

METAHEURISTIC APPROACHES FOR BI-OBJECTIVE STOCHASTIC OPTIMIZATION OF A GRID-CONNECTED DECENTRALIZED ENERGY SYSTEM

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METAHEURISTIC APPROACHES FOR BI-OBJECTIVE
STOCHASTIC OPTIMIZATION OF A GRID-CONNECTED DE-
CENTRALIZED ENERGY SYSTEM

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August 2017

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.

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ABSTRACT

METAHEURISTIC APPROACHES FOR BI-OBJECTIVE STOCHASTIC OPTIMIZATION OF A GRID-CONNECTED DECENTRALIZED ENERGY SYSTEM

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With the growing tendency in shifting from centralized to decentralized energy systems, we investigate the sizing decision of a grid-connected decentralized energy system. This system is composed of renewable energy generation components which are solar panels and wind turbines, storage unit and grid connection. In the system, it is aimed to find the optimal sizes of these components while considering both cost and environment. Resulting from this consideration, there are two objectives which are total cost and carbon dioxide emission in the problem. Together with these two objectives, uncertainty introduced by the renewable energy sources and electricity demand makes the problem stochastic in nature. In order to solve the bi-objective stochastic optimization problem, we establish a metaheuristic-based solution approach in which metaheuristic algorithms and simulation tool are utilized in a simulation-optimization framework. By using three well-known metaheuristic algorithms such as Optimized Multi Objective Particle Swarm Optimization Algorithm (OMOPSO), Non-dominated Sorting Genetic Algorithm II (NSGA-II) and Strength Pareto Evolutionary Algorithm 2 (SPEA2) in the proposed methodology, a numerical study is carried out for alternative wind, solar and demand scenario sets. We show that OMOPSO is the best performing algorithm to be used in the metaheuristic approach. With OMOPSO algorithm's superior performance, metaheuristic approach is compared to a simulation-optimization approach that is previously developed for the same problem by using performance metrics.

Keywords: Hybrid Renewable Energy System, Bi-objective Stochastic Optimization, Simulation-based Optimization, Metaheuristic Algorithms.

ÖZET

ŞEBEKEYE BAĞLI MERKEZİ OLMAYAN ENERJİ SİSTEMLERİNİN İKİ AMAÇLI RASSAL ENİYİLEMESİ İÇİN METASEZGİSEL YAKLAŞIMLAR

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Bu çalışmada, merkezi enerji sistemlerinden merkezi olmayan enerji sistemlerine geçişin artmasından yola çıkarak, şebekeye bağlı merkezi olmayan bir enerji sisteminin kurulum problemini araştırmaktayız. Sistem, yenilenebilir enerji kaynakları üretim parçaları olan güneş panelleri ve rüzgar türbinlerinden, depolama ünitesinden ve şebeke bağlantısından meydana gelmektedir. Kurulacak sistemde amaç, çevre ve maliyeti göz önünde bulundururken sistem bileşenlerinin en iyi boyutlarını hesaplamaktır. Çevre ve maliyeti göz önünde bulundurmanın sonucunda, toplam maliyet ve karbon salınımı şeklinde iki amaç ortaya çıkmaktadır. Bu iki amacın yanında, yenilenebilir enerji kaynakları ve elektrik talep verisindeki belirsizlikler problemi rassal hale getirmektedir. İki amaçlı rassal eniyileme probleminin çözümü için, metasezgisel algoritmaların ve benzetim aracının benzetim-eniyileme çerçevesinde kullanıldığı metasezgisel tabanlı bir çözüm yöntemi geliştirilmiştir. Üç tane iyi bilinen, OMOPSO, NSGA-II ve SPEA2, metasezgisel algoritmaları kullanarak, alternatif güneş, rüzgar ve elektrik talep senaryoları için sayısal bir çalışma yapılmıştır. Metasezgisel çözüm yaklaşımı için kullanılacak en iyi algoritmanın OMOPSO olduğu gösterilmiştir. OMOPSO algoritmasının yüksek performansı ile, metasezgisel yöntem aynı problem için daha önceden geliştirilmiş olan benzetim-eniyileme yöntemiyle karşılaştırılmıştır. Sonuç olarak, iki yöntemin sonuçları bazı performans ölçütleri kullanılarak değerlendirilmiştir.

Anahtar sözcükler: Yenilenebilir Enerji Sistemleri, İki Amaçlı Rassal Eniyileme, Benzetim Tabanlı Eniyileme, Metasezgisel Algoritmalar.

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To my father . . .

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Chapter 1

Introduction

The total number of individuals who do not have access to the electricity is estimated as 1.2 billion, which is almost the quarter of the worlds' population [1]. When the increasing energy demand is considered, hundreds of millions of people are believed to lack energy services still in 2040 if necessary actions are not taken. In addition to the energy deficit issue faced by 1.2 billion people, increasing greenhouse gas emissions is another great concern for the planet. If the radiation of toxic gases continues in the same fashion, the environment will be damaged in an irreversible way. Although many solutions have been proposed in recent years regarding these two problems, most of them would fail to fulfill the energy need without causing harm on the environment based on the projections demonstrated by International Energy Agency [2]. One of the approaches that is regarded as a key to success is switching from the centralized to decentralized power systems [3]. Thanks to their dependence on renewable energy, decentralized systems are able to meet the electricity demand with minimum detrimental effects of poisonous gases on the nature. Aside from the environmental benefits, it is approximated that if decentralized energy strategy is chosen over the centralized system, total savings would reach 2.7 trillion dollars by 2030 [4].

