events. There are a finite number of possible outcomes with certain probability but problem size increases enormously depending on the number of outcomes. Let Θ be the number of possible outcomes and p_θ be the corresponding occurance probability of scenario θ. Then, two stage stochastic program with discrete random events becomes:

$$
\begin{aligned}
\text{Min} \quad & c^T X + \sum_{\theta=1}^{\Theta} \left[p_\theta q_\theta Y_\theta \right] \\
s.t \quad & AX = b \\
& t_\theta X + w_\theta Y_\theta = h_\theta && \theta = 1...\Theta \\
& X \geq 0, \ \ Y_\theta \geq 0 && \theta = 1...\Theta
\end{aligned}
$$

In our study, we model our problem using a bi-objective two stage stochastic mixed integer program. Examples of stochastic programming applications in energy systems planning are widely encountered in the literature [50]. To be able to model random availabilities of resources, a scenario-based approach is followed. Renewable energy generation depends on uncertain data such as wind speed and solar radiation and sizing decision has to be made before these uncertainties are realized. Once component sizes of the decentralized system are determined, amount of renewable energy generation can be calculated and operational decisions (storing, outsourcing and meeting local demand) can be adjusted accordingly.

There are two objectives in our stochastic model. First one is minimizing total system cost, which includes investment and operational costs. The second objective is minimizing the amount of emitted CO_2 equivalent gases while satisfying the local demand. Non-dominated solutions are found using ε-constraint method, which is one of the most commonly used methods for bi-objective models [54]. In this method, first objective is minimized as second objective is bounded with a constraint. For each solution, model is solved with a bound on the second objective which gets tightened by the amount of a predetermined step size.

4.1 GCDES Model

The parameters and decision variables of our grid-connected decentralized energy system (GCDES) model are introduced in Table 4.1 and Table 4.2.

This model decides on the capacity of renewable energy generation and storage components to be built in the area of interest. Fixed costs (c_b, c_s, c_w^i) represent cost of renewable resource investment, which includes both capital and operation & maintenance costs. Investment costs are annualized by multiplying each component by its annualization factor. Annualization factor is calculated using Equivalent Annual Cost (EAC) formula (4.1) considering discount rate (dr) and the respective lifetime of a component (L) as an example. This formula is represented as an example of the calculation of annualization factor of solar panel. For other components, the same formula is used to calculate annualization factor for each component which is used in the mathematical model.

$$\alpha_s = \frac{dr}{1 + (1 - dr)^{-L_s}} \tag{4.1}$$

Electricity purchase price (p^g) represents the average spot price of electricity in the market. Governments which practice feed-in tariff policy offer different elevated sale prices (higher than the spot price of electricity) for each renewable energy resource to renewable energy system investors [52]. This policy has different sale prices for each renewable energy source (p^w, p^s) and is only available for a limited amount of time. Therefore, incentivized prices cannot be utilized throughout the

Table 4.1: Parameters and Sets

T	time horizon
I	set of wind turbine generator types
Θ	set of scenarios
dr	discount rate
c_b	investment cost of storage unit (\$/kWh)
c_s	investment cost of solar panel (\$/m^2)
c_w^i	investment cost of wind turbine generator (WTG) type i (\$/unit)
α_b	annualization factor for storage unit
α_s	annualization factor for solar panel
α_w	annualization factor for wind turbines
α_{ps}	annualization factor for sale price of solar energy
α_{pw}	annualization factor for sale price of wind energy
p^g	price of electricity purchased from grid (spot price) (\$/kWh)
p^s	elevated sale price of solar energy (\$/kWh)
p^w	elevated sale price of wind energy (\$/kWh)
d_t	local demand in time unit t (kWh)
v_t^θ	wind speed in time unit t in scenario θ (m/s)
r_t^θ	solar radiation in time unit t in scenario θ (kW/m^2)
η_s	overall efficiency of solar panel (%)
η_{dch}	discharging efficiency (%)
η_{ch}	charging efficiency (%)
dod	depth of Discharge
κ	electricity generation limit multiplier
M	maximum unit time demand (kWh)
β	CO_2 equivalent emission by electricity grid (tonne/kWh)

lifespan of the system. After feed-in tariff is expired, green energy can be sold to the market at spot price. Thus, effect of an elevated sale price (p^s, p^w) is distributed across the lifetime of the system. Formula 4.2 is used to calculate the annualization factor for the sale price of solar energy (α_{ps}), where L_{FT} represents the duration of the feed-in tariff policy. Same formula is also used to calculate the annualization factor for the sale price of wind energy (α_{pw}) by replacing (p^s) with (p^w).

$$\alpha_{ps} = \frac{p^s L_{FT} + p^g(L_{system} - L_{FT})}{p^s L_{system}} \tag{4.2}$$

Parameters (v_t^θ,r_t^θ) represent the wind speed and solar radiation in the model.

Table 4.2: Decision Variables

A_b	size of storage unit (kWh)
A_s	size of solar panels (m^2)
A_w^i	number of wind turbine generators of type i
S_t^θ	electricity generated by solar panels in time unit t in scenario θ (kWh)
SD_t^θ	solar electricity used to satisfy demand in time unit t in scenario θ (kWh)
SB_t^θ	solar electricity used to charge battery in time unit t in scenario θ (kWh)
SS_t^θ	solar electricity sold to grid in time unit t in scenario θ (kWh)
W_t^θ	electricity generated by WTGs in time unit t in scenario θ (kWh)
WD_t^θ	wind electricity used to satisfy demand in time unit t in scenario θ (kWh)
WB_t^θ	wind electricity used to charge battery in time unit t in scenario θ (kWh)
WS_t^θ	wind electricity sold to grid in time unit t in scenario θ (kWh)
B_t^θ	state of charge at the end of time t in scenario θ (kWh)
BD_t^θ	discharge amount in time unit t in scenario θ (kWh)
G_t^θ	amount of electricity supplied from grid in time unit t in scenario θ (kWh)
X_t^θ	1, if electricity is not purchased from the grid at time t in scenario θ 0, if electricity is not fed to the grid at time t in scenario θ

Notice that, uncertainty of renewable resources are taken into account by having scenario based resource availability parameters. Also, we assume that uncertainty in demand (d_t) is negligible, therefore deterministic demand data is utilized in the model.

Renewable energy generation depends on the efficiency of components. Efficiency of solar panel (η_s) is used for the calculation of solar energy output. For wind energy generation, the efficiency of the wind turbine is already included in wind turbine power curve, therefore no additional parameter is added to model. Energy losses in transmission for storage are also taken into account and efficiency of transmission to the storage and from the storage are represented by the parameters (η_{ch}, η_{dch}), respectively. In energy storage systems, discharging by the amount of total capacity of the storage device wears the device. Therefore, only a portion of the total capacity can be actively used. This is to increase lifespan of the storage. In our model, parameter (dod) represents the ratio of the inactive storage capacity.

Mathematical Model Formulation

$$\min \ \ \text{Z1}: \alpha_b c_b A_b + \alpha_s c_s A_s + \alpha_w \sum_{i \in I} c_w^i A_w^i + \frac{1}{|\Theta|} \sum_{\theta \in \Theta} \sum_{t \in T} \left[p^g G_t^\theta - \alpha_{ps} p^s SS_t^\theta - \alpha_{pw} p^w WS_t^\theta \right] \tag{4.3}$$

$$\min \ \ \text{Z2}: \beta \frac{1}{|\Theta|} \sum_{\theta \in \Theta} \sum_{t \in T} G_t^\theta \tag{4.4}$$

s.t

$$S_t^\theta = \eta_s r_t^\theta A_s \qquad \forall t \in T, \ \forall \theta \in \Theta \tag{4.5}$$

$$W_t^\theta = \sum_{i \in I} f^i(v_t^\theta) A_w^i \qquad \forall t \in T, \ \forall \theta \in \Theta \tag{4.6}$$

$$S_t^\theta = SS_t^\theta + SD_t^\theta + SB_t^\theta \qquad \forall t \in T, \ \forall \theta \in \Theta \tag{4.7}$$

$$W_t^\theta = WS_t^\theta + WD_t^\theta + WB_t^\theta \qquad \forall t \in T, \ \forall \theta \in \Theta \tag{4.8}$$

$$d_t = SD_t^\theta + WD_t^\theta + \eta_{dch} BD_t^\theta + G_t^\theta \qquad \forall t \in T, \ \forall \theta \in \Theta \tag{4.9}$$

$$B_t^\theta = B_{t-1}^\theta + \eta_{ch}(SB_t^\theta + WB_t^\theta) - BD_t^\theta \qquad \forall t \in T, \ \forall \theta \in \Theta \tag{4.10}$$

$$\kappa M \geq S_t^\theta + W_t^\theta \qquad \forall t \in T, \ \forall \theta \in \Theta \tag{4.11}$$

$$\kappa M X_t^\theta \geq SS_t^\theta + WS_t^\theta \qquad \forall t \in T, \ \forall \theta \in \Theta \tag{4.12}$$

$$|T| \, M X_t^\theta \geq SB_t^\theta + WB_t^\theta \qquad \forall t \in T, \ \forall \theta \in \Theta \tag{4.13}$$

$$M(1 - X_t^\theta) \geq BD_t^\theta \qquad \forall t \in T, \ \forall \theta \in \Theta \tag{4.14}$$

$$M(1 - X_t^\theta) \geq G_t^\theta \qquad \forall t \in T, \ \forall \theta \in \Theta \tag{4.15}$$

$$A_b \geq B_t^\theta \qquad \forall t \in T, \ \forall \theta \in \Theta \tag{4.16}$$

$$B_t^\theta \geq A_b(1 - dod) \qquad \forall t \in T, \ \forall \theta \in \Theta \tag{4.17}$$

$$B_0^\theta = A_b(1 - dod) \qquad \forall \theta \in \Theta \tag{4.18}$$

$$B_T^\theta = A_b(1 - dod) \qquad \forall \theta \in \Theta \tag{4.19}$$

$$S_t^\theta, B_t^\theta, W_t^\theta, G_t^\theta \geq 0 \qquad \forall t \in T, \ \forall \theta \in \Theta \tag{4.20}$$

$$SB_t^\theta, SS_t^\theta, WS_t^\theta, WB_t^\theta \geq 0 \qquad \forall t \in T, \ \forall \theta \in \Theta \tag{4.21}$$

$$A_s, A_b, A_w^i \geq 0 \qquad A_w^i \in \mathbb{Z}_{\geq 0} \tag{4.22}$$

$$X_t^\theta \in \{0, 1\} \qquad \forall t \in T, \ \forall \theta \in \Theta \tag{4.23}$$

In our mathematical model, we have two objective functions Z1 and Z2. The first objective represents the summation of total investment and expected operational costs which correspond to first stage and second stage decision variables. As mentioned before, investment decision has to be made before uncertainty is revealed. Once uncertainty is resolved, operational decisions can be made depending on first stage variables. At the stage of investment decision, expectation is taken over all realizations. The second objective function, Z2, is for CO_2 equivalent emission amount. This amount can be represented by using different forms of functions. In this setting, a linear function of electricity purchased from grid is used as an objective function. Rate of emission (β) depends on the proportion of fossil fuel based electricity in the grid network. It increases as the proportion of the fossil fuel increases.

For each scenario θ and time unit t, generated solar and wind energy are calculated in constraints (4.5) and (4.6), respectively. In constraint (4.6), wind energy output at time t in scenario θ is calculated using f^i, the piecewice linear function of wind turbine generator type i. In our system, the generated wind and solar energy can be used to meet the local demand or sold to the grid directly or can be stored. Constraints (4.7) and (4.8) are used to represent the distribution of generated energy. Constraint (4.9) guarantees that the demand is met in each time unit. Demand can be met by generated renewable energy, energy in storage device and electricity from the grid. Amount of discharged energy from storage device cannot be used for demand totally due to the technical lost. Only portion of discharged energy ($\eta_{dch} BD_t^\theta$) can be transmitted to demand points. Constraint (4.10) is the flow balance of the storage device. The state of charge can be increased by renewable energy sent to the storage unit and discharging energy cause storage level to decrease. Portion of the renewable energy sent to the storage is lost, therefore amount of renewable energy sent to the storage device is multiplied by the charging efficiency parameter (η_{ch}). Energy production has to be limited with a bound, due to the physical limitations of the area. With constraint (4.11), total energy production within a unit time is limited by κM where M can be considered as a very big number and κ is a constant multiplier. For this study, M is taken as maximum of demand observed during the planning horizon. By changing κ, dependency of optimal sizes to physical limitations can be investigated.

Binary variable X_t^θ is used in constraints (4.12–4.15) in order to ensure that local demand has priority over storage and selling, i.e. only excess energy can be sold or stored. In our setting, we use storage and grid network as backup components. Therefore, only in case of an energy deficit, grid can be used by purchasing electricity and storage can be used by discharging energy to satisfy demand. If the system is able to sell or/and charge energy then purchasing and discharging operations should not take place since we use grid network and storage as backup. These constraints (4.12–4.15) guarantee that generated renewable energy will be to used on satisfy local demand. In constraint (4.16), it is ensured that state of charge at time unit t cannot exceed nominal capacity of the storage. The storage unit is protected from over-discharging in order to increase the lifespan. Constraint (4.17) prevents storage units to be over-discharged. The storage unit is protected from over-discharging in order to increase the lifespan, that is there is a predetermined maximum allowable depth of discharge (dod). Constraint (4.17) prevents storage unit to be over-discharged by guaranteeing that at least a certain amount of energy is always available in storage. It is also assumed that the storage level is the same at the beginning and at the end of the horizon, i.e., the energy stored at the storage unit is equal to a predetermined amount (1-dod of the capacity), which is ensured by constraints (4.18) and (4.19). In this way, all generated renewable energy must be used throughout the horizon and cycle of storage device is bounded by the length of the horizon. Non-negativity of variables is satisfied with (4.20–4.22).

4.2 Numerical Study

In this part of the study, the main aim is to analyze the trade off between CO_2 emission and total system cost. Our model determines optimal sizing of renewable system components for any given location. Therefore, different data sets are used in order to analyze the effect of location differences. Three different levels of resource availability are determined (high, medium and low) both for solar and wind energy. Solar radiation and wind speed data are gathered using Hybrid Optimization of Multiple Energy Resources (HOMER) software [55]. Statistics of three levels of availability data can be found in Table 4.3. Also, to illustrate, wind speed and solar radiation profiles for medium resource availability level are represented in Figures 4.1 and 4.2, respectively.

Table 4.3: Statistics of Renewable Resources Availability Data

	Wind Speed (m/s)			Solar Radiation (kW/m^2)		
Data Set	Min	Mean	Max	Min	Mean	Max
High	0.21	7.81	29.90	0	0.24	1.09
Medium	0.13	5.14	19.35	0	0.17	0.97
Low	0.02	3.33	11.92	0	0.08	0.66

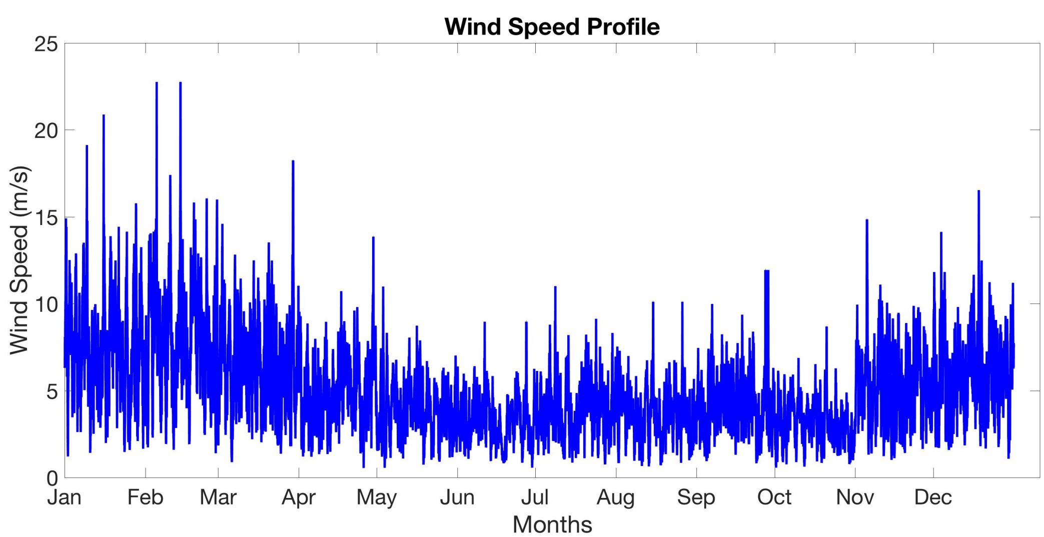

Figure 4.1: Wind Speed Profile for Medium Availability Level

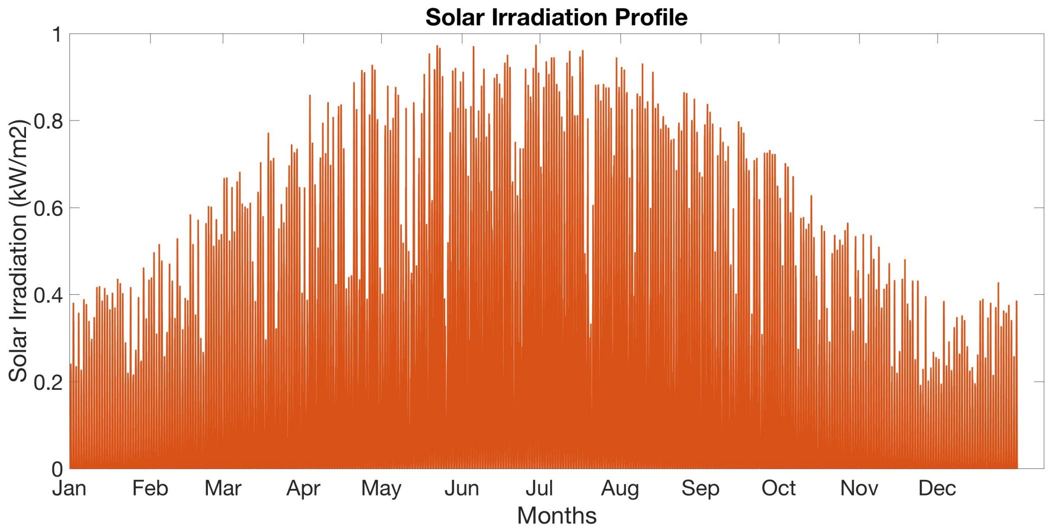

Figure 4.2: Solar Irradiation Profile for Medium Availability Level

The GCDES Model is independent from scale therefore it can be utilized for small scale demand points such as residential areas with a few houses as well as large scale points such as a whole city. For our numerical study, we consider a medium-scale demand point like a university campus. To generate an illustrative data set, one month of hourly average electricity consumption data of Bilkent University campus is attained. By preserving the electricity consumption characteristics of Bilkent University campus, hourly consumption profile for one year is generated using HOMER software. The average hourly and monthly electricity consumption of Bilkent University campus can be found in Figure 4.3 and Figure 4.4, respectively.

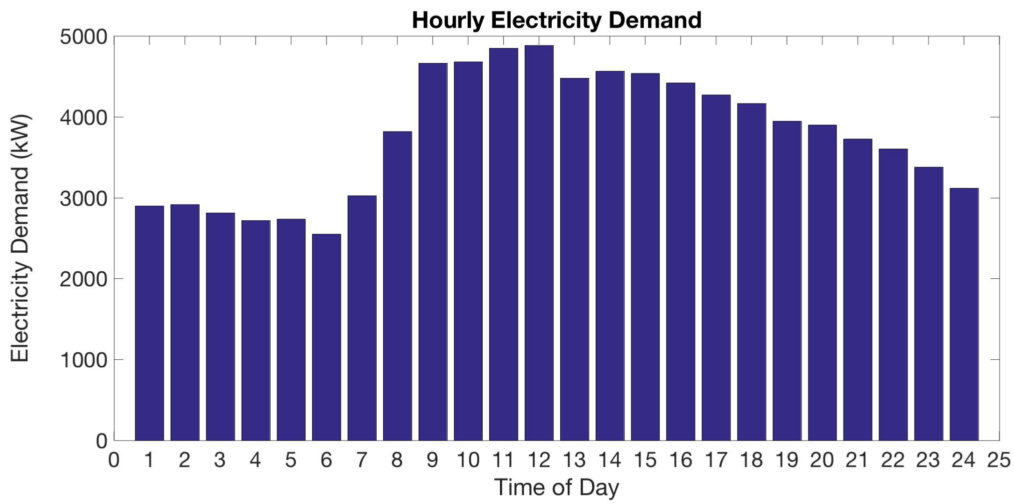

Figure 4.3: Hourly Average of Campus Demand Profile

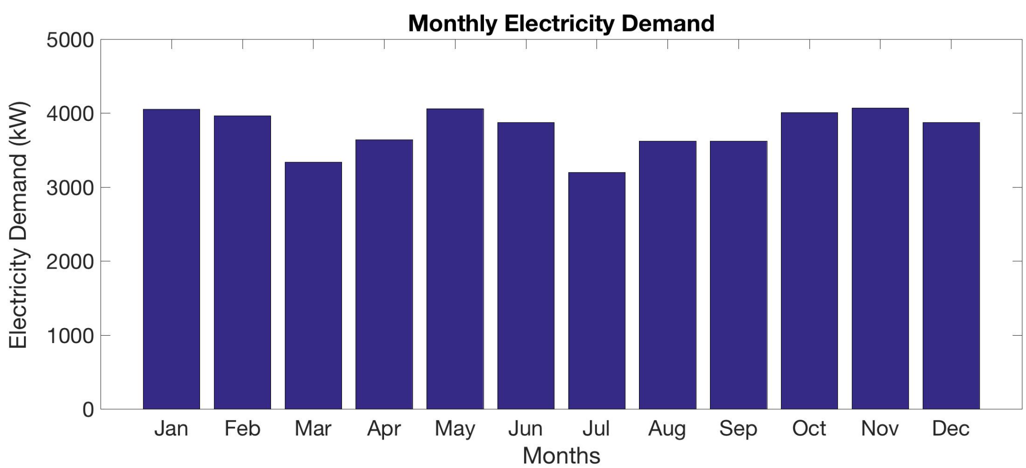

Figure 4.4: Monthly Average of Campus Demand Profile

Three different wind turbine types with different rated power are used in the analysis. These turbines are specified as Enercon E44 (900kW), E82 (2MW), E101 (3MW). Wind energy generation calculations are made based on respective power curve of each turbine [56]. The parameters for the numerical analysis along with their references are provided in Table 4.4. The model and algorithm are coded in MATLAB 9.0 and solved by a dual core (Intel Core i3 3.3 GHz) computer with 10 GB RAM. The model is solved by CPLEX 12.6. The solution times are expressed in central processing unit seconds.