In centralized energy systems, power is generated in large scales and then distributed to the end users [5]. Differently from this system, in decentralized

settings the electricity production and consumption areas are very close to each other. While satisfying the energy requirement of a region, these systems benefit from the renewable energy resources. Considering the renewable energy potential of the area of the interest, different sources such as solar, wind and hydro could be incorporated into the setting. Decentralized networks can operate either as stand-alone (SA) or they can stay connected to the grid (GC) [5]. Based on the location of the system to be built, SA or GC systems could be chosen. If the grid network is already available in the area, grid connection is extended and a grid-connected decentralized system is constructed. For the remote places where the grid networks cannot penetrate stand-alone systems are established. In both cases, renewable energy sources are implemented to fulfill the demand (see [5] for a review paper on decentralized systems).

Although decentralization trend could be observed in many developed countries, the transition process may be difficult for the decision makers because of the conflicting objectives which are minimizing expenses and the impact on the environment [6]. Since it is not possible to achieve both of the goals at the same time, a trade-off occurs between cost and environmental concerns. In traditional centralized settings, energy requirement is fulfilled by burning fossil fuels which have low unit costs. Despite the fact that these systems provide energy at reduced costs, they have negative effects on the environment. On the other hand, by adapting renewable energy, decentralized power systems are able to reduce carbon dioxide (CO_2) emissions in great amounts. However, saving the environment can be expensive since renewable energy sources have higher unit costs [6]. As the number of objectives increases in the problem, the necessity of using multi-objective approach becomes clear.

Decentralized systems are adopted instead of the centralized settings in recent years as a result of the clean energy provided by renewable energy sources [3]. Even though these sources have favorable effects on the environment, they are intermittent in nature. Due to the uncertainty incorporated, modeling systems with renewables becomes a challenging task. Because of this difficulty, few studies in the literature conduct a stochastic analysis while designing a decentralized energy system. Moreover, most of these studies perform the analysis using basic

techniques which cannot capture the stochastic nature fully (see Table 2.1 for the Literature Review). Since these methods neglect peak values or only consider the averages of a data set, they lose important information which reduces the quality of the analysis [7, 8]. Considering the situation, it is clear that a more concrete stochastic analysis should be included in the sizing of a decentralized energy system.

When solving the sizing problem of a decentralized energy system, various methods are developed in the literature. Some of these studies only conduct feasibility analyses. While others propose new algorithms for solving the sizing problem (see Table 2.1 for the Literature Review). Among all the solution approaches, metaheuristic algorithms constitute an important portion due to the computational performance [9]. These algorithms are generally named after a genetic principle or a nature phenomenon since they mimic the nature or genetics as they try to find an optimal solution. Despite the fact that metaheuristics are used extensively for planning problem of a decentralized energy system, only one algorithm is preferred at a time for solving the problem. Instead of restricting solution approach to a single algorithm, it is necessary to develop a framework which enables the usage of different algorithms with slight modifications.

For a grid-connected decentralized energy system's sizing decision, Altıntaş [10] is the first to provide a mathematical formulation together with a novel simulation-optimization approach to handle the two aspects, multi-objectivity and stochasticity of the problem. In this study, we consider the grid-connected decentralized energy system problem discussed in [10] and propose alternative solution approaches. The system contains renewable energy components such as solar panel and wind turbine. Additionally storage units are included as back-up sources due to the intermittent nature of renewable sources. While finding the optimal sizes of the components, it is assumed that the decision makers are both cost and carbon sensitive. This assumption results in two objectives which are minimizing total cost and CO₂ emission of the system. Together with these two objectives, uncertainty introduced by the renewable energy sources and electricity demand makes the problem stochastic in nature. For managing the stochasticity, scenario sets generated from solar, wind and demand data are employed.

As an alternative to the simulation-optimization (SO) method developed in [10], we suggest a metaheuristic approach including three well-known algorithms, Optimized Multi Objective Particle Swarm Optimization Algorithm (OMOPSO), Non-dominated Sorting Genetic Algorithm-II (NSGA-II) and Strength Pareto Evolutionary Algorithm 2 (SPEA2) in order to solve the described problem. We modify these algorithms to handle stochasticity, as will be elaborated later. Among these metaheuristics, we first show that OMOPSO has superior performance according to a set of metrics. Having OMOPSO as the best performing algorithm, an extensive comparative analysis is conducted between SO and metaheuristic approaches by creating scenario sets in different numbers for different cases. Lastly, a sensitivity analysis is completed concerning the impact of some price parameters in the solution set.

In Chapter 2, we make the literature review and discuss the work conducted in the field of renewable energy systems' stochastic optimization. We define the grid-connected decentralized energy system problem addressed in this paper in Chapter 3. In Chapter 4, we present our alternative metaheuristic approaches to this problem. Chapter 5 is dedicated to the performance metrics used in assessing the quality of Pareto fronts (PF) obtained by the metaheuristic algorithms. In Chapter 6, we first give information about the data to be used in the analyses and then provide extensive comparative analyses between the solution methods. Lastly, Chapter 7 summarizes the findings of the study and demonstrates the research opportunities open for the future.