Table 4.4: Parameters for Numerical Study

c_b	330 $/kWh [57]	p^g	0.06 $/kWh [58]
c_s	300 $/m^2 [59]	p^s	0.13 $/kWh [60]
c_w^{900kW}	1.77 M $ [61]	p^w	0.07 $/kWh [60]
c_w^{2MW}	4.3 M $ [61]	η_s	12 [51]
c_w^{3MW}	5.49 M $ [62]	η_{dch}	89.5 [38]
r	0.05 [51]	η_{ch}	89.5 [38]
L_b	10 years [42]	dod	1
L_s	30 years [51]	κ	2
L_w	20 years [42, 62]	β	0.0004836 [63–65]
L_{system}	30 years	T	8760 (hours)
L_{FT}	10 years [60]		

4.2.1 Single Scenario Analysis

First, bi-objective two-stage stochastic mixed integer model is solved with single scenario data for nine different cases in order to analyze how component sizes and investment amount change with respect to different availability levels of renewable sources. For this purpose, nine cases are generated using the combinations of low, medium and high availability levels for both wind and solar. Pareto solutions are obtained for each case by implementing ε-constraint method. The pareto solutions of the medium solar-medium wind case obtained by the parameters and the data discussed above is provided below (Figure 4.5). The pareto solutions for the rest of the cases can be found in Appendix A.

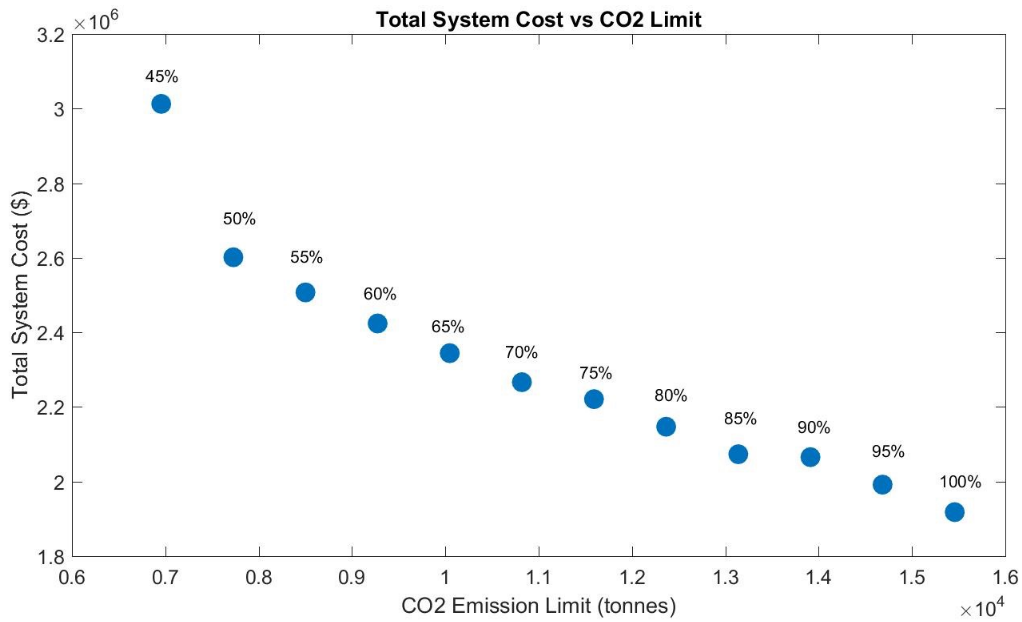

Figure 4.5: Pareto Solution Set of Medium Availability Case

The numbers above the solution points represent the percentage of demand satisfied by using grid electricity. Step size used in the CO_2 emission limit is determined as the emission amount that is released when 5 percent of the total demand is satisfied by the grid. Therefore, in the rest of the thesis CO_2 emission limit will be measured as the percentage of energy purchased from the grid to meet the local demand.

Table 4.5: Unit Cost ($) of Solar and Wind Energy Generation

Av. Level	Wind(900kW)	Wind(2MW)	Wind(3MW)	Solar
High	0.055	0.046	0.039	0.076
Medium	0.145	0.107	0.092	0.106
Low	0.567	0.382	0.331	0.222

Based on the cost parameters obtained from the literature, wind speed and solar radiation data, the unit costs of renewable energy for each component are calculated as in Table 4.5. When these units costs are compared to the price of electricity purchased from the grid, which we calculated as 6 cents/kWh, we can see that generating electricity can be less expensive than purchasing electricity from the grid in a highly sunny or windy place. As the trade-off between CO_2 and the cost disappears in this case, an investor would like to invest on renewable sources as much as possible and can also sell excess energy to the grid at an incentivized price. In the low and medium solar and wind cases, however, the unit cost of renewables are higher than the grid electricity price and the only motivation an investor might have to invest on renewables is to reduce the CO_2. In Table 4.6, number of pareto solutions found, solution times, minimum level of carbon emission that can be achieved depending on the availability of renewable sources and the percentage of demand that is satisfied using grid electricity for the first and the last pareto solution are reported separately for each case. For locations with high wind speed, low CO_2 emission values can be achieved without a limitation on the emission (as seen in Table 4.6, around 70% of the demand can be satisfied by renewable resources in the Pareto solution with minimum cost). In other words, decision maker does not have to be carbon sensitive to invest in renewables when resource availability is high, since the unit cost of renewable energy becomes less than the cost of grid electricity in such cases. In this way, total system cost can be decreased by using green electricity to satisfy demand and selling it to the grid and making profit.

Table 4.6: Single Scenario GCDES Model Output

Solar Av. Level	Wind Av. Level	# Soln	Soln Time (s)	Start GP	End GP
High	High	7	6309	33.3%	3.3%
Medium	High	7	3395	33.3%	3.3%
Low	High	7	3384	33.3%	3.3%
High	Medium	13	12273	100.0%	31.7%
Medium	Medium	12	4628	100.0%	45.0%
Low	Medium	8	3167	100.0%	49.6%
High	Low	13	8088	100.0%	33.0%
Medium	Low	13	2546	100.0%	40.0%
Low	Low	10	1451	100.0%	55.0%

Start/End GP: Percentage of demand satisfied by the grid for the first/last pareto solution.

In low and medium cases, unit costs are higher than annualized selling prices (p^w, p^s), therefore there is no profit margin to exploit (see Table 4.5). Therefore, the only way to increase investment in renewables is using a CO_2 emission limit (limit on the grid electricity usage), which can be seen in Figure 4.6. As CO_2 emission limit gets tighter, sizes of renewable system components enlarge until the physical limitation is reached, which is represented as maximum hourly production limit. It is necessary to use storage device to shift the supply after renewable energy production reaches the limit. Storage size and maximum of hourly renewable energy production (for medium solar-medium wind resource availability case) can be found in Figure 4.7 for different Pareto solutions.

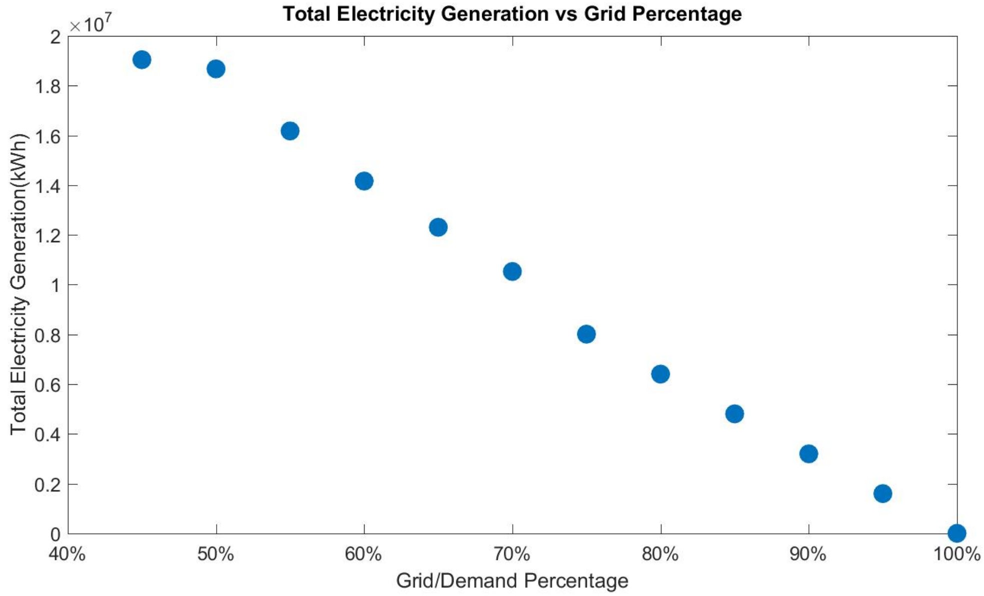

Figure 4.6: Total Renewable Electricity Generation for Medium Resources Availabilities

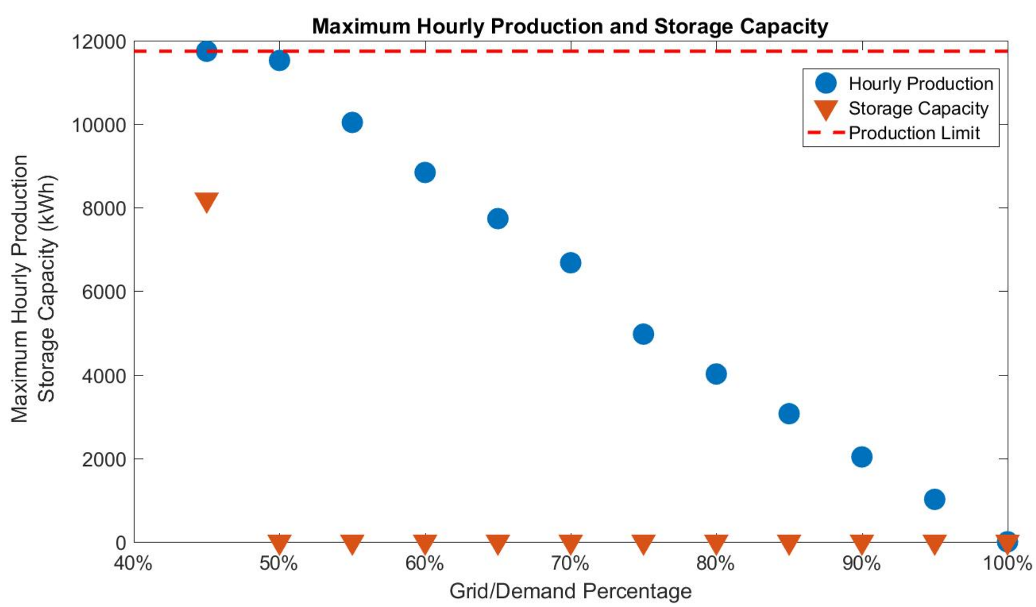

Figure 4.7: Hourly Production and Storage Capacity Behavior under Grid Usage Limitation for Medium Resource Availabilities

4.2.2 Multi Scenario Analysis

In this part, stochasticity of renewable availabilities of a location is also taken into consideration. Scenario generation is handled by two different techniques. For solar data, scenarios are generated via perturbation of the data used for single scenario analysis by 5%. For wind data, techniques that are introduced by [66] and [67] are used to generate scenarios. In the literature, Weibull distribution is commonly used to generate synthetic wind speed data [68]. In this technique, different states are constructed and wind speed is generated using Markov Transition Matrix, which is constructed using Weibull distribution. Wind speed values are centered around the given mean value and correlation between time units are handled by a decreasing exponential function.

For each of our low, medium and high solar and wind case, three scenarios are generated and the statistics of these scenarios are provided in Table 4.7. Our GCDES Model is solved with the nine scenarios, which are the combinations of generated three scenarios for each case and the outputs of the model can be found in Table 4.8. It is seen that the model can not be solved in reasonable time. We observed that the binary variables introduced in the model have an effect on this difficulty and that the complexity of the problem increases enormously with the number of scenarios.

Table 4.7: Attributes of Generated Scenarios

	Solar Radiation (kW/m^2)								
	Scenario 1			Scenario 2			Scenario 3		
Av. Level	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max
High	0	0.2442	1.1108	0	0.244	1.1412	0	0.2441	1.1354
Medium	0	0.1748	0.9987	0	0.1749	1.0029	0	0.1748	0.9916
Low	0	0.0835	0.6757	0	0.0835	0.6634	0	0.0835	0.6872

	Wind Speed (m/s)								
	Scenario 1			Scenario 2			Scenario 3		
Av. Level	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max
High	0	7.3669	26.9398	0.0066	7.5248	26.6697	0.0309	7.3283	24.5682
Medium	0.0001	4.6157	17.3236	0.0025	4.6938	17.6675	0.0004	4.6461	18.5492
Low	0.0019	3.0054	9.6265	0.0048	3.0585	10.6093	0.0014	2.9368	10.7751

Table 4.8: Multi Scenario GCDES Model Output

Solar Av. Level	Wind Av. Level	# Solns	Soln Time	Start GP	End GP	Gap
High	High	1	18000*	100.0%	100.0%	42.7%
Medium	High	1	18000*	100.0%	100.0%	42.7%
Low	High	1	18000*	100.0%	100.0%	42.7%
High	Medium	2	34110*	100.0%	95.0%	7.3%
Medium	Medium	2	46156*	100.0%	95.0%	246.3%
Low	Medium	2	29042*	100.0%	95.0%	4.8%
High	Low	2	33210*	100.0%	95.0%	0.06%
Medium	Low	5	71996*	100.0%	80.0%	NA
Low	Low	5	65446*	100.0%	75.0%	42.2%

Start/End GP: *Percentage of demand satisfied by the grid for the first/last found solution*
Gap: *The optimality gap of the last solution*
(*) *indicates that computational time limit has been reached for the last solution (18000 seconds)*
NA: *No integer solution has been found for the last iteration*

In addition to intractable solution times, another drawback of our bi-objective two stage stochastic mixed integer model is the scenario based approach, which violates non-ancipativity constraints, i.e. it makes operational decisions assuming that the availability pattern reflected in each scenario is known in advance (e.g. knowing what the hourly wind speed will be for the whole planning horizon), which is not the case in real life. In real life, operators observe the availability of renewables in a time period and make operational decisions accordingly, following a given policy. With the hope of addressing this multi-stage decision making process in a computationally tractable way, we introduce a simulation optimization algorithm in the next chapter, which includes variations of the two stage stochastic programming model and a simulation module, where simulation module handles non-ancipativity issues.

Chapter 5

Simulation Optimization Approach

In this chapter, the simulation optimization algorithm that we propose as a solution methodology to our problem, will be explained in detail. Then, numerical study conducted using the algorithm and the outcomes will be discussed.

5.1 Algorithm

We propose a simulation optimization algorithm which can handle the multi-stage nature of our problem. The simulation optimization algorithm consists of two variants of the GCDES Model (a reduced version, called Module 1, and a restricted version, called Module 3) and a simulation module (Module 2). The overall algorithm works as a variant of the ε-constraint method which is one of the widely used methods, especially for bi-objective problems [54]. The method is based on solving single objective models iteratively, limiting the second objective function value by a constraint. In our system, we minimize cost while limiting the total CO_2 emission value iteratively. The result of the algorithm is a set of solutions with varying levels of cost and CO_2 emission amount, which enables decision maker to evaluate different investment options. The flow diagram of this simulation optimization algorithm can be seen in Figure 5.1

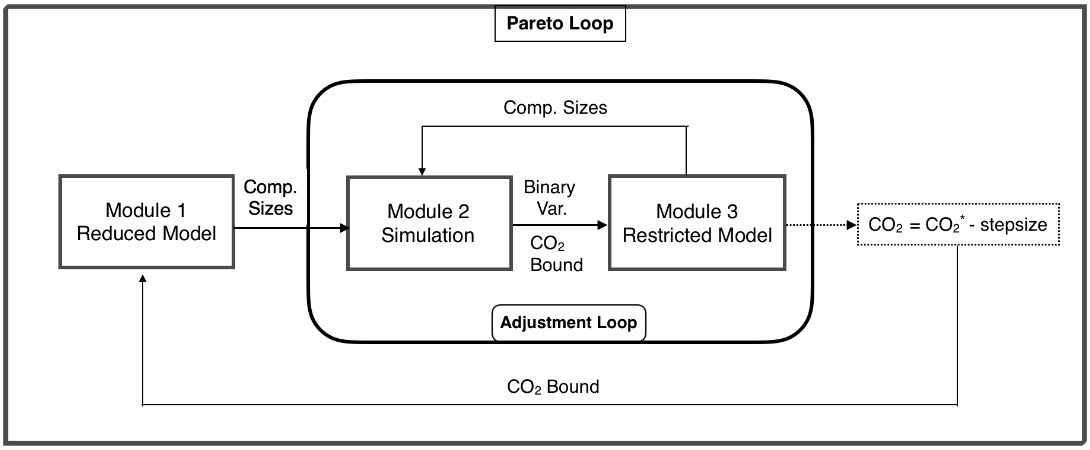

Figure 5.1: Simulation Optimization Algorithm

5.1.1 Module 1 - Reduced Version of the GCDES Model

Our algorithm starts with solving the reduced version of the GCDES Model. The main purpose of using reduced version is to obtain the initial component sizes to be fed into the simulation model. In this version, constraints (4.14–4.17), which include binary variable X_t^{θ}, are relaxed in order to reduce the computational effort. This enables model to obtain the optimal component sizes of a setting in which renewable energy can be sold to the grid while meeting the demand using the electricity purchased from the grid. The results of this model (the number of wind turbines, the solar panel area and the storage size) are used as an input for the simulation model. The mathematical formulation of the reduced model can be found below:

Reduced Version of the GCDES Model

$$\min \;\; Z1 : \alpha_b c_b A_b + \alpha_s c_s A_s + \alpha_w \sum_{i \in I} c_w^i A_w^i + \frac{1}{|\Theta|} \sum_{\theta \in \Theta} \sum_{t \in T} \left[p^g G_t^\theta - \alpha_{ps} p^s SS_t^\theta - \alpha_{pw} p^w WS_t^\theta \right] \tag{5.1}$$

s.t

$$S_t^\theta = \eta_s r_t^\theta A_s \qquad \forall t \in T,\ \forall \theta \in \Theta \tag{5.2}$$

$$W_t^\theta = \sum_{i \in I} f^i(v_t^\theta) A_w^i \qquad \forall t \in T,\ \forall \theta \in \Theta \tag{5.3}$$

$$S_t^\theta = SS_t^\theta + SD_t^\theta + SB_t^\theta \qquad \forall t \in T,\ \forall \theta \in \Theta \tag{5.4}$$

$$W_t^\theta = WS_t^\theta + WD_t^\theta + WB_t^\theta \qquad \forall t \in T,\ \forall \theta \in \Theta \tag{5.5}$$

$$d_t = SD_t^\theta + WD_t^\theta + \eta_{dch} BD_t^\theta + G_t^\theta \qquad \forall t \in T,\ \forall \theta \in \Theta \tag{5.6}$$

$$B_t^\theta = B_{t-1}^\theta + \eta_{ch}(SB_t^\theta + WB_t^\theta) - BD_t^\theta \qquad \forall t \in T,\ \forall \theta \in \Theta \tag{5.7}$$

$$\kappa M \geq S_t^\theta + W_t^\theta \qquad \forall t \in T,\ \forall \theta \in \Theta \tag{5.8}$$

$$A_b \geq B_t^\theta \qquad \forall t \in T,\ \forall \theta \in \Theta \tag{5.9}$$

$$B_t^\theta \geq A_b(1 - dod) \qquad \forall t \in T,\ \forall \theta \in \Theta \tag{5.10}$$

$$B_0^\theta = A_b(1 - dod) \qquad \forall \theta \in \Theta \tag{5.11}$$

$$B_T^\theta = A_b(1 - dod) \qquad \forall \theta \in \Theta \tag{5.12}$$

$$S_t^\theta, B_t^\theta, W_t^\theta, G_t^\theta \geq 0 \qquad \forall t \in T,\ \forall \theta \in \Theta \tag{5.13}$$

$$SB_t^\theta, SS_t^\theta, WS_t^\theta, WB_t^\theta \geq 0 \qquad \forall t \in T,\ \forall \theta \in \Theta \tag{5.14}$$

$$A_s, A_b, A_w^i \geq 0 \qquad A_w^i \in \mathbb{Z}_{\geq 0} \tag{5.15}$$

5.1.2 Module 2 - Simulation Model

Taking the component sizes (first stage decision variables) as an input, in the simulation module, operator follows a policy to make operational decisions (second stage decision variables) without the knowledge of future availability of wind and solar resources. The policy is designed to prioritize renewable sources while meeting local demand, which is in line with the objective of minimizing CO_2

emission value. This module takes the investment decisions (the number of wind turbines, the solar panel area and the storage size) obtained from the reduced version of the GCDES Model and calculates the renewable energy generated at each time period of the planning horizon for each scenario. First, the local demand is satisfied using less profitable renewable energy source and then excess energy is stored in storage unit (until it is fully charged). If there is still excess energy, it is fed to the grid. If there is not enough renewable energy to meet local demand, the deficit amount is purchased from the grid. In this way, the simulation model determines whether to sell renewable energy or outsource fossil-fuel based electricity from the grid, which corresponds to binary variables in the GCDES Model (X_t^θ). The resulting total CO_2 emission value and related binary variables (X_t^θ) are used as an input in Module 3 (the restricted version of the GCDES Model).