Chapter 2

Literature Review

With the growing popularity of decentralized energy systems, many studies are found in the literature regarding the sizing problem of these systems. In the survey, we categorize these studies with respect to different aspects such as whether the underlying problem considers a grid connected (GC) or stand-alone (SA) system, and whether the problem and the solution method used is multi-objective and/or stochastic. We also indicate the type of the solution method used in these studies. We specifically focus on the studies that propose metaheuristic algorithms since we also use metaheuristic methods for solving our problem.

There are numerous metaheuristics which are applied to the different problem types due to their convergence performance [9]. Working with the principles of nature or genetics, these algorithms are proved to be successful in solving both single and multi-objective problems. Since we consider a bi-objective optimization problem, we are going to examine the studies considering multiple objective problems and hence use multi-objective metaheuristic algorithms. Summary of the literature review can be seen in Table 2.1.

Bernal-Agustín et al. [11] investigate the multi-objective optimization of a stand-alone system which includes solar and wind energy as the sources of energy production. In addition to these sources, diesel and storage units are incorporated

Table 2.1: Summary of the Literature Review

AUTHORS	SYSTEM COMPONENTS				SA / GC	STOC.	OBJ FUNC.	METHOD
	Wind Turbine	PV Panel	FC	Storage	Diesel	Other		
Bernal-Aguistin et al. [11]	•	•	•	•	•		Min. Cost Min. Pollutant Emission No	SPEA
Dufo-López et al. [12]	•	•	•	•	•		Min. Total Cost Min. Unmet Load No	MOEA & GA
Katsigiannis et al. [13]	•	•	•	•	•		Min. Pollutant Emission Min. Cost of Energy Min. Greenhouse Gas Emissions No	NSGA2
Dufo-López et al. [14]	•	•	•	•	•		Min. Levelized Cost of Energy Min. Life Cycle Emissions No	SPEA
Sharafi et al. [15]	•	•	•	•	•		Min. Total Cost Min. Unmet Load Min. Fuel Emission No	PSO-Simulation
Zhao et al. [16]	•	•	•	•	•		Min. Life Cycle Cost Max. Renewable Energy Source Penetration Min. Pollutant Emission No	GA
Sharafi and ElMekawy [17]	•	•	•	•	•		Min. Total Net Present of the System Min. Loss of Load Probability Min. CO ₂ Emission No	DMOPSO - Simulation
Wang et al. [18]	•	•	•	•	•		Min. The Lifetime System Cost Min. The Lifetime CO ₂ Min. The Lifetime SO ₂ Max. The System Output Power No	MOEAD
Shi et al. [19]	•	•	•	•	•		Min. Annualized Cost of System Min. Loss of Power Supply Probability Min. Fuel Emissions No	PICEA
Wang et al. [20]	•	•	•	•	•		Min. Total Cost Min. Pollutant Emissions Max. Reliability No	MOPSO
Kornelakis [21]	•	•	•	•	•		Min. Net Present Cost Min. Pollutant Gas Emissions No	PSO
Avril et al. [22]	•	•	•	•	•		Min. Total Levelized Cost Min. Connection to Grid No	PSO
Kaval et al. [23]	•	•	•	•	•		Min. Payback Year Min. Yearly Average Power Loss Min. (-Yearly Average Voltage Stability) No	MOPSO
Sharafi et al. [24]	•	•	•	•	•	Boiler & Gasoline	Max. Renewable Energy Ratio Min. Net Present Cost Min. CO ₂ Emission No	DMOPSO-Simulation
Sharafi and ElMekawy [25]	•	•	•	•	•	Boiler & Gasoline	Min. Net Present Cost Max. Renewable Energy Ratio Min. Fuel Emission Yes	DMOPSO-Simulation

into the system in order to lessen the intermittency impact of renewables. In the optimization part, two objectives which are total system cost and pollutant emission are minimized using Strength Pareto Evolutionary Algorithm (SPEA) [11]. In the end, various investment options are presented to decision makers.

Dufo-López et al. [12] deal with the sizing of a hybrid system which contains photovoltaic (PV) panel, wind turbine, diesel, fuel cell and storage systems. In the sizing decision, three objective functions, total system cost, CO₂ emissions and unmet load, are optimized simultaneously. In order to find the best configuration and operation policy two algorithms are implemented. Joint work of the multi-objective evolutionary algorithm (MOEA) and a genetic algorithm results in a Pareto set of solutions for this problem [12].

Katsigiannis et al. [13] attempt to find the optimal size of a stand-alone system using Non-dominated Sorting Genetic Algorithm-II (NSGA-II). Components of the system are specified as PV panel, wind turbine, fuel cell, diesel and storage units. The decision maker in this setting considers both cost and environment and this consideration results in two objectives: cost of energy and greenhouse gas emissions. The main contribution of the article is noted as conducting life cycle analysis while calculating the second objective. These objectives are minimized at the same time for different configurations of the system which are obtained by changing the energy storage type [13].

As in [12], Dufo-López et al. [14] examine a stand-alone system with solar and wind components which provide energy to the system. Other than these parts, diesel and storage units are inserted into the setting to be used in case of energy deficit. Although the objective functions are similar to the ones considered in [12], they are computed in different ways. In this study total cost is represented as levelized cost of energy whereas pollutant emissions is measured in terms of life cycle emissions. These objectives are optimized by applying SPEA [14].

Sharafi et al. [15] consider a hybrid system consisting of PV panel, wind turbine, fuel cell, batteries and diesel generator. This setting is constructed to operate in remote places where the grid-connection is not available. In finding

the optimal component sizes, minimum total cost, unmet load and fuel emission are tried to be achieved through a Particle Swarm Optimization (PSO)-based simulation approach. After this method is tested on a case study, the authors conduct a sensitivity analysis to be able to see the effect of parameters on the Pareto solutions [15].

Zhao et al. [16] work on multi-objective optimization of a microgrid which is located on Dongfushan Island. In terms of the renewable energy, solar and wind resources are employed. Since the considered region is not connected to the grid, battery banks and diesel generators are included in the system in order to prevent energy disruptions. With the objectives of minimizing cost, pollutant emission and maximizing rate of renewable energy, optimum size and operational strategy of the microgrid are reached using a genetic algorithm. In the last section of the study, issues and lessons learned through operational experience are shared [16].

Sharafi and ElMekkawy [17] propose a dynamic multi-objective particle swarm optimization algorithm (DMOPSO) for the solution of the problem discussed in [15]. With this newly developed method, three objective functions, total net present cost of the system, loss of load probability and CO₂ emission, are minimized and a Pareto set of solutions is generated. For assessing the performance of the Pareto front, several metrics from the literature are taken into account. Similar to the previous study [15], a sensitivity analysis is carried out regarding the price parameters.

Due to the satisfactory performance of traditional evolutionary algorithms, new approaches have been established in the literature by preserving the characteristics of the traditional ones. Implementing one of these algorithms, multi-objective evolutionary algorithm based on decomposition (MOEA/D), Wang et al. [18] consider designing a stand-alone renewable energy system with multiple objectives. In a system containing PV, wind, diesel and battery components, the system's lifetime cost, CO₂, SO₂ emissions and output power are optimized. After a Pareto front is generated, different sizing options are introduced to decision makers for the selection [18].

Shi et al. [19] utilize the preference-inspired coevolutionary algorithm (PICEA) for the first time in the literature while designing a stand-alone system in the presence of conflicting objectives. Minimization of annual cost of the system, loss of load probability and fuel emissions gives the optimal setting of the system components, which are PV panel, wind turbine, storage unit and diesel generator. Once the Pareto front is attained, various alternatives become available to investors [19].

Studies within the range of [11] - [19] discuss the size optimization of stand-alone systems. These systems are generally located on the remote areas where the grid connection cannot penetrate. Differently from these studies, Wang et al. [20] consider a hybrid energy system where the grid-connection is already available. In the system to be built, solar and wind energy generators are placed with higher priorities for the energy requirement. While planning the system, cost, environment and reliability criteria are taken into account and resulting objectives from these criteria are solved with Multi-Objective Particle Swarm Optimization Algorithm (MOPSO) [20].

Kornelakis [21] is interested in the size optimization of a single-source system where the grid connection is used as a backup if the produced solar energy is not enough to meet the local demand. Given the system setting, net present value and pollutant gas emissions are taken as the objectives of the problem. For minimization of these objectives, PSO algorithm is executed [21].

Avril et al. [22] study the photovoltaic systems' sizing decision in a bi-objective deterministic problem setting. For the system constructed with PV panels, storage devices and grid connection, minimizing total levelized cost and electricity purchased from the grid are used as the two objectives. For the solution of the problem, PSO method is selected. As an application of the proposed methodology, PV systems are built in several locations in France and the findings are demonstrated in the end [22].

Kayal et al. [23] integrate renewable energy resources, which are solar and wind into an electrical distribution network with the purpose of decreasing dependence

on fossil-fuel based energy generators. Rearranging the system with these newly added components constitutes a multi-objective problem in which payback year, yearly average power loss and negative value of yearly average voltage stability are minimized simultaneously. After renewables are incorporated into the system, it is ensured that the network operates as usual via a number of constraints. The whole optimization model is solved by running MOPSO algorithm. For evaluating the solution approach's performance, an Indian rural distribution network is selected [23].

Sharafi et al. [24] design an energy system in buildings in order to fulfill heating, cooling and electricity needs of households. For these requirements, PV panels, wind turbines, biomass boilers, gasoline providers and grid connection are put into the setting. In addition to the inner operations of the equipments, they are utilized outside of the buildings while providing energy for two different cars which could work with solar energy and gasoline. Three objectives resulting from this complex structure, rate of renewable energy, net present cost and CO₂ emission are optimized by adopting the DMOPSO-simulation methodology which is introduced in the previous study by the authors [17]. Performance evaluation of the solution method and sensitivity analysis for the parameters are completed lastly.

Sharafi and ElMekkawy [25] work on the same problem mentioned in [24] by taking stochastic attributes of the renewables, solar and wind, into consideration. For the described system, DMOPSO algorithm and simulation tool are run together. In order to handle uncertainty introduced by these energy sources, sampling average approximation method is preferred. Performance of the solution procedure is supported with a case study and three metrics from the literature [25].