5.1.3 Module 3 - Restricted Version of the GCDES Model

In the restricted version, the output of the simulation module is used to dictate purchase-sell decisions. These decisions are conveyed to the model by fixing binary variables (X_t^θ) in constraints (4.14–4.17). Moreover, the total CO_2 emission value observed in the simulation model is used to update the CO_2 limit in the restricted model. This restricted model is solved and the new investment decisions are fed back to the simulation model which now applies the policy using the new component sizes. In this way, both the component sizes and selling/outsourcing decisions can be adjusted iteratively. This adjustment continues until decisions made in Module 2 and Module 3 are in line and the (adjustment) loop terminates when the improvement in cost is less than 0.1%. Note that, since the restricted model (Module 3), which makes investment decisions, uses the CO_2 limit determined by the simulation model (Module 2), which dictates the operational policy, both investment and operational decisions made are in line with the corresponding CO_2 limit. Each such loop provides a solution with corresponding cost and CO_2 level. In order to move to next (neighbour) solution, we further restrict the CO_2 limit by subtracting a predetermined amount (step size) from the CO_2 level of the latest solution found. A new (Pareto) loop is initiated by solving Module

1 with this new CO_2 limit (see the outer loop in Figure 5.1). In order to move to next (neighbour) solution, we further restrict the CO_2 limit by subtracting a predetermined amount (step size) from the CO_2 level of the latest solution found. A new Pareto loop is initiated by solving Module 1 with this new CO_2 limit (see the outer loop in Figure 5.1).

We now summarize the overall process. The simulation optimization algorithm starts with solving the reduced version of the two-stage stochastic programming model (relaxing constraints with the binary variables) which determines optimal component sizes of a setting where selling and outsourcing can take place at the same time. Then, optimal component sizes are fed into the simulation module, which makes operational decisions based on our policy. Simulation module decides on whether to sell renewable energy or outsource fossil-fuel based electricity from the grid at each time unit t. As an output of the simulation, sell or outsource decisions which correspond to binary variables (X_t^θ) and total CO_2 emission value are fed into the restricted version of the GCDES Model. This restricted model is solved with this input and the new investment decisions are made based on fixed binary variables and CO_2 emission limit. Then, new component sizes are fed back to the simulation module. Again, the simulation module makes new sell or to outsource decision based on new component sizes. This adjustment loop terminates when improvement on total system cost obtained at the end of Module 3 is less than 0.1%. Then, CO_2 emission value determined by Module 3 is tightened by the amount of the step size and fed into the Module 1 in order to move a neighbour solution (Pareto Loop).

5.2 Numerical Study

In this part, single scenario data, introduced in Section 4.2 and nine scenario data, introduced in Section 4.2.2, are used for the analysis of the simulation optimization. Also, the same three types of wind turbine generators and the parameters in Table 4.4 are utilized. In single scenario analysis, the solution set of the GCDES Model is used as a benchmark to examine the performance of the simulation optimization algorithm. In multi scenario analysis, since the solution set of the GCDES Model cannot be found in reasonable time (the time limit is reached after finding the first few Pareto solutions), such a comparison is not possible. Therefore, in the multi-scenario case, output of the algorithm and the value of stochasticity will be analyzed.

5.2.1 Single Scenario Analysis

First, the simulation optimization algorithm is solved with one scenario and its output is compared with the solution of the GCDES Model. Even though these two models do not reflect the same framework, their comparison might give some valuable information about the quality of the simulation optimization algorithm solutions as the results of the GCDES Model will always provide a lower bound for the solutions of the simulation model. As an example, the set of solutions of both the GCDES Model and simulation optimization algorithm is represented in Figure 5.2 for medium solar low wind case. The rest of the single scenario pareto solutions of simulation optimization algoritm can be found in Appendix B.

Due to the non-anticipativity violation (i.e. assuming that future availability of the renewable resources is known), the GCDES Model is able to adjust its operational variables so that the best operational policies are determined for each scenario benefiting from future availability information. On the other hand, in the simulation optimization algorithm, we follow a predetermined policy without knowing the future (in the simulation module). Hence, in the simulation optimization algorithm selling or purchasing decision variables (X_t^{θ}), values of which are determined by the simulation module, are fixed in the GCDES Model (the restricted model). In this way, the feasible region of the GCDES Model is restricted. As a result, the output of the model sets a lower bound for the output of our simulation optimization algorithm. For the cases where no storage is used in the Pareto solutions of the GCDES Model, both the model and the simulation optimization algorithm (the policy) give the same solutions. This is because, both the GCDES Model (which assumes future availability is known)

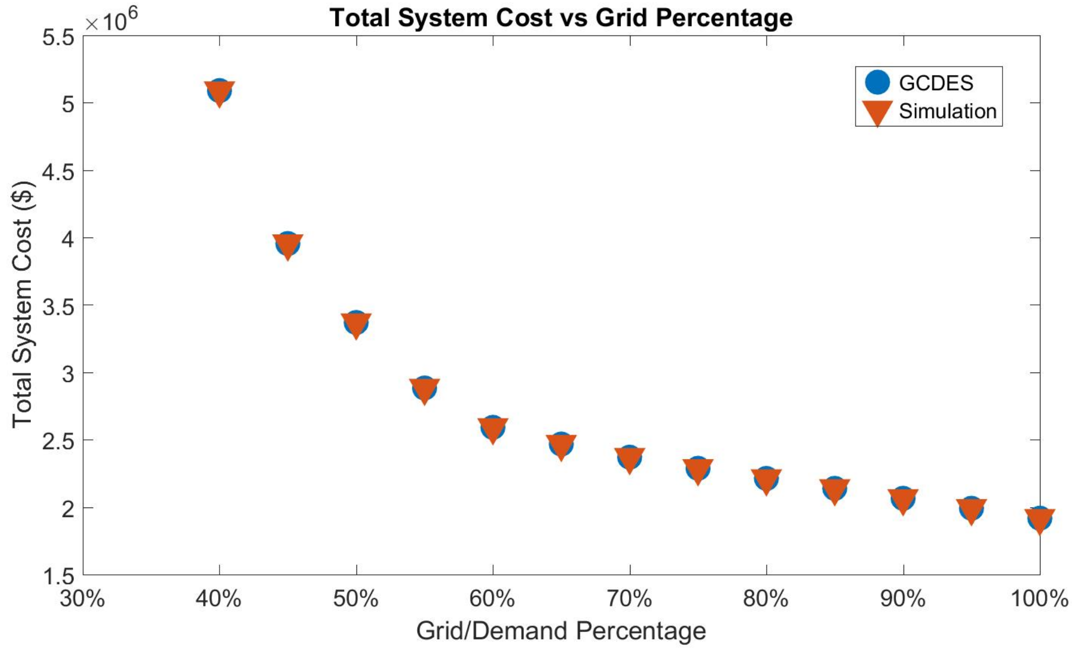

Figure 5.2: Total System Cost vs CO_2 Emission Limit Solutions of the GCDES Model and Simulation for Medium Solar-Low Wind Case

and the simulation policy (which does not make this assumption) make the same operational decisions for the same solar and wind investment levels. This result is expected since for fixed solar and wind investment level, once energy is produced at each time unit, the only way the GCDES Model can assign operational decision variables optimally is to send the produced energy to local demand first and sell any excess energy or purchase any deficit energy from the grid, which is exactly the policy followed in the simulation optimization algorithm. Note however that when storage unit is used in the system, the above result is not valid anymore and the set of solutions returned by the simulation optimization algorithm may not coincide with the solutions of the GCDES Model. This is because while the GCDES Model uses storage in the most cost-effective way, the simulation optimization algorithm cannot (as decisions are made without knowing future availability, which is the case in real life). When we compare the outcomes of both the model and simulation optimization algorithm (Table 5.1), we can see that simulation algorithm generates less number of solutions compared to the GCDES Model for the same step size value for most cases. The main reason is

Table 5.1: Single Scenario Simulation Optimization Algorithm and GCDES Model Outputs

Solar Level	Wind Level	Simulation Optimization				GCDES Model			
		# Solns	Soln Time	Start GP	End GP	# Solns	Soln Time	Start GP	End GP
High	High	6	325	31.6%	6.6%	7	6309	33.3%	3.3%
Medium	High	6	274	33.3%	8.3%	7	3395	33.3%	3.3%
Low	High	6	1740	33.3%	8.3%	7	3384	33.3%	3.3%
High	Medium	5	585	53.0%	31.7%	13	12273	100.0%	31.7%
Medium	Medium	12	2406	100.0%	42.8%	12	4628	100.0%	45.0%
Low	Medium	7	2179	100.0%	49.6%	8	3167	100.0%	49.6%
High	Low	5	248	53.0%	33.0%	13	8088	100.0%	33.0%
Medium	Low	13	555	100.0%	40.0%	13	2546	100.0%	40.0%
Low	Low	10	404	100.0%	55.0%	10	1451	100.0%	55.0%

Start/End GP: Percentage of demand satisfied by the grid of first/last candidate solution.

that simulation optimization algorithm dictates the policy outputs and this restricts the feasible region. Apart from the difference in the number of solutions, the algorithm might find solutions with different percentages and costs compared to the outputs of the GCDES Model, as in high solar-high wind case represented in Figure 5.3. Note, however, that the number of solutions may be increased by reducing the step size value.

As in high solar-high wind case represented in Figure 5.3, the algorithm might find solutions with different percentages and costs compared to the outputs of the GCDES Model. Even though that is the case, the number of solutions can be increased by shrinking the step size value. The solution sets of the GCDES Model and Simulation optimization with small step size (1% of the total demand) for high solar-high wind case are represented in Figure 5.4. Also, the models are solved with the same CO_2 emission limit in order to compare the outputs. It can be seen that the difference between solution sets of the GCDES Model and the simulation optimization is negligible. For single scenario analysis, our algorithm is able to find solutions that are close to lower bound value. For multi scenario cases, the difference between the GCDES Model and simulation optimization algorithm might increase.

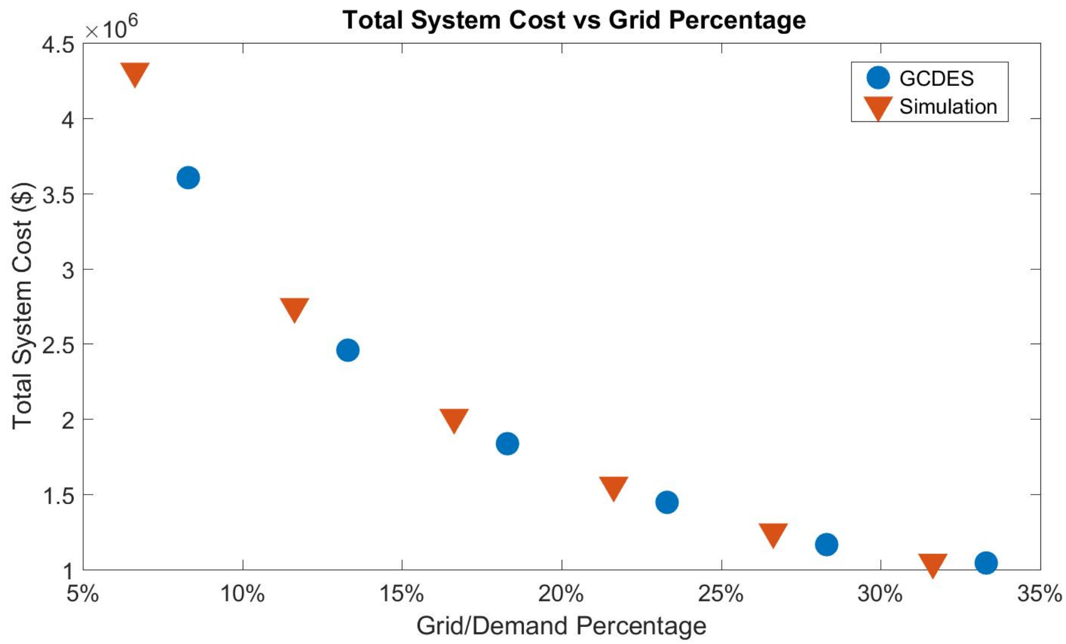

Figure 5.3: Total System Cost Comparison of Solutions of Simulation Algorithm and the GCDES Model for High Solar-High Wind Case

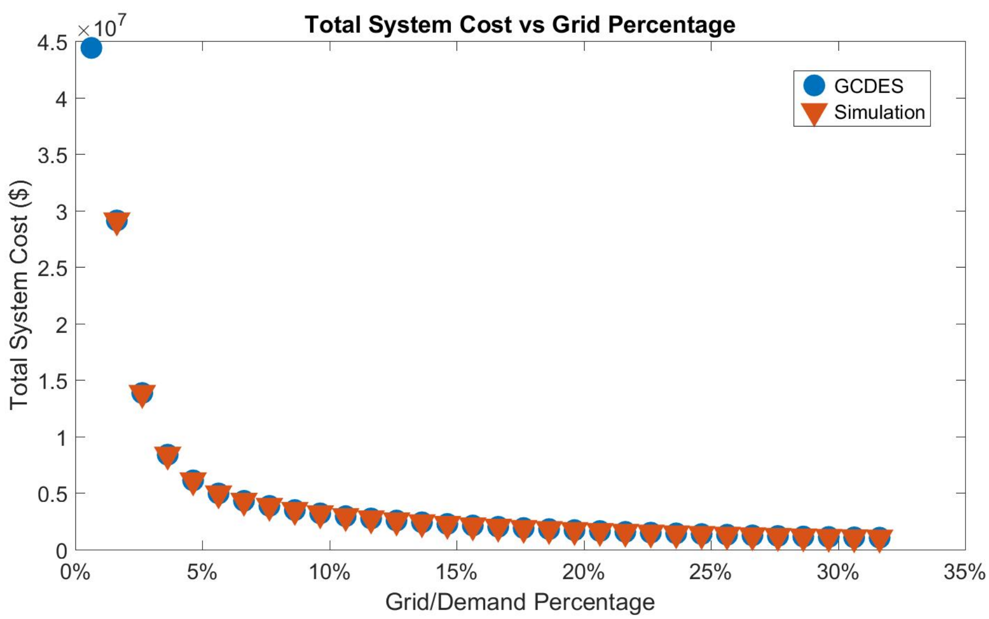

Figure 5.4: Total System Cost of the GCDES Model and Simulation Optimization with Step Size equals to 1% of the Total Demand

When we analyze storage usage as in Section 4.2.1, the output indicates that storage is needed the most when maximum production limit is reached as in the GCDES Model outputs. In such cases, storage is used to shift the supply (in order to meet the local demand in the upcoming periods). Maximum hourly production and storage capacity outputs of both the GCDES Model and simulation optimization for medium solar-low wind are represented in Figure 5.5 and Figure 5.6.

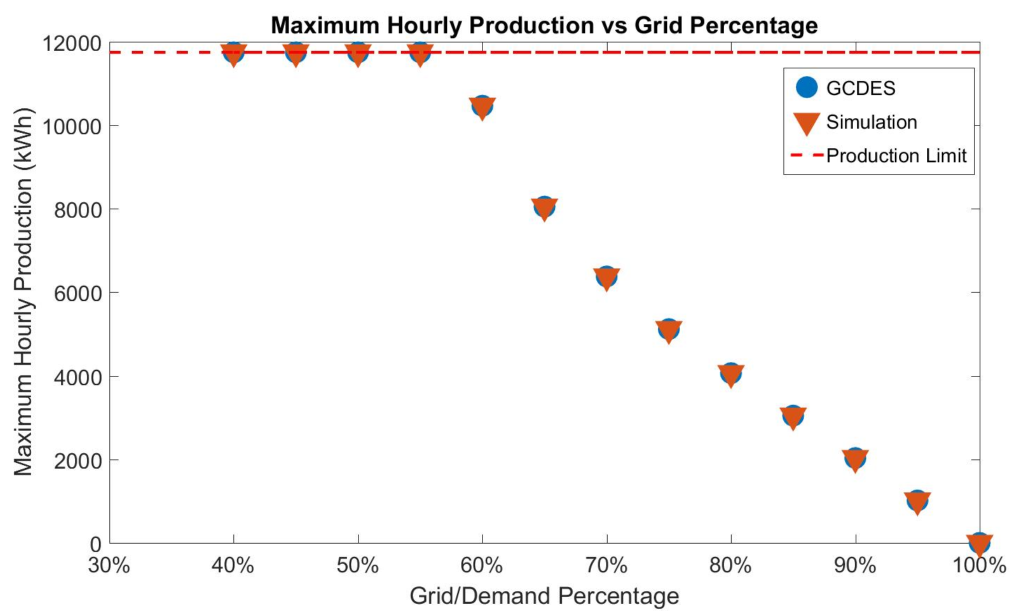

Figure 5.5: Maximum Hourly Production Output of GCDES Model and Simulation Optimization for Medium Solar-Low Wind Case

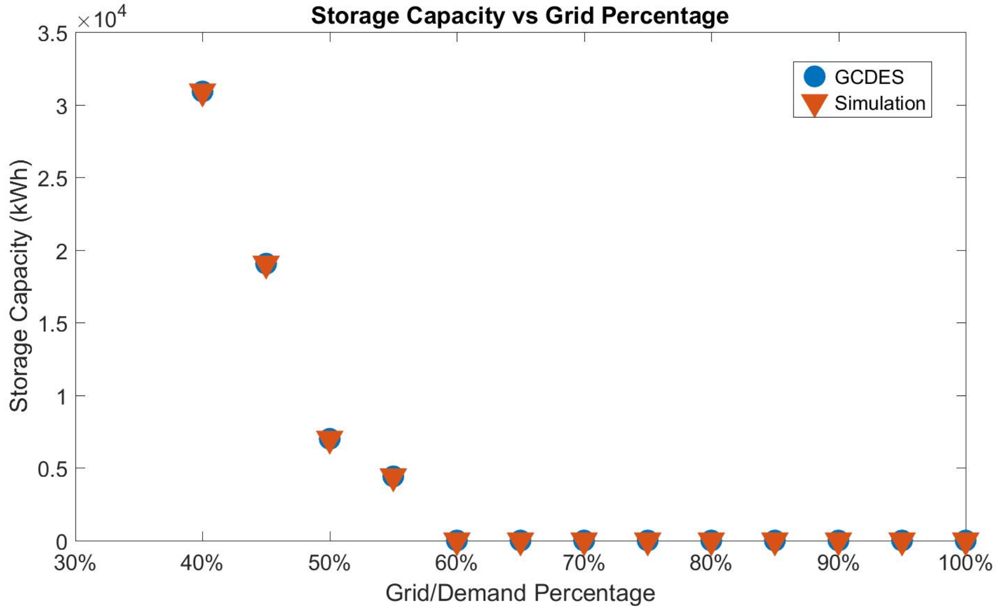

Figure 5.6: Storage Capacity Output of GCDES Model and Simulation Optimization for Medium Solar-Low Wind Case

At a location with highly available renewable resources, investors tend to invest in renewable systems. Our simulation algorithm works in line with this behavior. First, Module 1 determines the optimal component sizes for a reduced model (without the binary variables). Recall that, this module may return unrealistically large component sizes as it allows investors to sell and outsource at the same time. This is partly rectified in the simulation module. Also note that the simulation module uses a carbon sensitive policy and does not allow to sell renewable energy unless the local demand is met and storage unit is filled. This means, the algorithm tends to return solutions which are on the low CO_2 emission side of the frontier. An example is seen in Figure 5.7, where the outputs of the GCDES Model and the simulation optimization algorithm are shown for the high solar-medium wind case. In this case, the simulation algorithm returns only the highest five carbon sensitive solutions. However, it is possible to find other solutions lying on the high CO_2 emission edge if needed. One can change the initial component sizes the simulation optimization algorithm starts with or the policy that the operator follows in order to explore other parts of the solution set.