To conclude, above discussion about the literature reveals the success of meta-heuristic algorithms in managing the problem's multi-objective nature efficiently. However, among these studies only Sharafi et al. [25] consider the uncertainty of renewable energy sources and therefore investigate stochastic, multi-objective structures together. For this reason, regarding a grid-connected decentralized

energy system, we propose a metaheuristic-based simulation approach, where metaheuristic algorithms are used with some modification according to the problem structure. In this study, we try three of these algorithms, Optimized Multi-Objective Particle Swarm Optimization Algorithm (OMOPSO), NSGA-II and SPEA2, and narrow to a single one, OMOPSO, in the end because of computational advantages. Resulting from the joint work between metaheuristics and simulation tool, two objectives, total cost and carbon emission, and uncertainties in the problem are taken care of in less amount of time.

Chapter 3

The Grid-Connected Decentralized Energy System Planning Problem

Altıntaş [10] investigates the sizing problem of a grid-connected decentralized energy system which is called as the grid-connected decentralized energy system (GCDES) problem. In this setting, it is aimed to find the optimal sizes of the system components as conflicting objectives and uncertainty of renewable resources are taken into account. Incorporating the two sides, bi-objectivity and stochasticity, the problem is modeled as a bi-objective two-stage stochastic programming model. Together with the mathematical formulation, a simulation-optimization method is established for the solution.

In this thesis, we suggest alternative solution approaches introduced in Altıntaş [10] and compare the performances of the suggested approaches with that of the ones discussed in Altıntaş. Therefore, in this chapter, we first discuss the studied GCDES problem and provide its mathematical model. Following these sections, the solution approach proposed by Altıntaş, simulation-optimization, is analyzed in detail.

3.1 Problem Definition

Altıntaş [10] considers the sizing problem of a decentralized energy system where the grid connection is already available. The GC system to be built contains renewable energy sources that are solar and wind. Together with the clean energy providers, storage device is placed in the system in order to reduce the intermittency effects of these resources. Three wind turbine options which have different costs and rated powers are considered while finding the optimal configuration of the system components. Although technical details regarding solar unit and storage device are not specified, generic efficiency parameters are incorporated into the GC system as their operation characteristics.

Given the elements and operation characteristics, GC system could be established in different areas independently of their locations so as to satisfy the energy need. While providing electricity power for the region, solar and wind resources are prioritized in the system. When there is surplus from the production, green energy could be reserved in the storage unit for later usage. This energy cell could be charged up to its capacity. Quantity which exceeds the capacity is not spoiled owing to the incentive that allows selling renewable energy to the grid at higher prices [26]. If these renewable energy sources are not able to produce the required amount due to their intermittent nature, remaining quantity is taken from the storage device. Storage device supplies power until it reaches the zero point. When the device is discharged completely and demand is not fully met, grid connection is used as a backup source. As a result, fossil-fuel-based electricity is purchased from the grid at a specific price. Representation of the system could be seen in Figure 3.1.

With the technical details and operation policy provided, in this problem a decision maker tries to find the optimal size of the system components which are wind turbine, solar panel and storage device. While making a sizing decision, conflicting objectives arise since the decision maker is assumed to be both cost and carbon sensitive. Total cost of the system is considered as the first objective whereas the second objective is the total CO₂ emission measured in terms