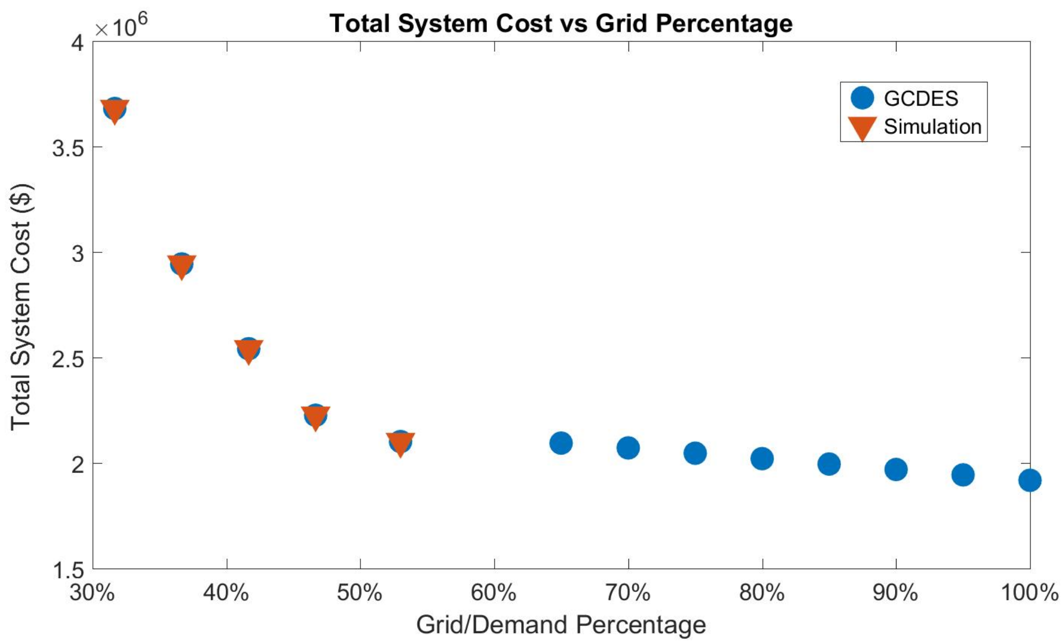

Figure 5.7: Total System Cost vs CO_2 Emission Limit Solutions of GCDES Model and Simulation for High Solar-Medium Wind Case

5.2.2 Multi Scenario Analysis

In this part, the simulation optimization algorithm is run for nine different locations (combinations of high-medium-low resource availability levels) using nine different scenarios (combinations of three solar and three wind scenarios) whose data are introduced in Section 4.2.2. Output of the algorithm can be found in Table 5.2. Our simulation optimization algorithm is able to handle problems with nine scenarios and returns a wide range of solutions. The solution set of medium solar-medium wind case is represented in Figure 5.8 as an example. The outputs of other cases can be found in Appendix C.

Table 5.2: Nine Scenario Simulation Optimization Algorithm Output

Solar Av. Level	Wind Av. Level	# Solns	Soln Time (s)	Start GP	End GP
High	High	7	13085	35.9%	4.7%
Medium	High	8	12491	37.9%	1.5%
Low	High	7	8323	37.9%	5.1%
High	Medium	4	3319	53.5%	35.5%
Medium	Medium	11	36043	100.0%	48.7%
Low	Medium	9	49073	100.0%	52.7%
High	Low	4	3964	53.5%	37.1%
Medium	Low	11	4310	100.0%	48.9%
Low	Low	9	3912	100.0%	58.7%

Start/End GP: Percentage of demand satisfied by the grid for the first/last candidate solution.

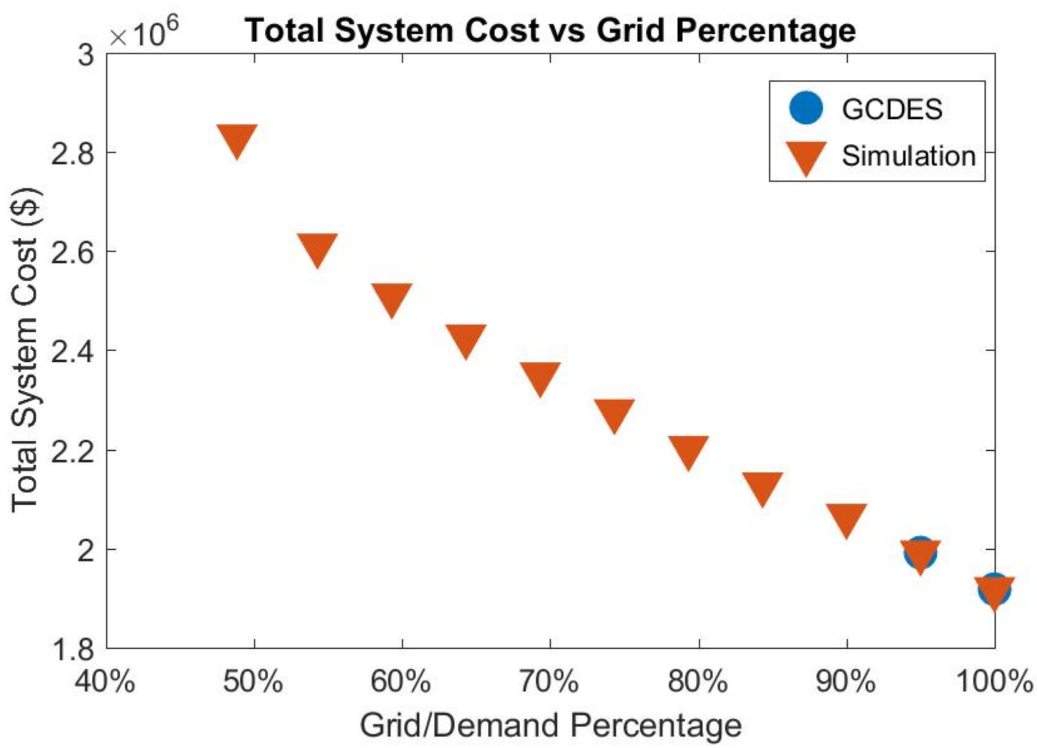

Figure 5.8: Solution Set of Nine Scenario Simulation Optimization Algorithm and GDES Model for Medium Solar-Medium Wind Case

It can be seen in the table that the algorithm finds more carbon sensitive solutions for high resource availability cases. This is mainly due to the reasons discussed in Section 5.2.1 before. Note also that the solution times that are shown in the table are for the generation of whole set of solutions. Therefore, the algorithm outperforms the GCDES Model in terms of both solution time and the range of solutions found.

Considering only three scenarios for the availability of renewable resources (nine scenarios in total) may seem too restrictive to model a real life setting. However, even with this relatively low number of scenarios, it is possible to make more informed decisions compared to a setting where the problem is handled in a deterministic manner. We performed further analysis in order to observe the contribution of taking stochasticity into account while making investment decisions, i.e. we calculated the value of stochasticity (VSS).

As the name implies, this value points out the possible gain from solving a stochastic problem rather than a deterministic problem, which uses mean values of the random parameters only. The formulation of VSS is given below:

$$\text{For minimization,} \quad VSS = EEV - RP \tag{5.16}$$

where EEV (expected outcome of expected value solution) represents the solution of the deterministic model where mean values of random parameters are used. RP (recourse problem) is the solution of stochastic problem. The difference between these solutions gives the value of stochastic solution.

The calculation of EEV is not straightforward in our setting due to a number of technical reasons, one of which is the existence of capacity limit constraints. We, however, calculated an adjusted EEV and showed that the solutions of RP might dominate the solutions of EEV. An example analysis can be found in Figure 5.9. The solutions of RP in dashed ellipses dominate the solutions of EEV in the ellipses with straight line (they give lower values for both objective functions). We expect the difference between these two sets of solutions, hence the value of stochasticity to increase as the number of scenarios used increases. We believe that, finding ways to handle the computational challenges of considering larger number of scenarios and investigating VSS for these cases, is a future research topic worth exploring.

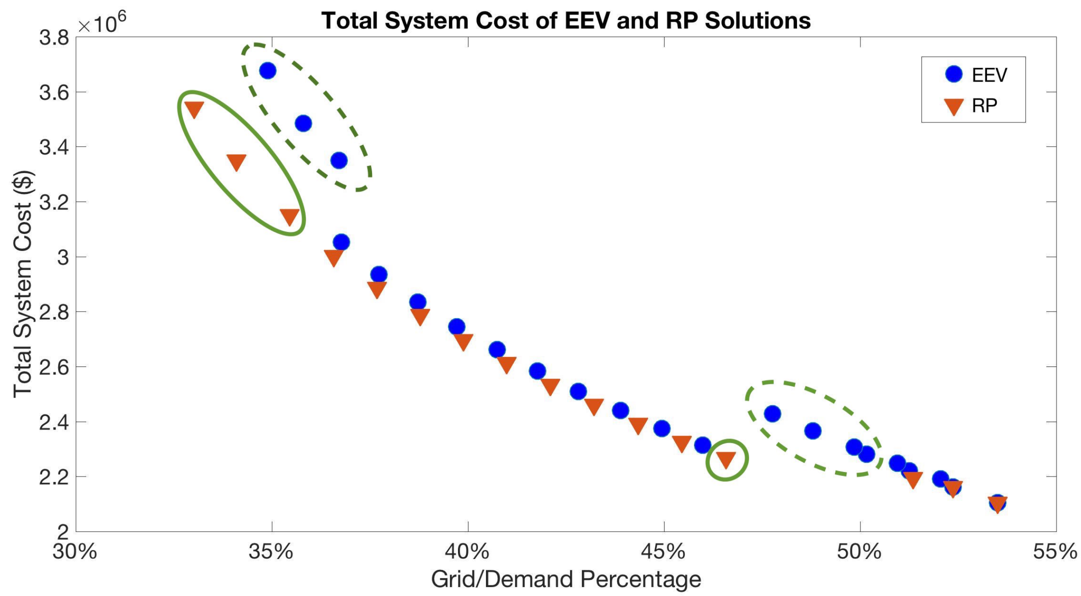

Figure 5.9: Comparison of Outputs of EEV and RP for High Solar-Medium Wind Case

Chapter 6

Conclusion

Motivated by the interest in shifting from fossil fuel based energy systems to renewable energy systems to mitigate emissions, we consider the sizing problem of a grid-connected decentralized system which can include solar and wind generation and an energy storage components. Our main aim is to give insights to decision makers about the optimal scale of the decentralized system they plan to invest in. The optimal sizing decision problem includes two important aspects, which are stochasticity (intermittency of renewable resources) and multi-objective structure (having concerns for multiple criteria such as cost and emission). In our study, we considered these two aspects elaborately by assuming that the decision maker is sensitive to both cost and carbon emission and by modeling the problem as a stochastic problem, using random resource availabilities. In the literature, there are some studies that deal with multi-objective optimal design problem of decentralized energy systems. However, in these studies, the problem is modeled and solved using deterministic approaches. The drawbacks of using deterministic tools for stochastic environments were explained explicitly by Powell et al. [50]. Using deterministic tools cause outputs of these models to be far from the real cases. As stochastic elements are increased in the model, output of the optimal design problem give more valuable insights.

To the best of our knowledge, our study is the first one that provides a mathematical programming formulation along with a novel solution approach for multi-objective design of a grid-connected decentralized energy system while incorporating uncertainty of renewable resources. The system considered is a special type of a hybrid decentralized system consisting of renewable (solar and wind) energy generation units and a storage unit, and is connected to the main grid, hence can purchase energy from and sell energy to the grid as opposed to a stand-alone system. We presented two different solution approaches to our problem. First, we modeled the problem using a bi-objective two stage stochastic mixed integer program. Our grid-connected decentralized energy system (GCDES) model has two objective functions, which are minimizing the annualized system cost and the amount of emitted CO_2 equivalent gases while satisfying the local demand. Non-dominated solutions of this model are generated using the ε-constraint method. This model does not only decide on the optimal component sizes for a predetermined CO_2 emission limit but also determines the optimal operational decisions such as selling, outsourcing and storing energy in each time unit. Uncertainty in solar radiation and wind speed are included in the system as scenarios. We provided and analyzed the results of an illustrative case study using the energy consumption data of Bilkent University campus.

Motivated by the fact that the GCDES Model fails to address the multi-stage nature of the problem and provide solutions in reasonable time when multiple scenarios are used, we developed a simulation optimization algorithm which can handle both multi-stage and multi-objective nature of the problem. This algorithm consists of two variants of the GCDES Model and a simulation algorithm. Two variants of the GCDES Model (reduced and restricted versions) are used to decide optimal component sizes where the simulation algorithm determines operational decisions by following a predetermined policy. In our system, we minimize cost while limiting the total CO_2 emission value iteratively. Therefore, the overall algorithm works as a variant of the ε-constraint method.

The numerical studies were conducted using three levels of wind and solar resource availabilities in order to investigate the impact of different resource availabilities on investment decision. Also, numerical analysis of both methods (the

GCDES Model and the simulation optimization algorithm) was performed for single and multiple scenario cases. For single scenario analysis, hourly time series data for solar and wind for one year were obtained by HOMER software and synthetic multiple scenario time series are generated based on this data. The outputs of the study indicate that even if a decision maker is not carbon sensitive, still, low carbon emission levels can be attained where the location has high solar and/or wind potential. Also, we observed that storage device is utilized only if a decision maker has high carbon sensitivity. Outputs of the GCDES Model and simulation optimization algorithm were compared for both single and multiple scenario problems. In the single scenario analysis, solution set of the GCDES Model is used as a benchmark for observing the quality of the solution set returned by our simulation optimization algorithm, since solutions of the GCDES Model can be considered as a lower bound for solutions of the simulation optimization algorithm. For multiple scenario case, the GCDES Model cannot find the whole pareto set in reasonable time while simulation optimization algorithm finds a wide range of solutions.

As future research, this study can be extended in multiple directions. One extension could be considering more objectives such as reliability, social acceptance and efficiency maximization. Interaction of these objectives can provide valuable insights for the decision maker. Another research direction worth exploring is considering ways to increase the uncertainty in the problem. We envisage two potential extensions in this direction: One can assume that the other parameters such as demand and electricity price are also uncertain and/or increase the number of scenarios considered. As the number of uncertain parameters and the number of scenarios increase the models will become more realistic, yet harder to solve. This gives an opportunity to investigate methodologies to tackle the computational challenges as well as to demonstrate the value of stochasticity in such cases. It is also worthwhile to investigate how different solution approaches such as particle swarm optimization, genetic algorithm and evolutionary algorithms would perform for this problem and any of its extensions.

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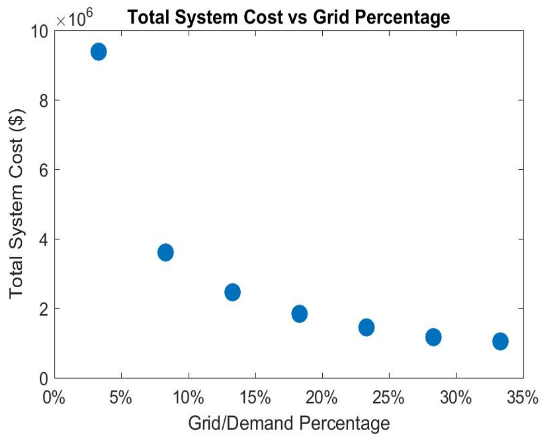
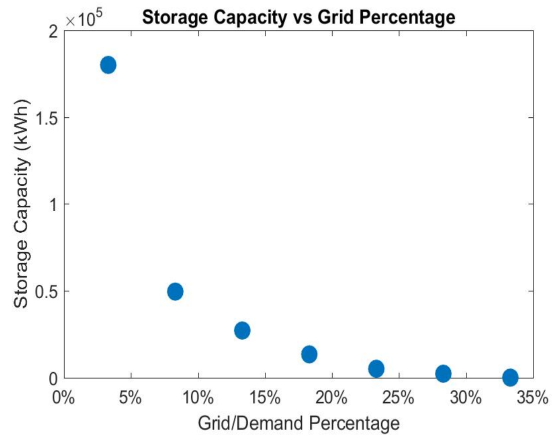
Appendix A

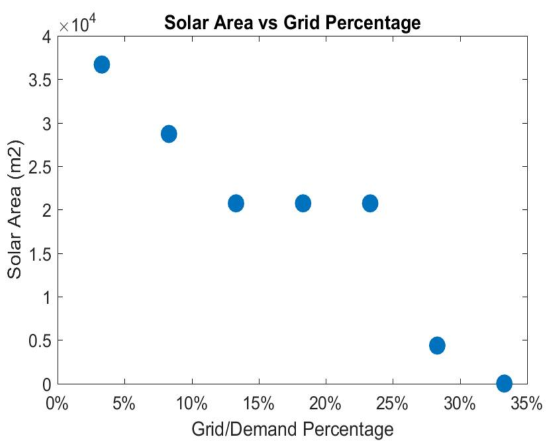
Single Scenario Outputs of the GCDES Model



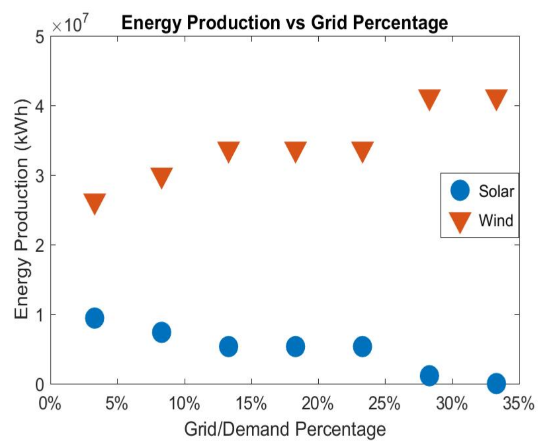
(a) Total System Cost vs Grid Percentage



(b) Battery Capacity vs Grid Percentage

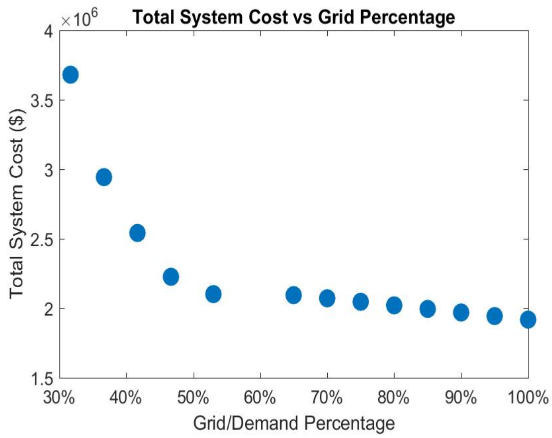


(c) Solar Area vs Grid Percentage

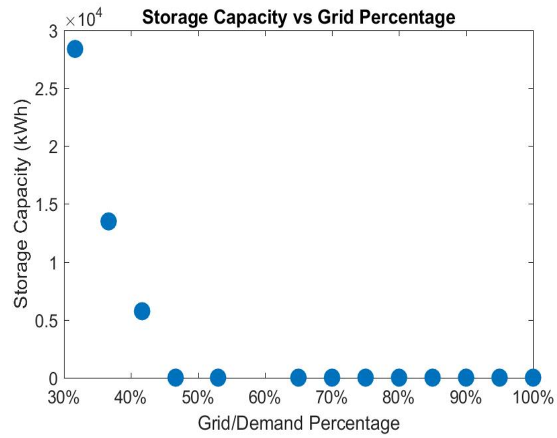


(d) Energy Production vs Grid Percent.

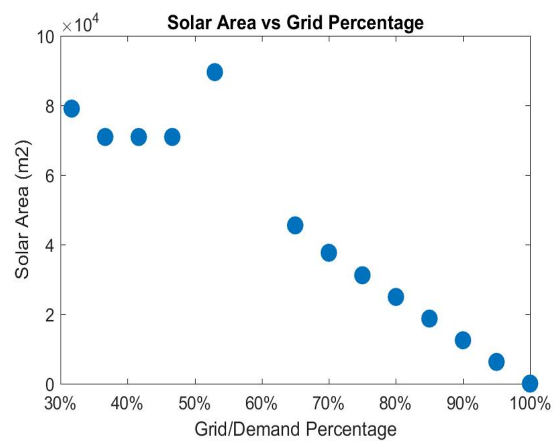
Figure A.1: Output of High Solar-High Wind Case



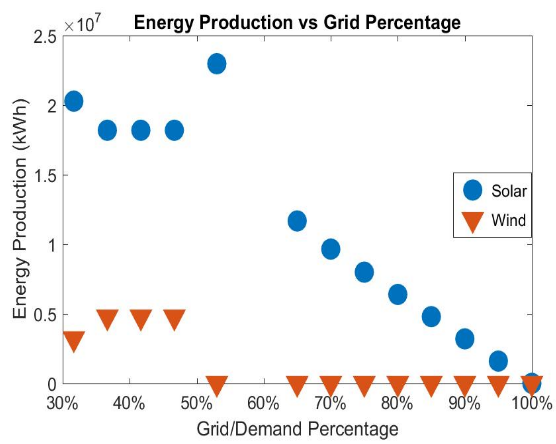
(a) Total System Cost vs Grid Percentage



(b) Battery Capacity vs Grid Percentage

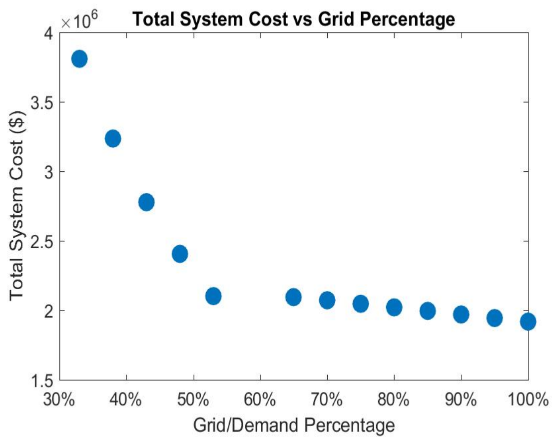


(c) Solar Area vs Grid Percentage

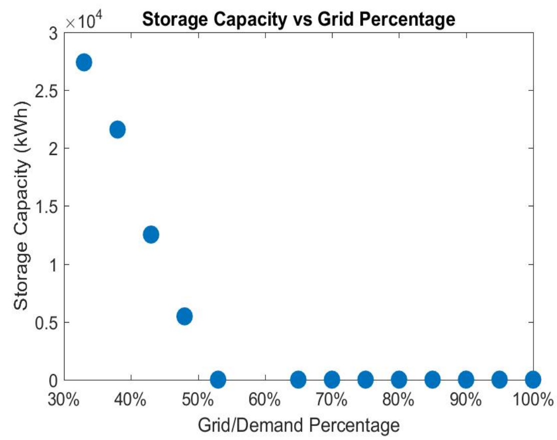


(d) Energy Production vs Grid Percent.