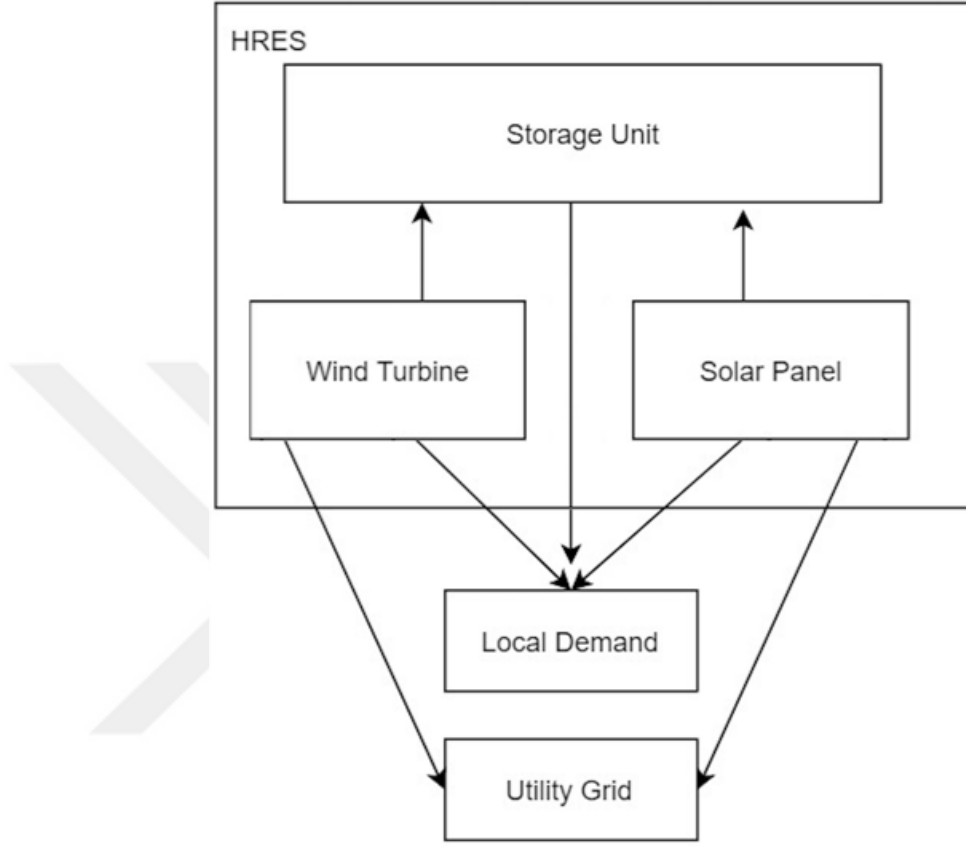


Figure 3.1: The Grid-Connected Decentralized Energy System

of the fossil-fuel-based electricity amount. In addition to the bi-objective nature of the problem, renewable sources that are solar and wind have stochastic attributes. Due to the uncertainty in wind speed and solar irradiation, the problem becomes stochastic. As a result of this structure, the problem is formulated as a bi-objective two-stage stochastic optimization problem, where a scenario-based approach is utilized for the uncertainties related to the renewables [10].

As Birge and Louveaux [27] explain, in two-stage stochastic optimization problems, the problem is divided into two-stages in which there are two types of decisions to be made: first stage (investment) and second stage (operational). Investment choices are made before the realization of the random parameters and once the random parameters are realized, operational decisions take place [27]. In the sizing problem, firstly component sizes are selected at the beginning of the time horizon and based on the energy production formulas, renewable

energy is produced at each period. After energy production is completed, this amount is distributed in the system according to the operation policy. Decisions which are made following the system policy can be called as operational decisions. Although investment decisions are made for one time only, operational ones continue throughout the time horizon.

Altıntaş [10] constructs the model with the parameters and decision variables given in Tables 3.1 and 3.2, respectively. Note that, we consider an extended version of this problem, where the demand can also be stochastic.

Table 3.1: Parameters, Sets

T	time horizon ($t \in \{1...T\}$)
I	set of wind turbine generator (WTG) types
Θ	set of scenarios ($\theta \in \Theta$)
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 WTG type i (\$/unit)
L_b	lifetime of storage unit (years)
L_s	lifetime of solar panel (years)
L_w^i	lifetime of WTG type i (years)
L_{FT}	duration of feed-in tariff policy (years)
L_{system}	duration of the GCDES (years)
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 selling price of solar energy
α_{pw}	annualization factor for selling price of wind energy
p^g	price of electricity purchased from grid (spot price) (\$/kWh)
p^s	elevated selling price of solar energy (\$/kWh)
p^w	elevated selling price of wind energy (\$/kWh)
d_t^θ	local demand in (t, θ) (kWh)
v_t^θ	wind speed in (t, θ) (m/s)
r_t^θ	solar irradiation in (t, θ) (kW/m ²)
η_s	overall efficiency of solar panel (%)
η_b	storage efficiency(%)
κ	electricity generation limit multiplier
M	maximum unit time demand (kWh)
β	CO ₂ equivalent emission by electricity grid (tonne/kWh)

Table 3.2: Decision Variables

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

3.2 Mathematical Formulation

$$\min \quad Z1 : \alpha_b c_b A_b + \alpha_s c_s A_s + \alpha_w \sum_{i \in I} c_w^i A_w^i + \frac{1}{|\Theta|} \sum_{\theta \in \Theta} \sum_{t \in T} [p^g G_t^\theta - \alpha_{ps} p^s SS_t^\theta - \alpha_{pw} p^w WS_t^\theta] \quad (3.1)$$

$$\min \quad Z2 : \beta \frac{1}{|\Theta|} \sum_{\theta \in \Theta} \sum_{t \in T} G_t^\theta \quad (3.2)$$

s.t

$$S_t^\theta = \eta_s r_t^\theta A_s \quad \forall t \in \{1 \dots T\}, \forall \theta \in \Theta \quad (3.3)$$

$$W_t^\theta = \sum_{i \in I} f^i(v_t^\theta) A_w^i \quad \forall t \in \{1 \dots T\}, \forall \theta \in \Theta \quad (3.4)$$

$$S_t^\theta = SS_t^\theta + SD_t^\theta + SB_t^\theta \quad \forall t \in \{1 \dots T\}, \forall \theta \in \Theta \quad (3.5)$$

$$W_t^\theta = WS_t^\theta + WD_t^\theta + WB_t^\theta \quad \forall t \in \{1 \dots T\}, \forall \theta \in \Theta \quad (3.6)$$

$$d_t^\theta = SD_t^\theta + WD_t^\theta + \eta_b BD_t^\theta + G_t^\theta \quad \forall t \in \{1 \dots T\}, \forall \theta \in \Theta \quad (3.7)$$

$$B_t^\theta = B_{t-1}^\theta + SB_t^\theta + WB_t^\theta - BD_t^\theta \quad \forall t \in \{1 \dots T\}, \forall \theta \in \Theta \quad (3.8)$$

$$\kappa M \geq S_t^\theta + W_t^\theta \quad \forall t \in \{1 \dots T\}, \forall \theta \in \Theta \quad (3.9)$$

$$\kappa MX_t^\theta \geq SS_t^\theta + WS_t^\theta \quad \forall t \in \{1 \dots T\}, \forall \theta \in \Theta \quad (3.10)$$