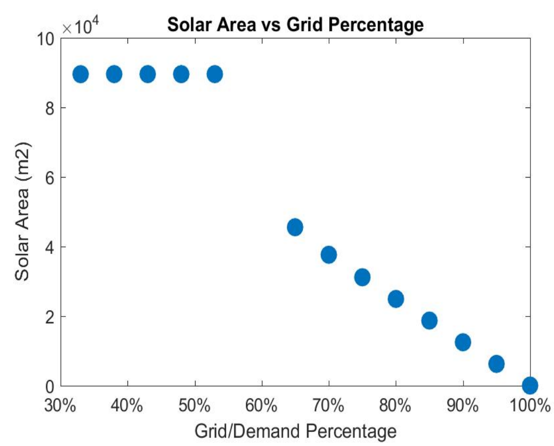
Figure A.2: Output of High Solar-Medium Wind Case



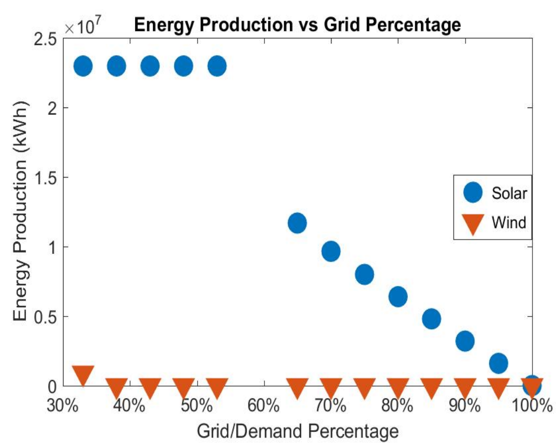
(a) Total System Cost vs Grid Percentage



(b) Battery Capacity vs Grid Percentage

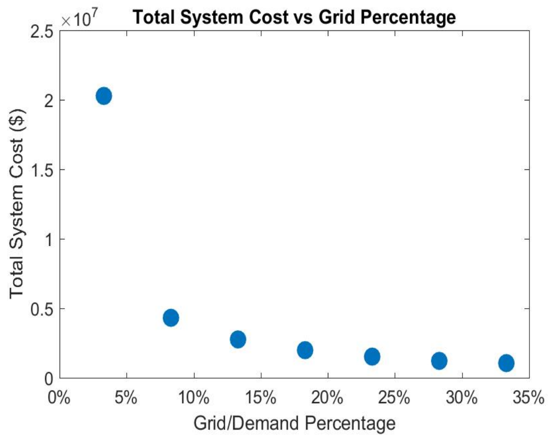


(c) Solar Area vs Grid Percentage

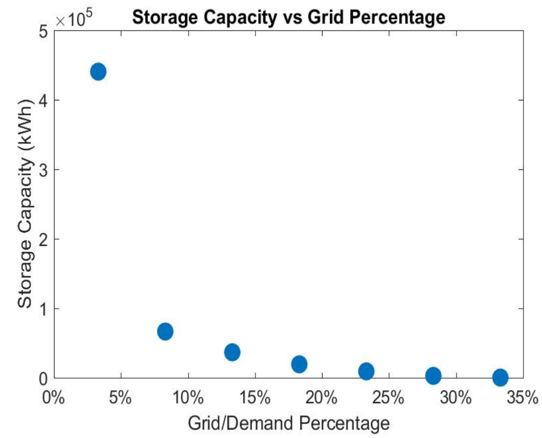


(d) Energy Production vs Grid Percent.

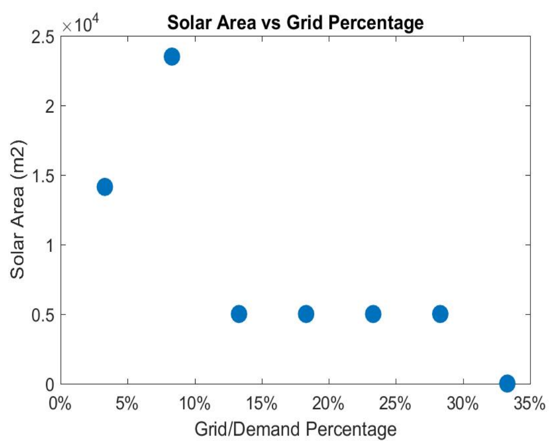
Figure A.3: Output of High Solar-Low Wind Case



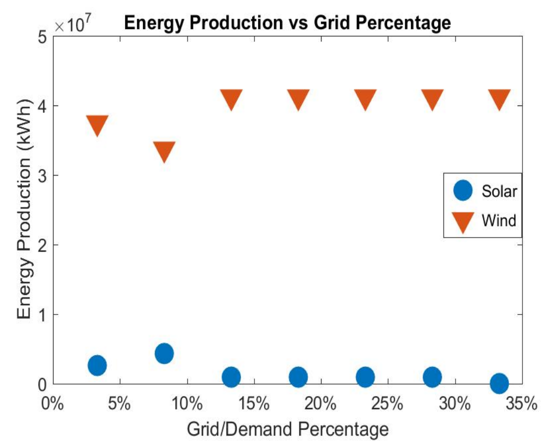
(a) Total System Cost vs Grid Percentage



(b) Battery Capacity vs Grid Percentage

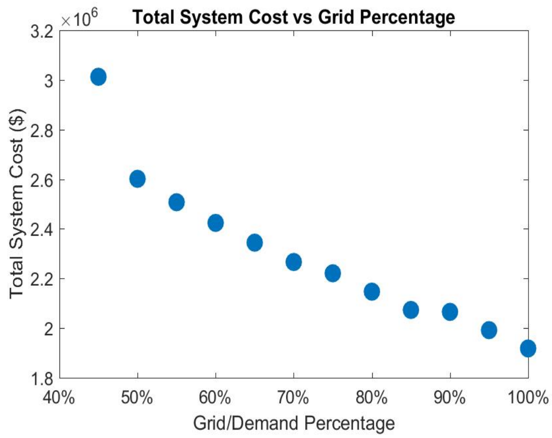


(c) Solar Area vs Grid Percentage

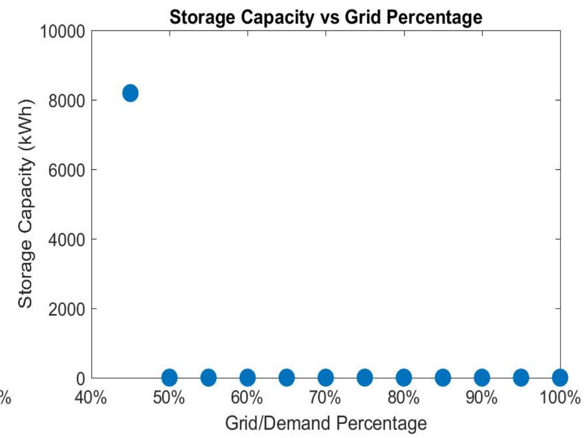


(d) Energy Production vs Grid Percent.

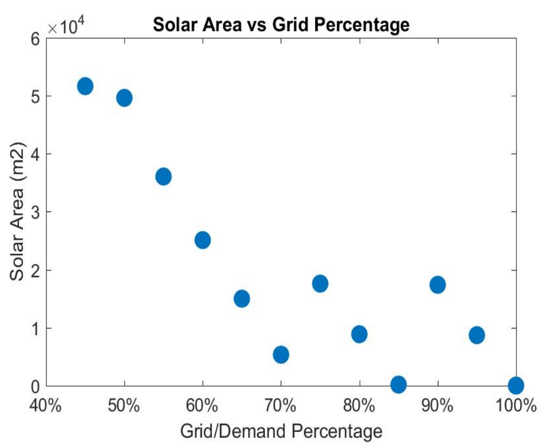
Figure A.4: Output of Medium Solar-High Wind Case



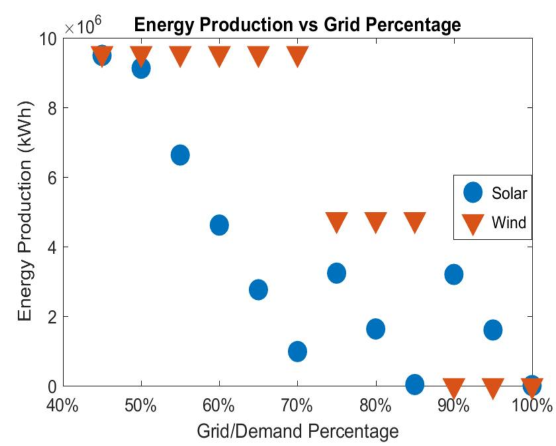
(a) Total System Cost vs Grid Percentage



(b) Battery Capacity vs Grid Percentage

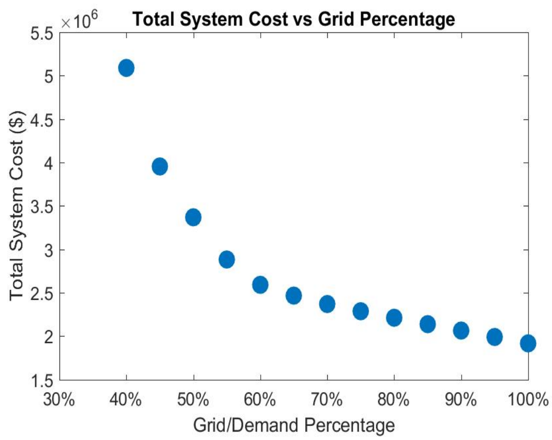


(c) Solar Area vs Grid Percentage

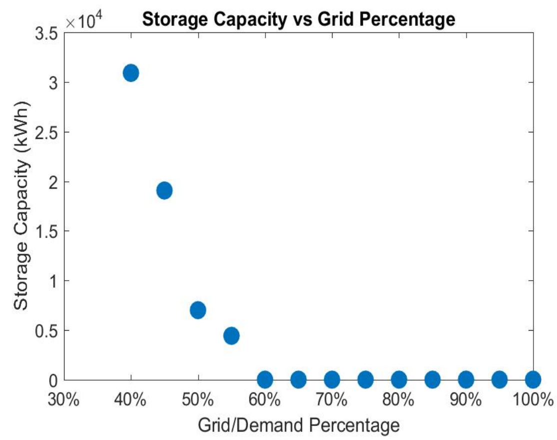


(d) Energy Production vs Grid Percent.

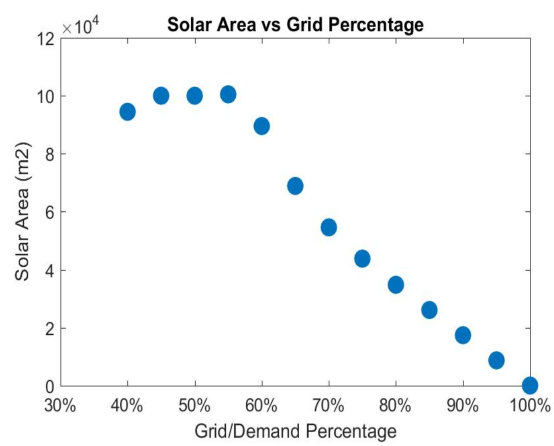
Figure A.5: Output of Medium Solar-Medium Wind Case



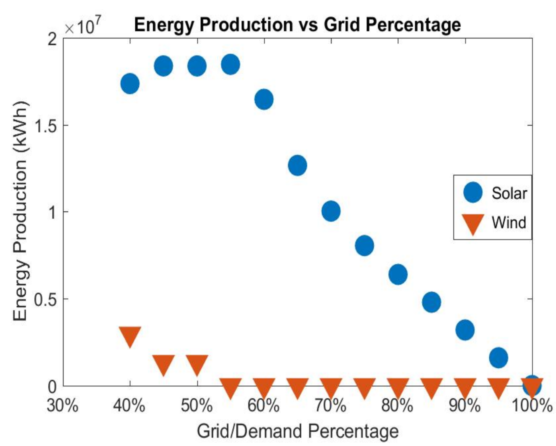
(a) Total System Cost vs Grid Percentage



(b) Battery Capacity vs Grid Percentage

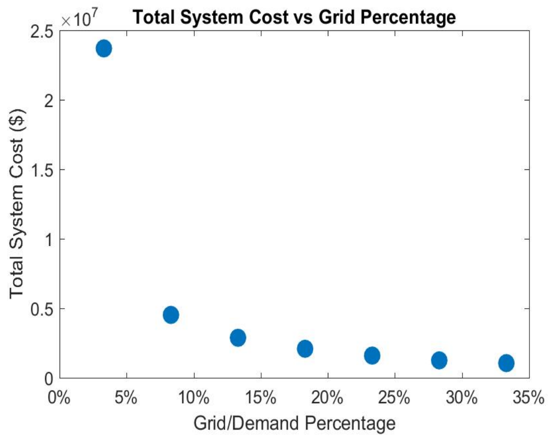


(c) Solar Area vs Grid Percentage

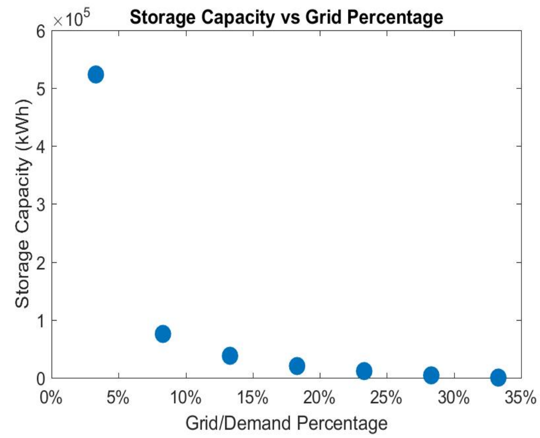


(d) Energy Production vs Grid Percent.

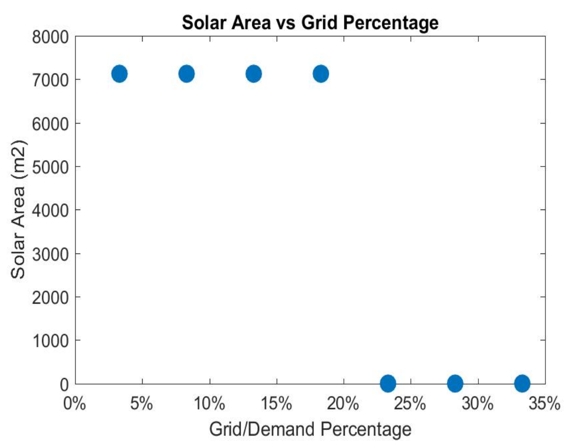
Figure A.6: Output of Medium Solar-Low Wind Case



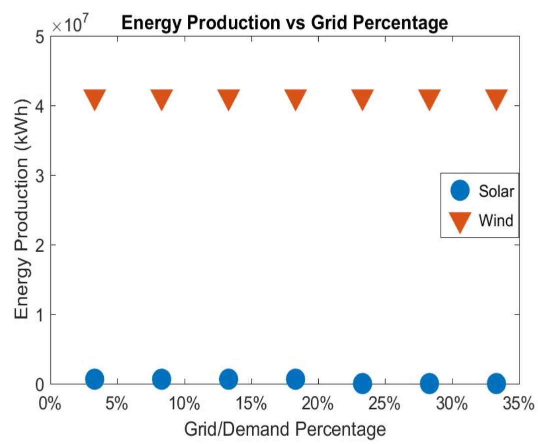
(a) Total System Cost vs Grid Percentage



(b) Battery Capacity vs Grid Percentage

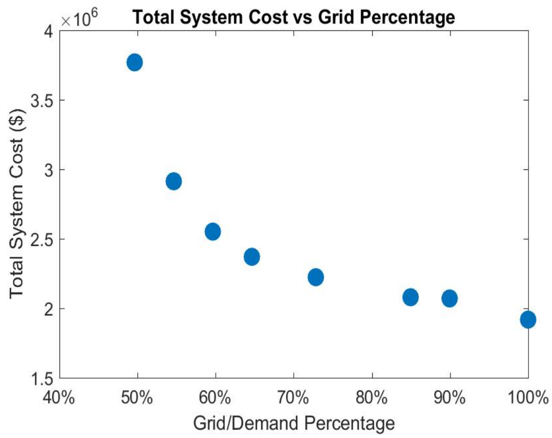


(c) Solar Area vs Grid Percentage

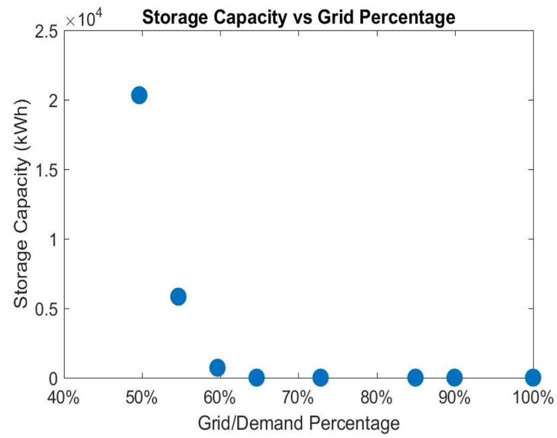


(d) Energy Production vs Grid Percent.

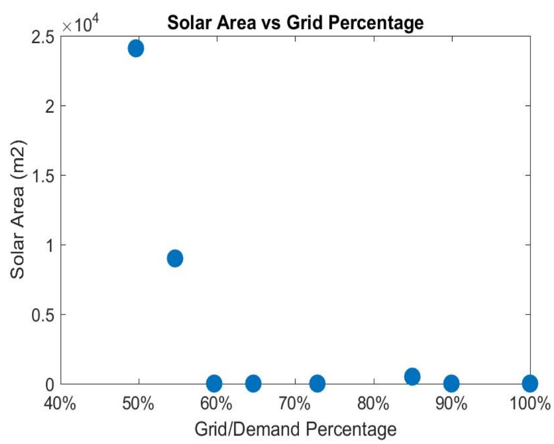
Figure A.7: Output of Low Solar-High Wind Case



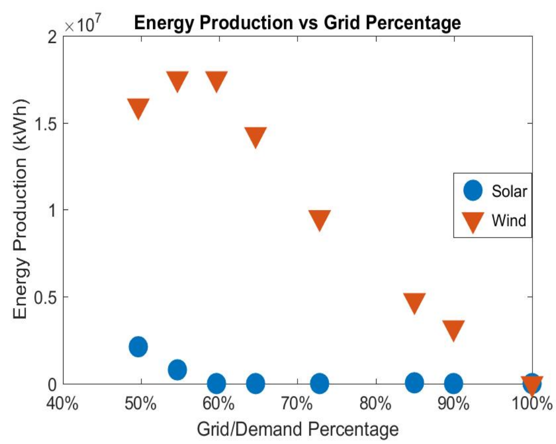
(a) Total System Cost vs Grid Percentage



(b) Battery Capacity vs Grid Percentage

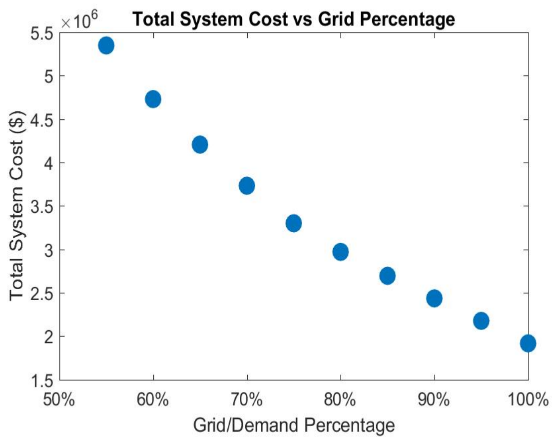


(c) Solar Area vs Grid Percentage

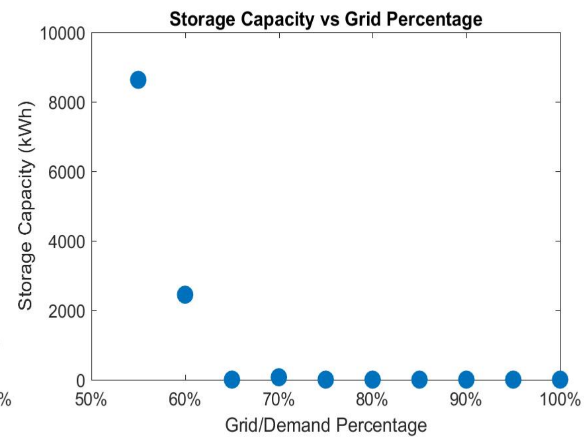


(d) Energy Production vs Grid Percent.

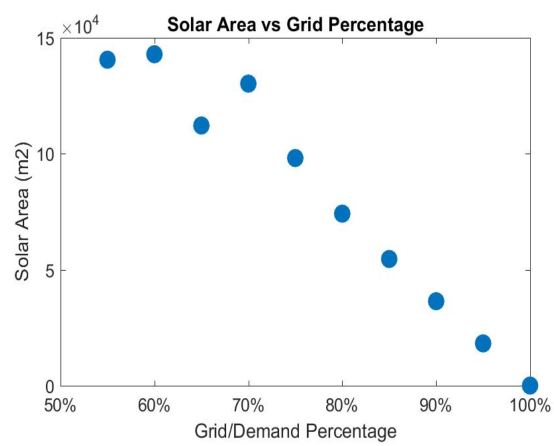
Figure A.8: Output of Low Solar-Medium Wind Case



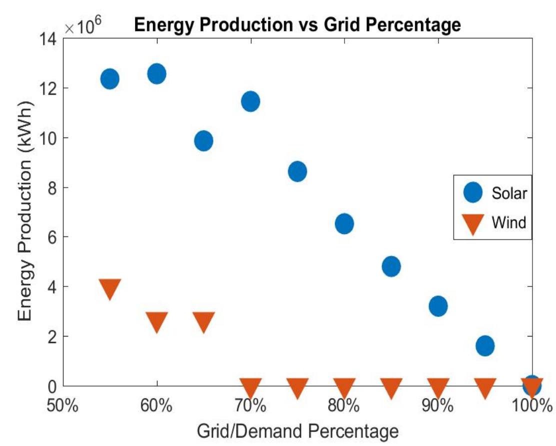
(a) Total System Cost vs Grid Percentage



(b) Battery Capacity vs Grid Percentage



(c) Solar Area vs Grid Percentage

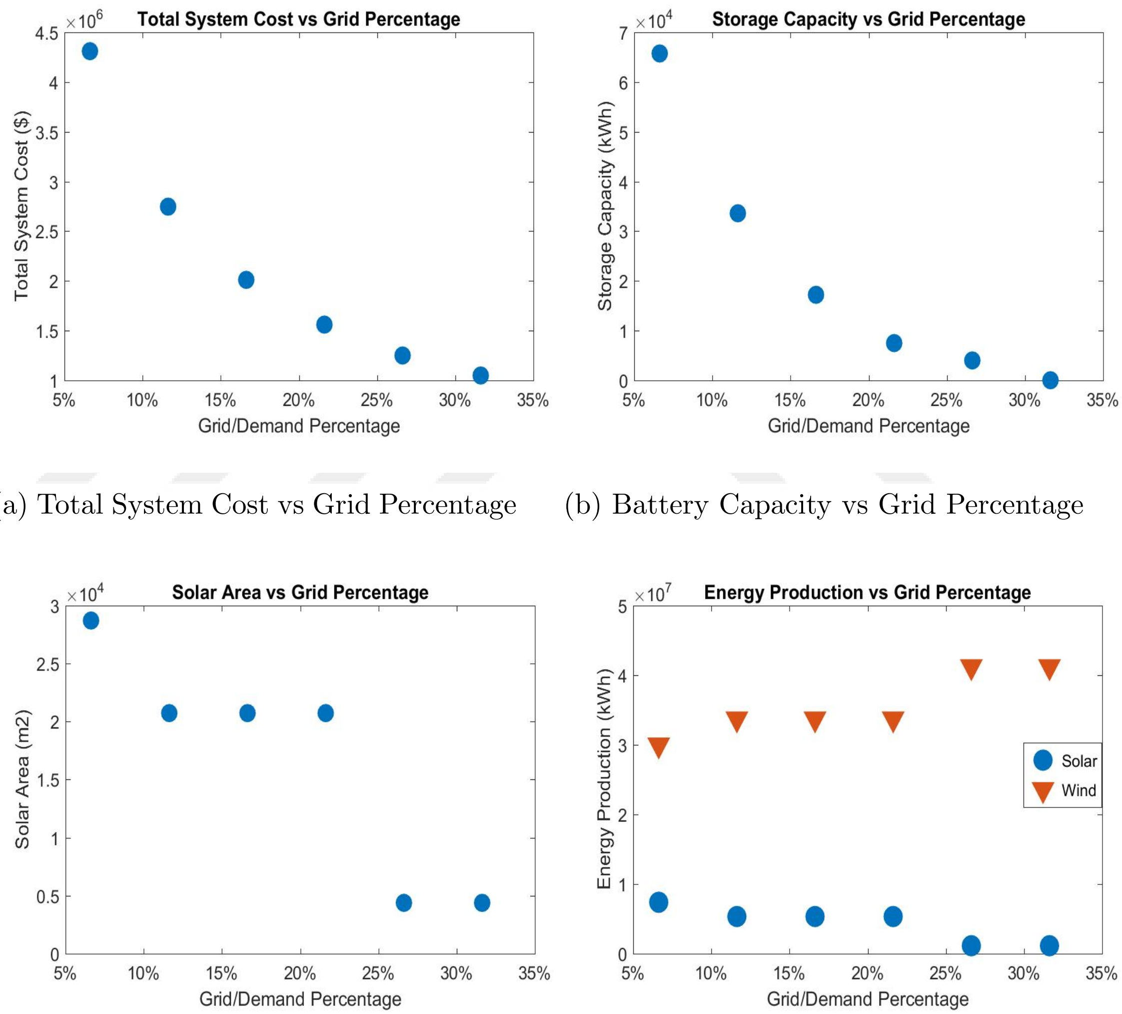


(d) Energy Production vs Grid Percent.

Figure A.9: Output of Low Solar-Low Wind Case

Appendix B

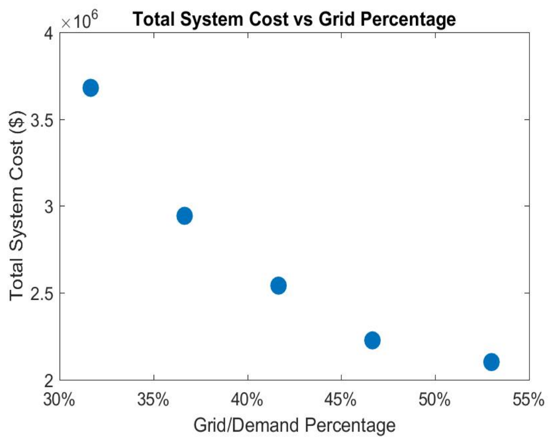
Single Scenario Outputs of the Simulation Optimization Approach



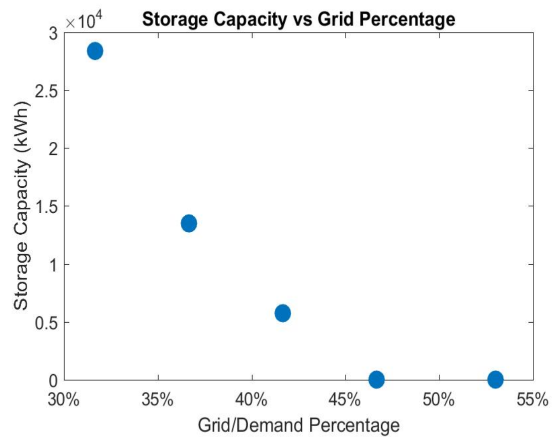
(a) Total System Cost vs Grid Percentage (b) Battery Capacity vs Grid Percentage

(c) Solar Area vs Grid Percentage (d) Energy Production vs Grid Percent.

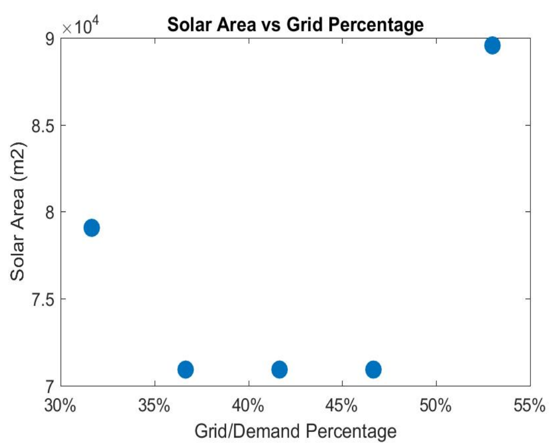
Figure B.1: Output of High Solar-High Wind Case



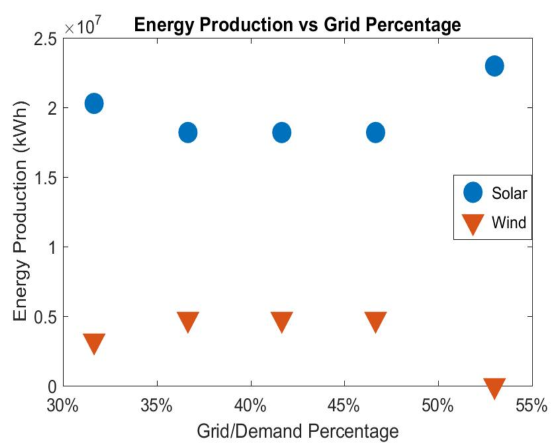
(a) Total System Cost vs Grid Percentage



(b) Battery Capacity vs Grid Percentage

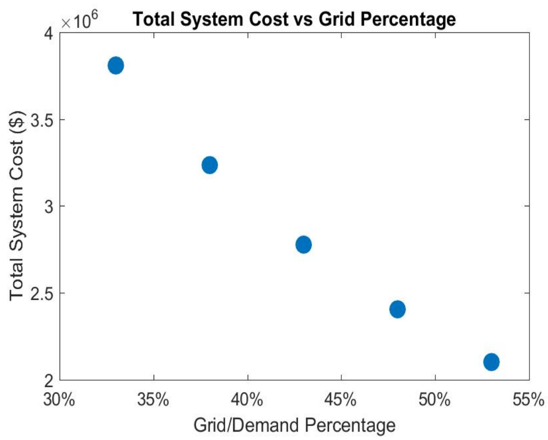


(c) Solar Area vs Grid Percentage

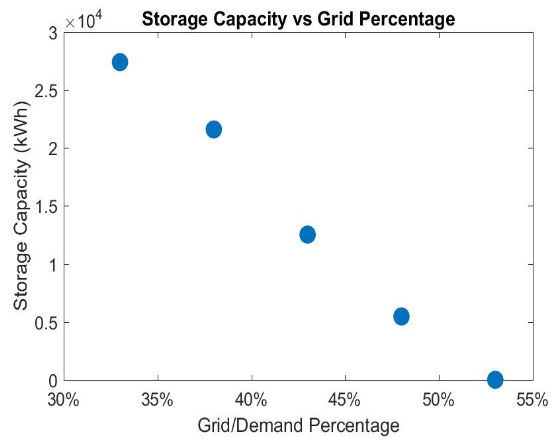


(d) Energy Production vs Grid Percent.

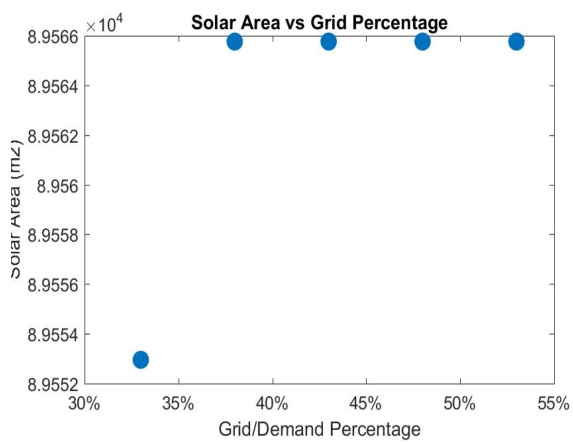
Figure B.2: Output of High Solar-Medium Wind Case



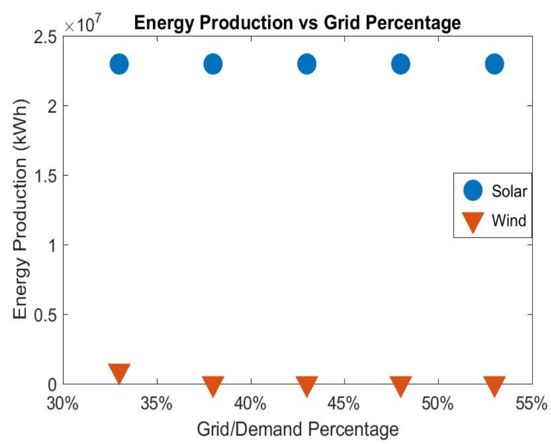
(a) Total System Cost vs Grid Percentage



(b) Battery Capacity vs Grid Percentage

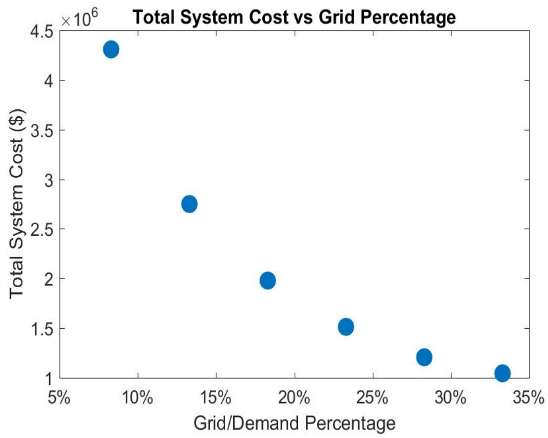


(c) Solar Area vs Grid Percentage

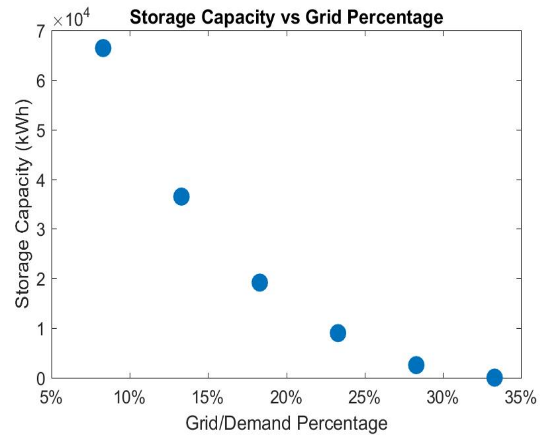


(d) Energy Production vs Grid Percent.

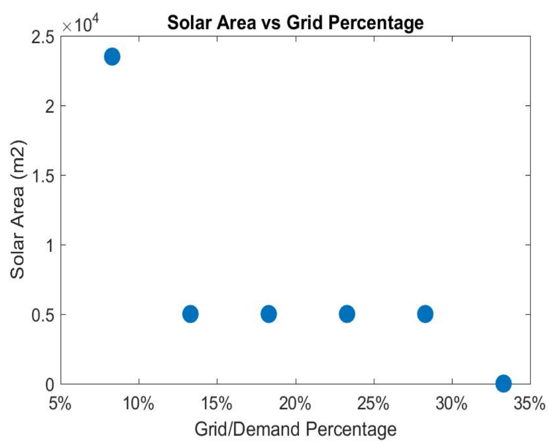
Figure B.3: Output of High Solar-Low Wind Case



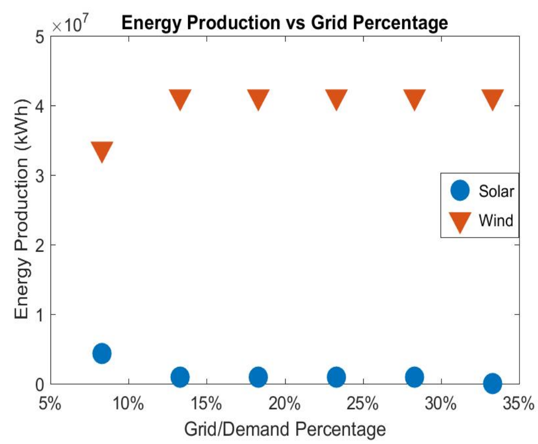
(a) Total System Cost vs Grid Percentage



(b) Battery Capacity vs Grid Percentage

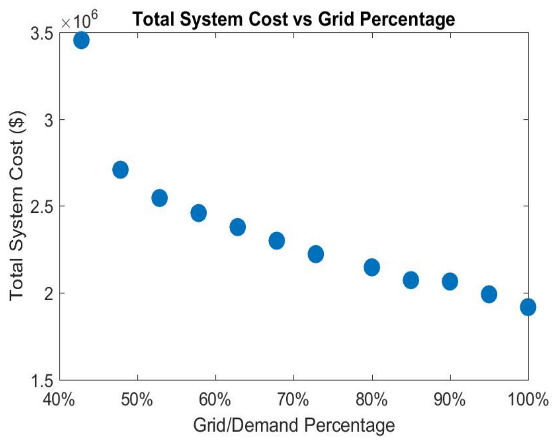


(c) Solar Area vs Grid Percentage

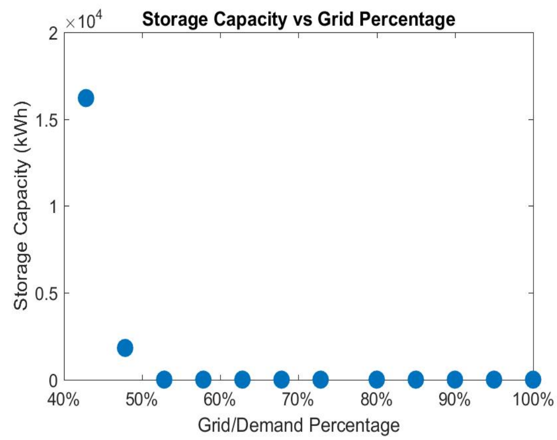


(d) Energy Production vs Grid Percent.

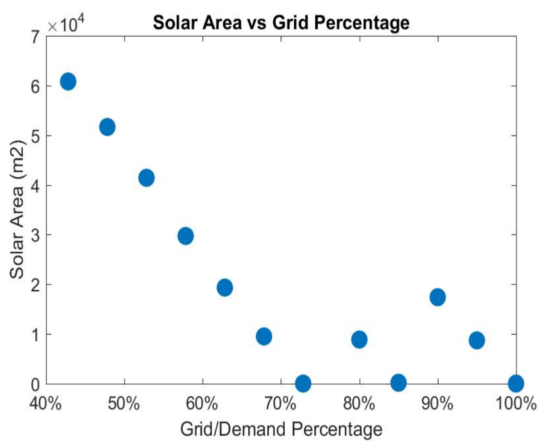
Figure B.4: Output of Medium Solar-High Wind Case



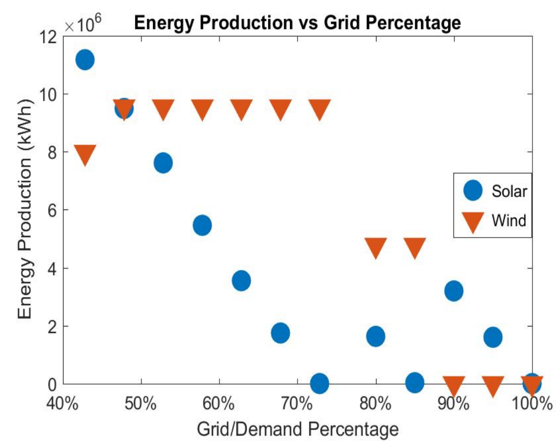
(a) Total System Cost vs Grid Percentage



(b) Battery Capacity vs Grid Percentage

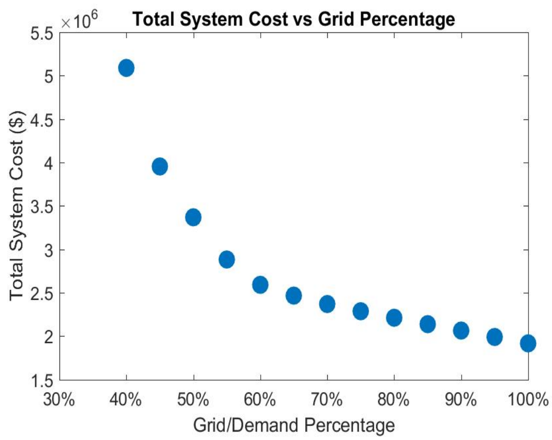


(c) Solar Area vs Grid Percentage

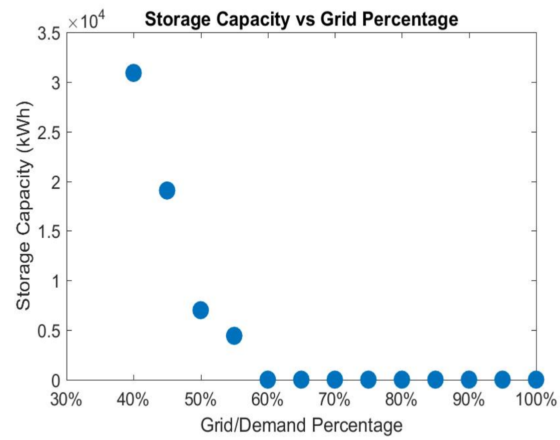


(d) Energy Production vs Grid Percent.