$$|T| MX_t^\theta \geq SB_t^\theta + WB_t^\theta \quad \forall t \in \{1 \dots T\}, \forall \theta \in \Theta \quad (3.11)$$

$$M(1 - X_t^\theta) \geq BD_t^\theta \quad \forall t \in \{1 \dots T\}, \forall \theta \in \Theta \quad (3.12)$$

$$M(1 - X_t^\theta) \geq G_t^\theta \quad \forall t \in \{1 \dots T\}, \forall \theta \in \Theta \quad (3.13)$$

$$A_b \geq B_t^\theta \quad \forall t \in \{1 \dots T\}, \forall \theta \in \Theta \quad (3.14)$$

$$B_0^\theta = 0 \quad \forall \theta \in \Theta \quad (3.15)$$

$$B_T^\theta = 0 \quad \forall \theta \in \Theta \quad (3.16)$$

$$S_t^\theta, B_t^\theta, W_t^\theta, G_t^\theta \geq 0 \quad \forall t \in \{1 \dots T\}, \forall \theta \in \Theta \quad (3.17)$$

$$SB_t^\theta, SS_t^\theta, WS_t^\theta, WB_t^\theta \geq 0 \quad \forall t \in \{1 \dots T\}, \forall \theta \in \Theta \quad (3.18)$$

$$SD_t^\theta, WD_t^\theta, BD_t^\theta \geq 0 \quad \forall t \in \{1 \dots T\}, \forall \theta \in \Theta \quad (3.19)$$

$$A_s, A_b, A_w^i \geq 0 \quad A_w^i \in \mathbb{Z}_{\geq 0}, \forall i \in I \quad (3.20)$$

$$X_t^\theta \in \{0, 1\} \quad \forall t \in \{1 \dots T\}, \forall \theta \in \Theta \quad (3.21)$$

In the mathematical model, two objective functions, total system cost and CO₂ emissions, are minimized. While minimizing the objectives, solar energy and wind energy are calculated in the constraints (3.3) and (3.4) with the corresponding formulas. Once the calculation is completed, the generated energy is distributed among the storage, demand and grid, which is ensured in the constraints (3.5) and (3.6). Complying with the operational policy, constraint (3.7) guarantees

that the demand is met via renewable energy, if necessary energy stored in the device and/or purchased from the grid. Due to the physical limitations of the area which the system is built, total renewable energy production is restricted in the constraint (3.9). Through the constraints (3.10 - 3.13) it is ensured that demand has priority over storage and grid in the distributed energy. With the domain constraints (3.17 - 3.21) of decision variables, the model is concluded. For more information regarding the GCDES model, the reader is referred to [10].

3.3 An Existing Solution Approach

In the modeling of the GCDES, renewable energy resources with intermittent solar and wind data are included in the system. As a result of the uncertainty, the problem turns out to have a multi-stage stochastic structure. In order to handle this multi-stage stochastic nature in a realistic and computationally feasible way, Altıntaş [10] proposes a simulation-optimization (SO) approach. Two different versions of the GCDES model and another simulation module are developed for the solution method. With these modules, the SO algorithm works as a variant of the ϵ -constraint algorithm [28]. The flow diagram of the process can be seen in Figure 3.2. For the details of the SO approach, please refer to [10]. We now explain the modules of this approach.

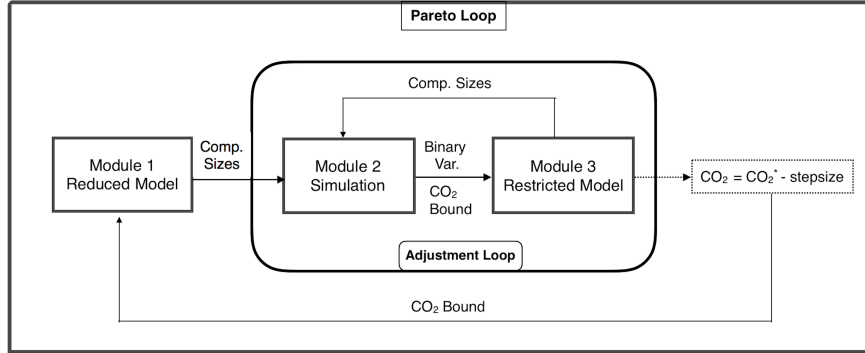


Figure 3.2: SO Approach

3.3.1 Module 1 - Reduced Version of the GCDES Model

In the first step of the algorithm, the reduced version, which is obtained by relaxing the constraints (3.12) and (3.13) in the original GCDES model, is solved for obtaining the initial component sizes. With less computational effort, optimal sizes of the system elements for a configuration, which allows purchasing from and selling to the grid at the same time, are found in this module. These optimal sizes are then conveyed to the simulation module.