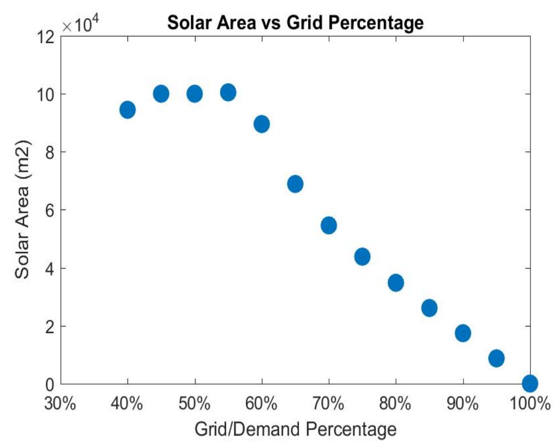
Figure B.5: Output of Medium Solar-Medium Wind Case



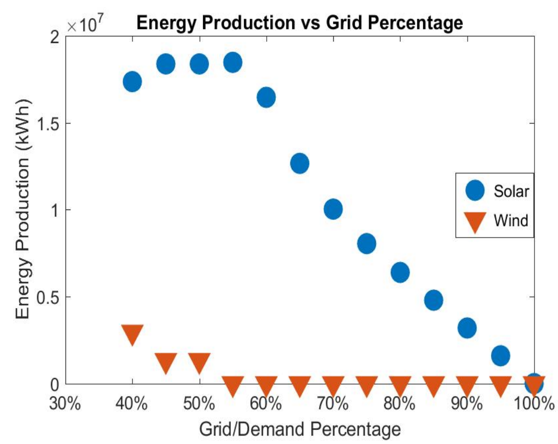
(a) Total System Cost vs Grid Percentage



(b) Battery Capacity vs Grid Percentage

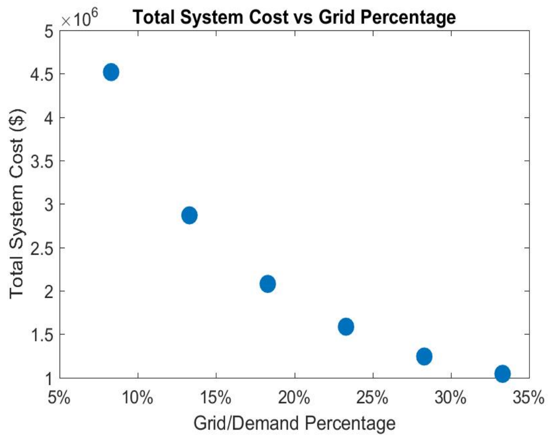


(c) Solar Area vs Grid Percentage

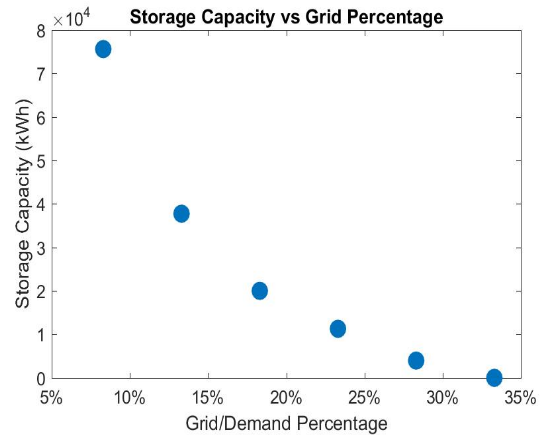


(d) Energy Production vs Grid Percent.

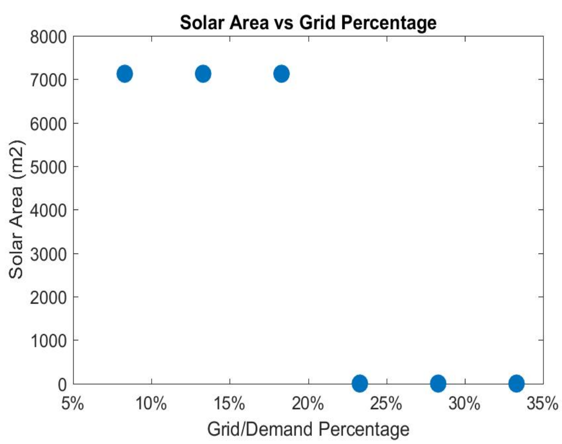
Figure B.6: Output of Medium Solar-Low Wind Case



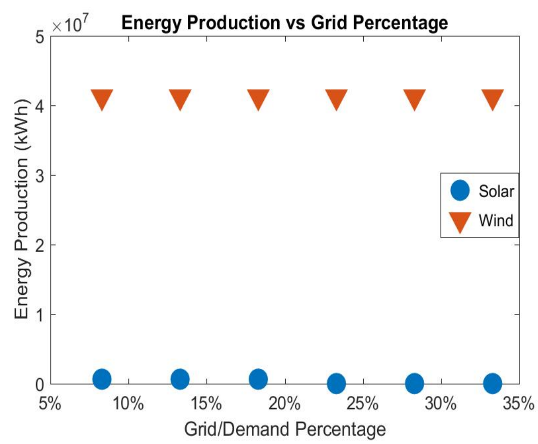
(a) Total System Cost vs Grid Percentage



(b) Battery Capacity vs Grid Percentage

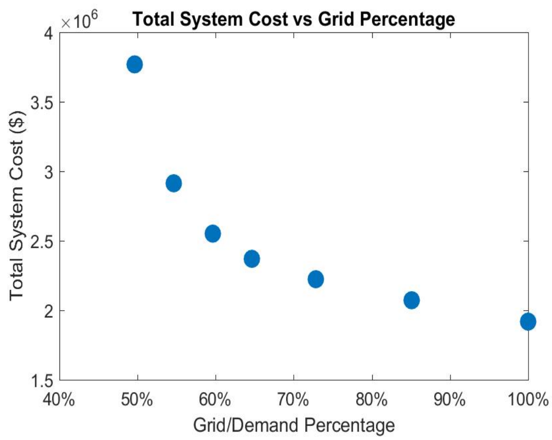


(c) Solar Area vs Grid Percentage

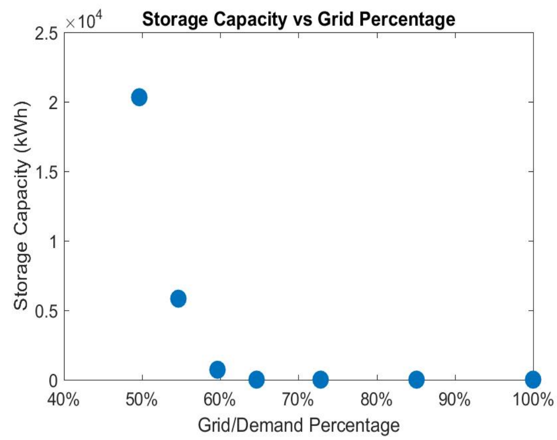


(d) Energy Production vs Grid Percent.

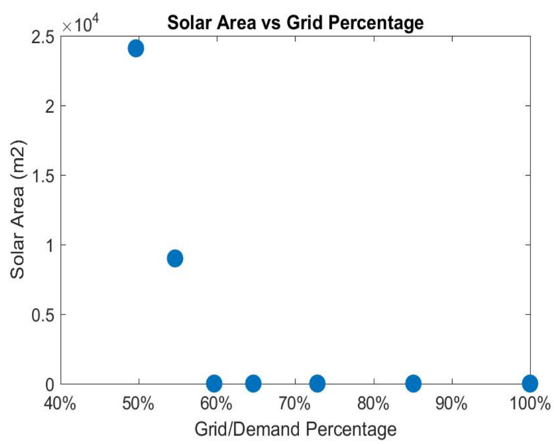
Figure B.7: Output of Low Solar-High Wind Case



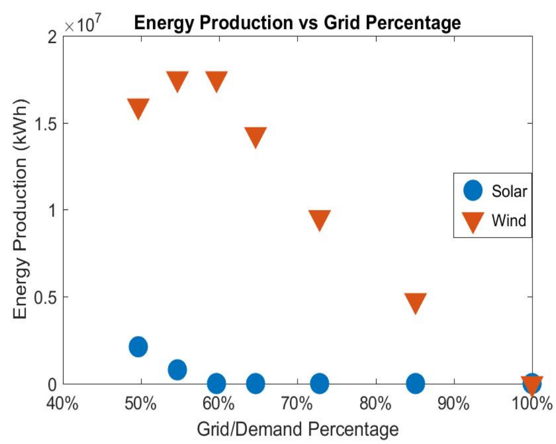
(a) Total System Cost vs Grid Percentage



(b) Battery Capacity vs Grid Percentage

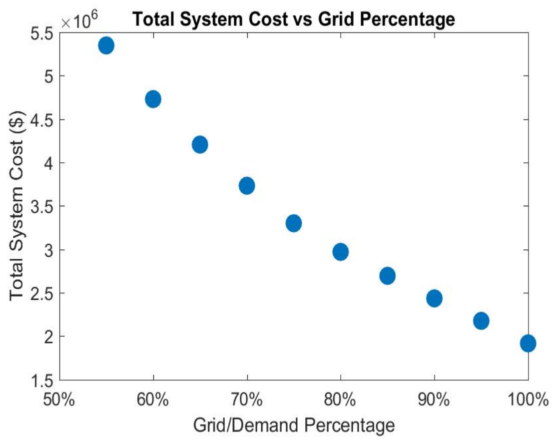


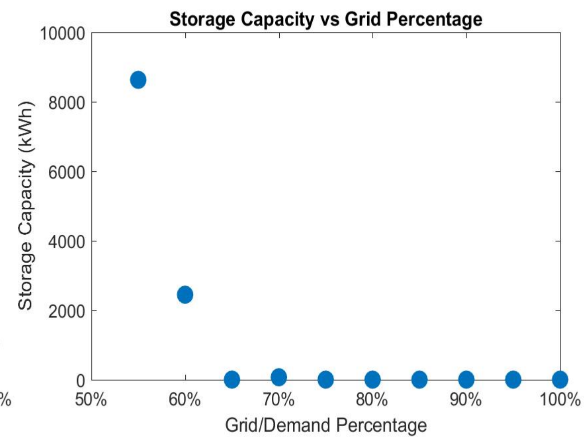
(c) Solar Area vs Grid Percentage



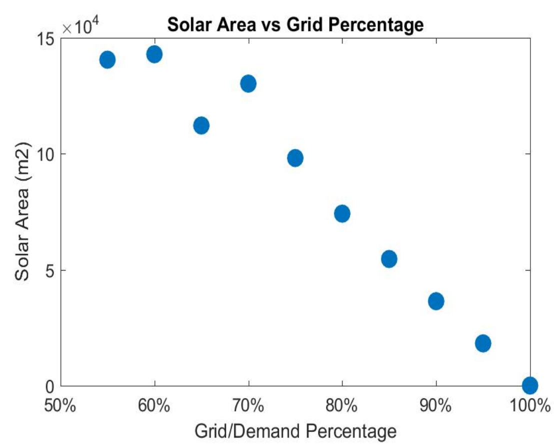
(d) Energy Production vs Grid Percent.

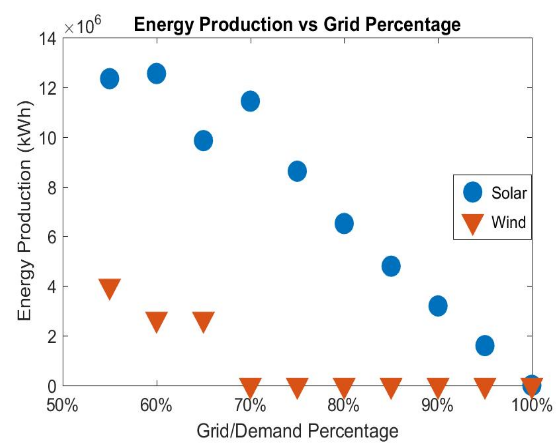
Figure B.8: Output of Low Solar-Medium Wind Case





(a) Total System Cost vs Grid Percentage (b) Battery Capacity vs Grid Percentage



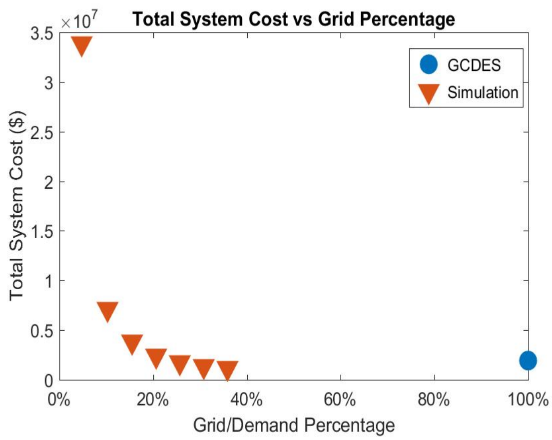


(c) Solar Area vs Grid Percentage (d) Energy Production vs Grid Percent.

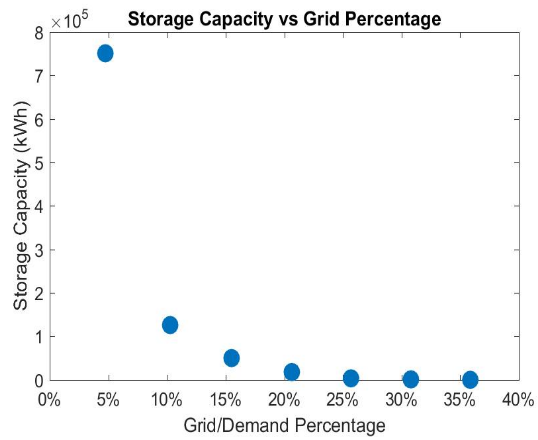
Figure B.9: Output of Low Solar-Low Wind Case

Appendix C

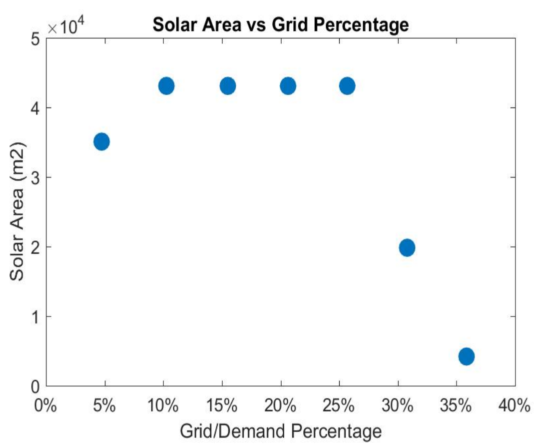
Multiple Scenario Output of the Simulation Optimization Approach



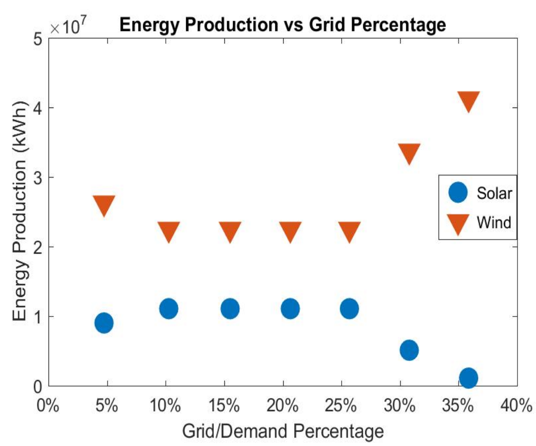
(a) Total System Cost vs Grid Percentage



(b) Battery Capacity vs Grid Percentage

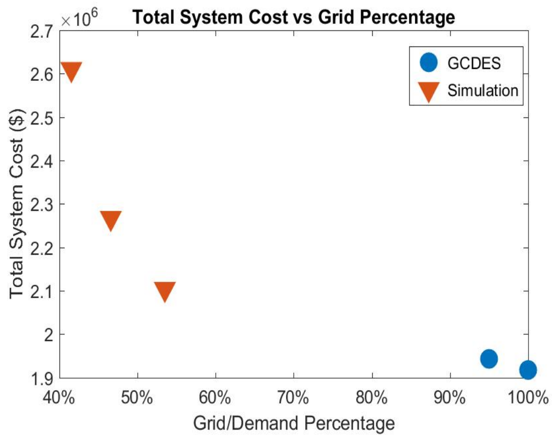


(c) Solar Area vs Grid Percentage

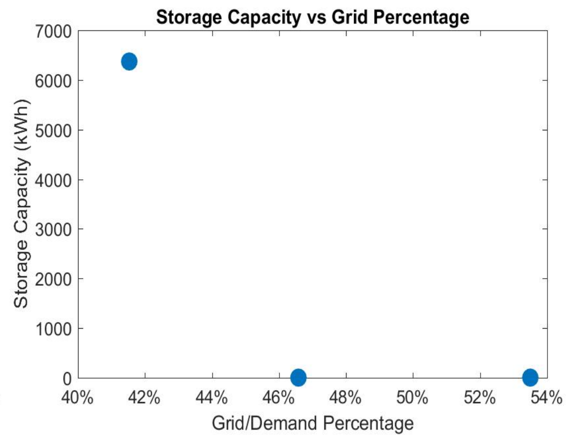


(d) Energy Production vs Grid Percent.

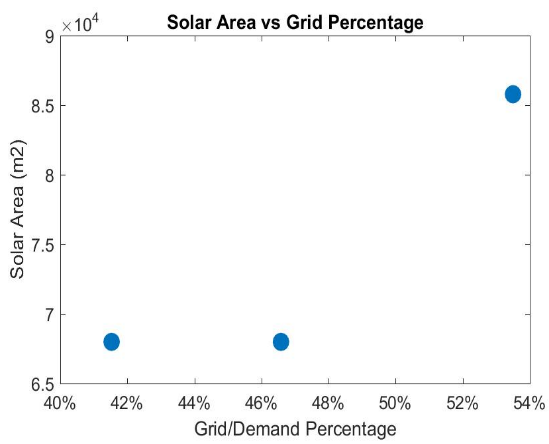
Figure C.1: Output of High Solar-High Wind Case



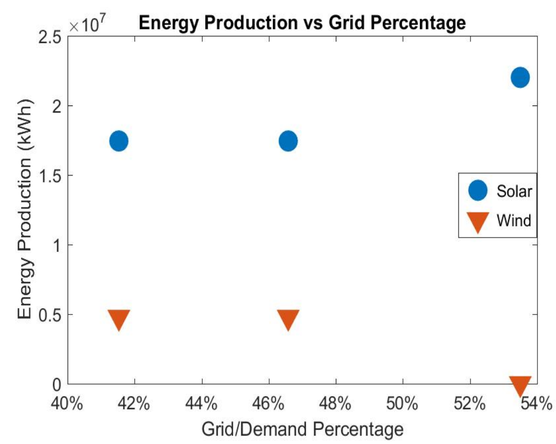
(a) Total System Cost vs Grid Percentage



(b) Battery Capacity vs Grid Percentage

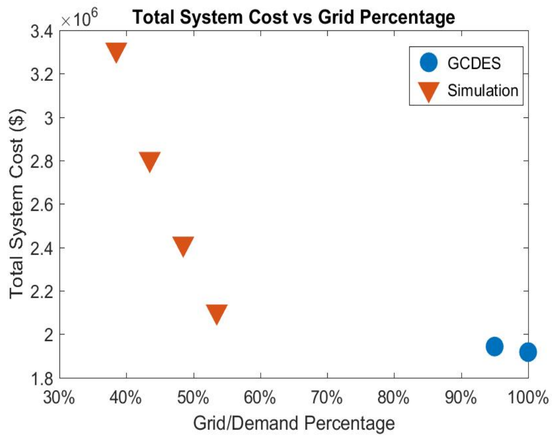


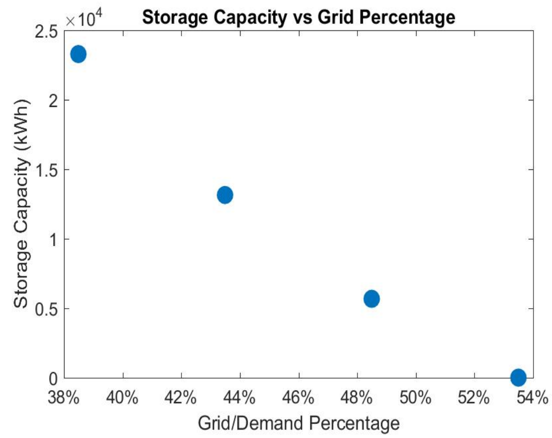
(c) Solar Area vs Grid Percentage



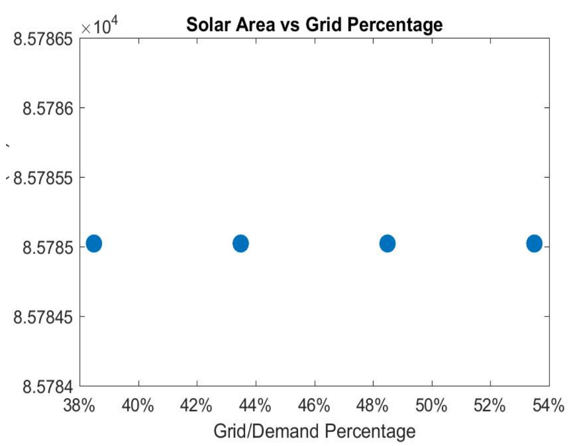
(d) Energy Production vs Grid Percent.

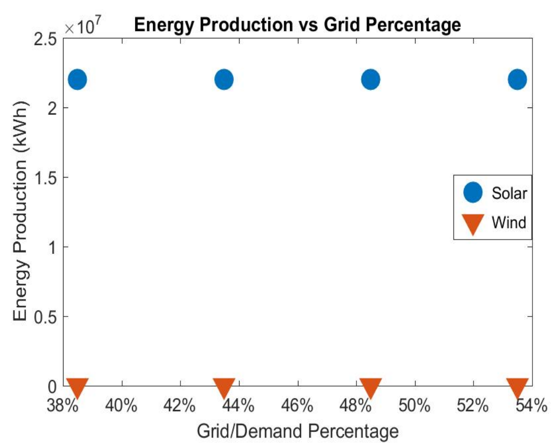
Figure C.2: Output of High Solar-Medium Wind Case





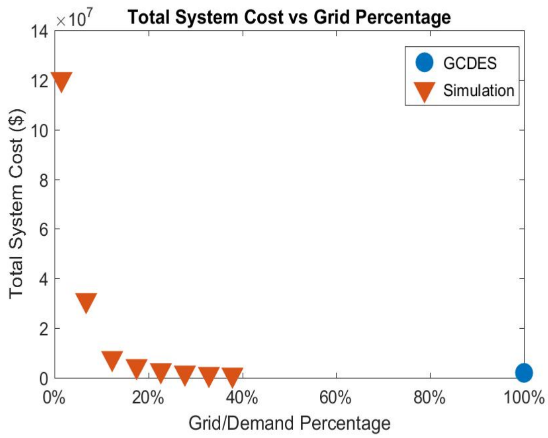
(a) Total System Cost vs Grid Percentage (b) Battery Capacity vs Grid Percentage



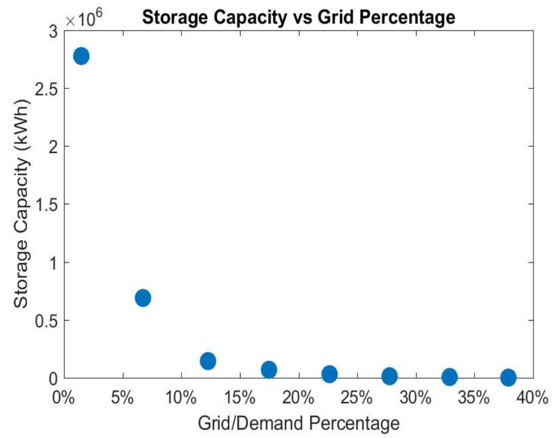


(c) Solar Area vs Grid Percentage (d) Energy Production vs Grid Percent.

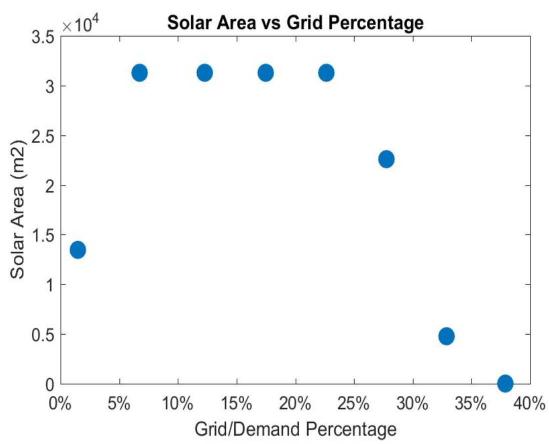
Figure C.3: Output of High Solar-Low Wind Case



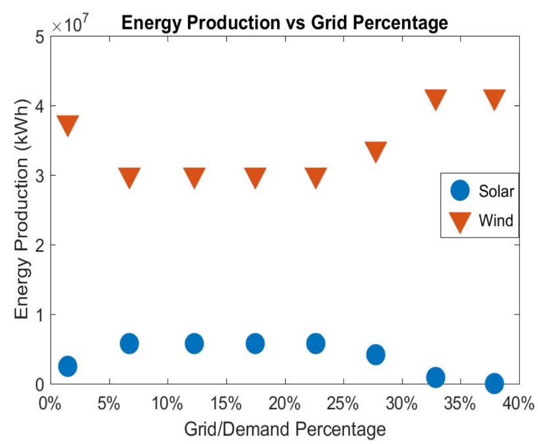
(a) Total System Cost vs Grid Percentage



(b) Battery Capacity vs Grid Percentage

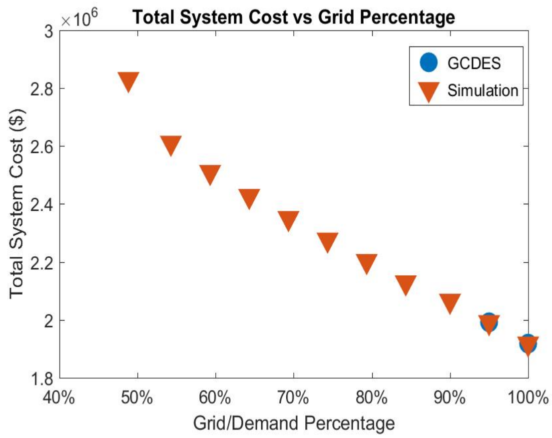


(c) Solar Area vs Grid Percentage

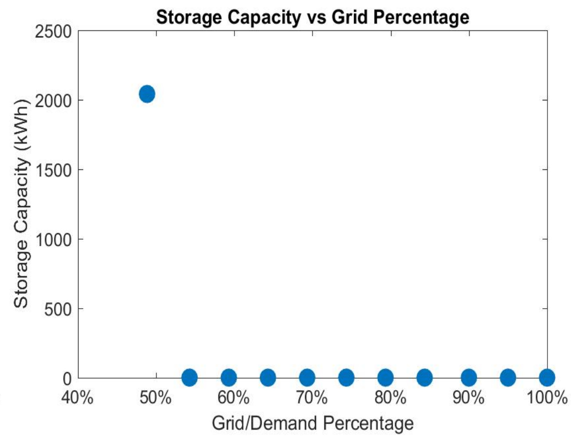


(d) Energy Production vs Grid Percent.

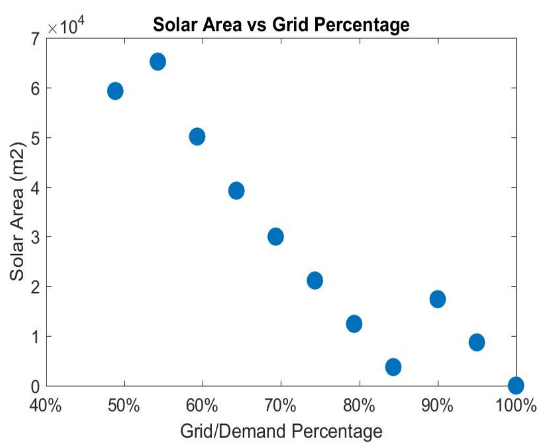
Figure C.4: Output of Medium Solar-High Wind Case



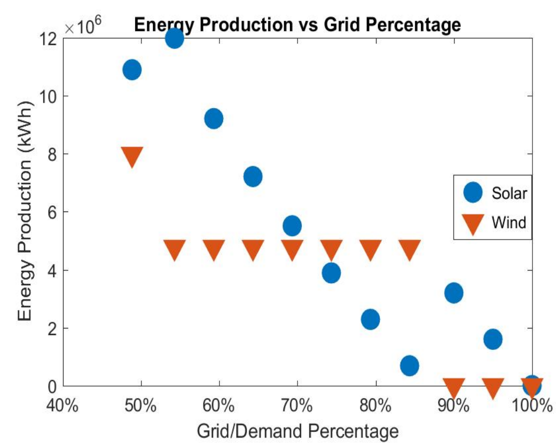
(a) Total System Cost vs Grid Percentage



(b) Battery Capacity vs Grid Percentage

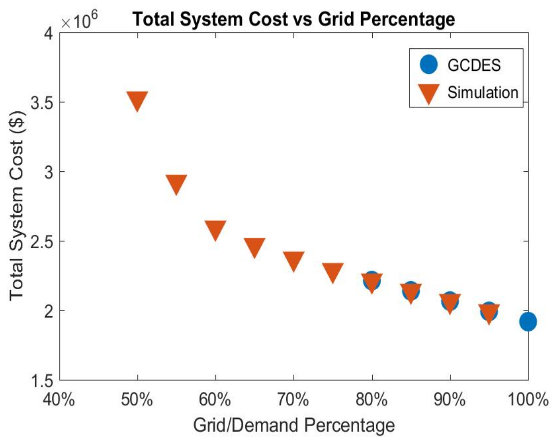


(c) Solar Area vs Grid Percentage

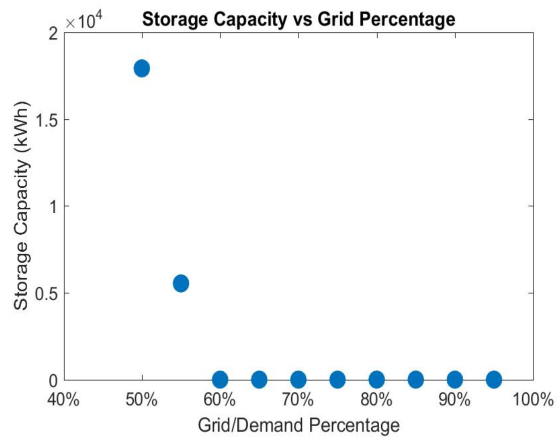


(d) Energy Production vs Grid Percent.

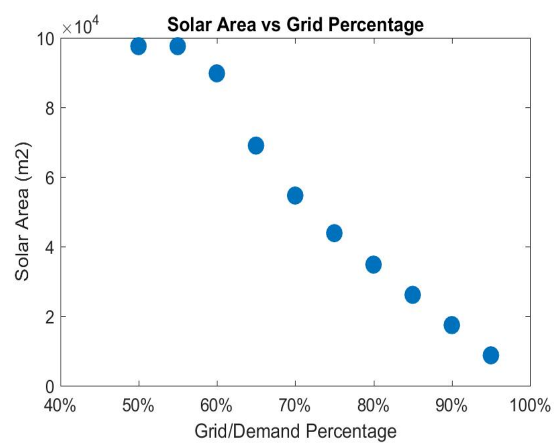
Figure C.5: Output of Medium Solar-Medium Wind Case



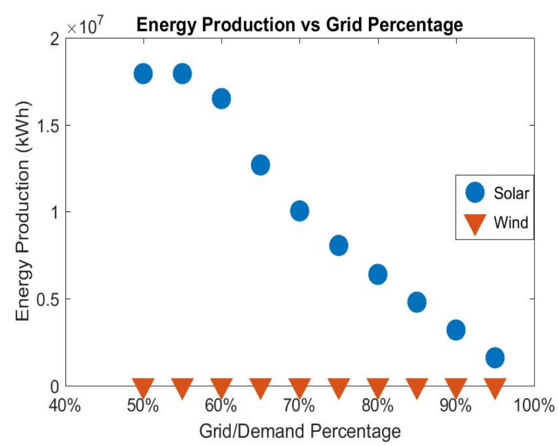
(a) Total System Cost vs Grid Percentage



(b) Battery Capacity vs Grid Percentage

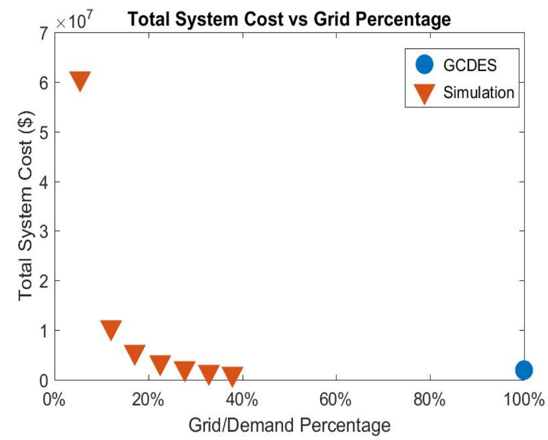


(c) Solar Area vs Grid Percentage

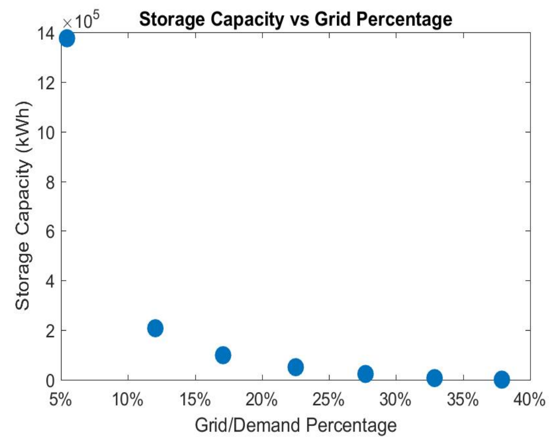


(d) Energy Production vs Grid Percent.

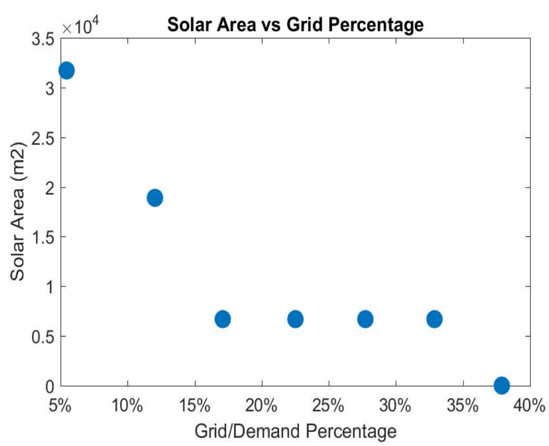
Figure C.6: Output of Medium Solar-Low Wind Case



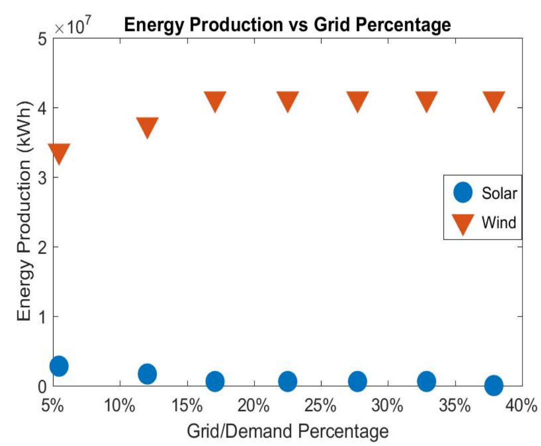
(a) Total System Cost vs Grid Percentage



(b) Battery Capacity vs Grid Percentage

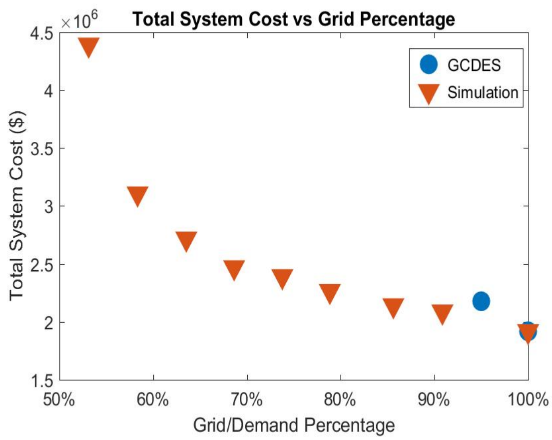


(c) Solar Area vs Grid Percentage

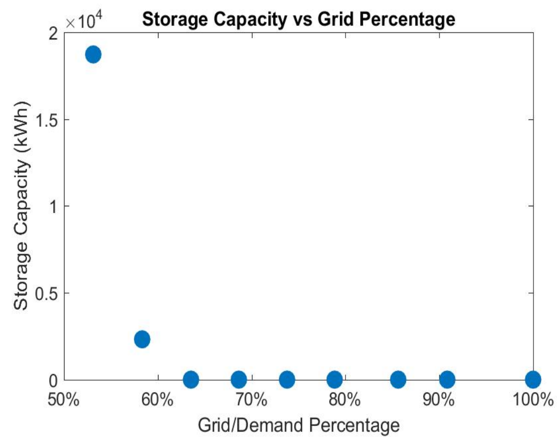


(d) Energy Production vs Grid Percent.

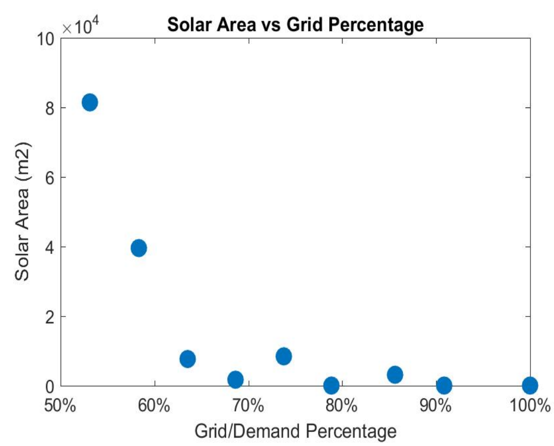
Figure C.7: Output of Low Solar-High Wind Case



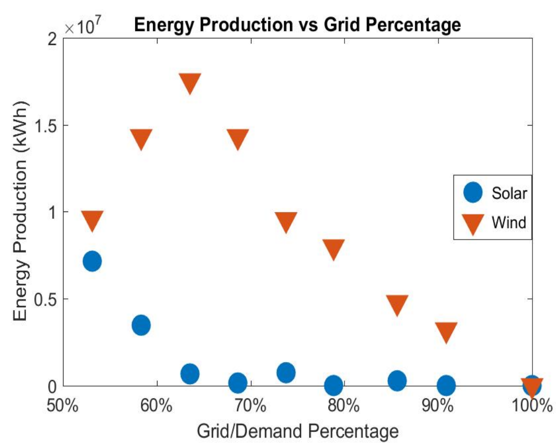
(a) Total System Cost vs Grid Percentage



(b) Battery Capacity vs Grid Percentage

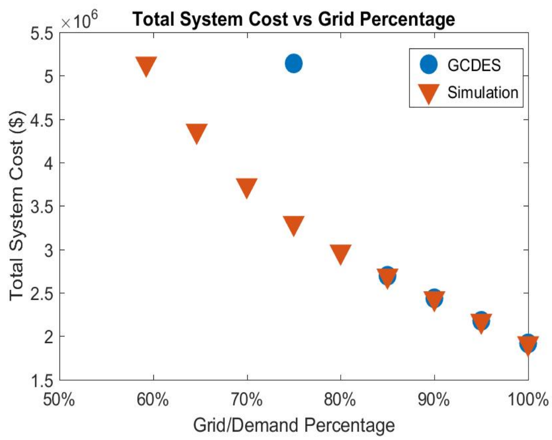


(c) Solar Area vs Grid Percentage

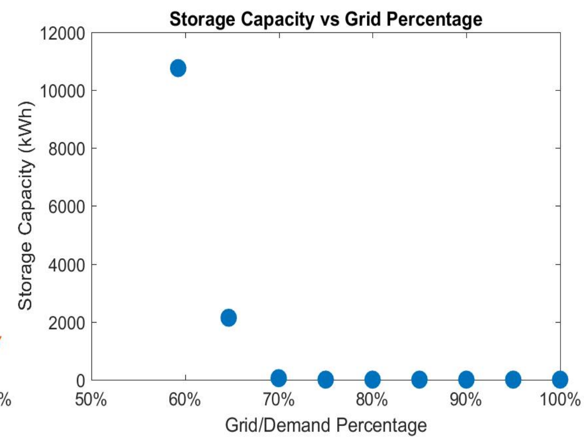


(d) Energy Production vs Grid Percent.

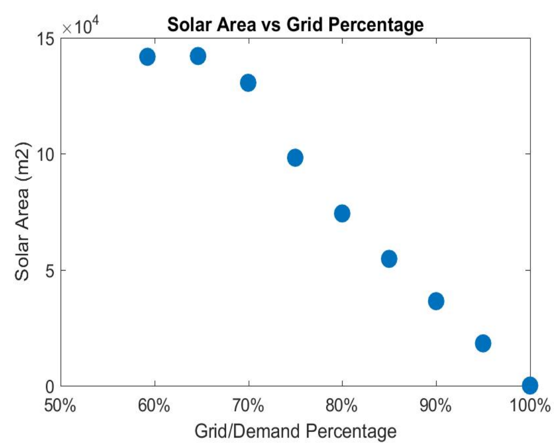
Figure C.8: Output of Low Solar-Medium Wind Case



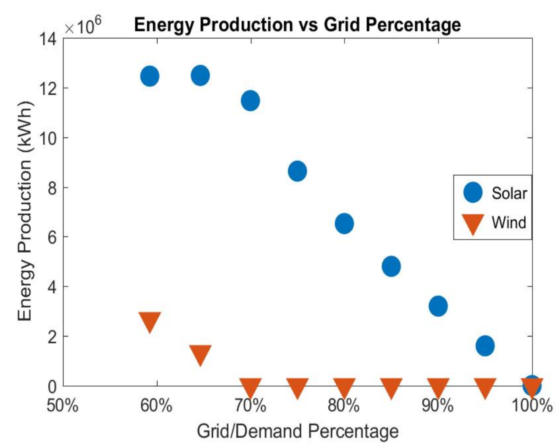
(a) Total System Cost vs Grid Percentage



(b) Battery Capacity vs Grid Percentage



(c) Solar Area vs Grid Percentage



(d) Energy Production vs Grid Percent.

Figure C.9: Output of Low Solar-Low Wind Case