3.3.2 Module 2 - Simulation

In this module, the second stage decision variables such as how much of renewable energy to sell or store are calculated following an operation policy. Using the component sizes obtained from the reduced version of the GCDES model, firstly renewable energy computations are completed based on some energy formulas. Generated renewable energy is distributed among the local demand, storage device and grid according to the operation policy, which is designed in a way that it gives a higher priority to the renewable energy sources while meeting the local demand. Following this strategy, solar and wind energy are used to satisfy the demand. After the demand is fully satisfied, remaining amount is stored in a device for the future use. Once the storage unit is fully charged and if some amount is still left from the renewable energy, the excess energy is not spoiled thanks to the government incentive [26]. With this policy, the remaining energy is sold to the grid at specific prices. On the opposite case, when there is deficiency of renewables in fulfilling the demand, storage unit is utilized in order to compensate the shortage. However, stored energy may not be adequate for the demand by itself and therefore necessary amount is purchased from the grid. All of these calculations are made for every time period in every scenario set. By running the simulation module for each time, the binary variables in the GCDES model (X_t^θ), which correspond to the decisions whether to sell or purchase electricity, and total CO₂ emission value are acquired in the end. These results are then sent to the Module 3 to be used as inputs.

3.3.3 Module 3 - Restricted Version of the GCDES Model

With the purchasing/selling decisions and total CO₂ emission value, the model is restricted such that the binary variables (X_t^θ) in constraints (3.12), (3.13) are fixed and the CO₂ limit is updated. Having these changes, the model is solved and the resulting component sizes are returned to the simulation module. The joint work of these two modules helps to adapt the investment and operational decisions. Once these decisions comply with each other and the total cost can be reduced at most 0.1%, this inner loop is ended. Collaboration of Module 2 and 3 yields a solution which has a cost and CO₂ value. The next solution in the Pareto front is acquired by restricting the CO₂ emission value with a limit which is calculated through the last solution's CO₂ emission. By subtracting a step size from the emission value, a cap on the second objective value is set. This new bound is then used while solving the reduced version of the GCDES model. In this way, at each step, it is aimed to find the solutions with less carbon emission.

Chapter 4

Metaheuristic Approaches

For the GCDES problem, we present metaheuristic approaches which consist of two modules. In this approach, a new optimization module is created and existing multi-objective metaheuristic algorithms are utilized in this module to obtain a Pareto front. The simulation module from the SO approach discussed in Section 3.3.2 is not changed and it is utilized in the metaheuristic approach for the simulation purposes. The procedure starts with an initial set of solutions with randomly generated component sizes. Then these solutions are conveyed to the simulation module so as to perform the simulation. Given an operational policy and the component sizes, the simulation module makes the operational decisions and the objective function values are calculated. The resulting cost and CO₂ emission values are returned to the optimization module. In this module, each solution with objective function values are given to the metaheuristic algorithms. The solutions which are called as particles or members based on the notation of the metaheuristic algorithm, follow the steps of these algorithms. At the end of these steps, an approximate Pareto front is generated. The working scheme of the approach can be found in Figure 4.1.

As seen in the Figure 4.1, simulation and optimization modules operate in a loop where they provide input for each other. For the simulation purposes, we resort to the previously discussed simulation module, while Optimized Multi

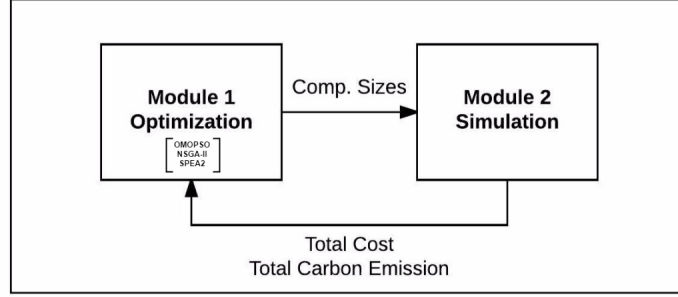


Figure 4.1: Metaheuristic Approach

Objective Particle Swarm Optimization Algorithm (OMOPSO), Non-dominated Sorting Genetic Algorithm II (NSGA-II) and Strength Pareto Evolutionary Algorithm 2 (SPEA2) are employed in the optimization module.

4.1 Optimized Multi Objective Particle Swarm Optimization Algorithm

Particle Swarm Optimization (PSO) algorithm proposed by Kennedy and Eberhart [29], is one of the popular metaheuristic algorithms used in diverse optimization tasks. This algorithm mimics the flocking of birds and tries to find an optimal solution throughout the search space. At the initial step of the procedure, a set of solutions called swarms or particles is generated. As these swarms fly over the feasible area, each particle updates its velocity and position according to a group of equations. These equations consider both the best solution that particle has found so far and all the best solutions found by the members of the swarm. In the end, the optimal solution is attained via particle experience and best global particle [29].

Although PSO performs well in a range of optimization problems, its application is restricted to the single objective problems [30]. Extending the idea of PSO to multi-objective problems, Coello and Lechuga [30] develop Multi-Objective

Particle Swarm Optimization (MOPSO) algorithm. The main idea of MOPSO is including a global repository in which each particle deposits its flight experience after a cycle. Later, this repository is used by the swarms to select the leader which guides the flight. Differently from the PSO, the output is a set of non-dominated solutions which are kept in the repository [30].

Many algorithms originated from MOPSO can be found in the literature [31]. Although they have the common idea of selecting the leader from the non-dominated particles, the selection process could be different. In order to compare these MOPSOs, an experimental study is conducted by Durillo et al. [31]. Three benchmark problems and performance metrics are employed so as to make the comparison. The results of the experiments indicate that OMOPSO performs best in all of the studied problems. Because of its superior performance, OMOPSO algorithm has been applied to the present problem, minimizing total cost and CO₂ emission simultaneously. The algorithm runs following the steps outlined in Figure 4.2.

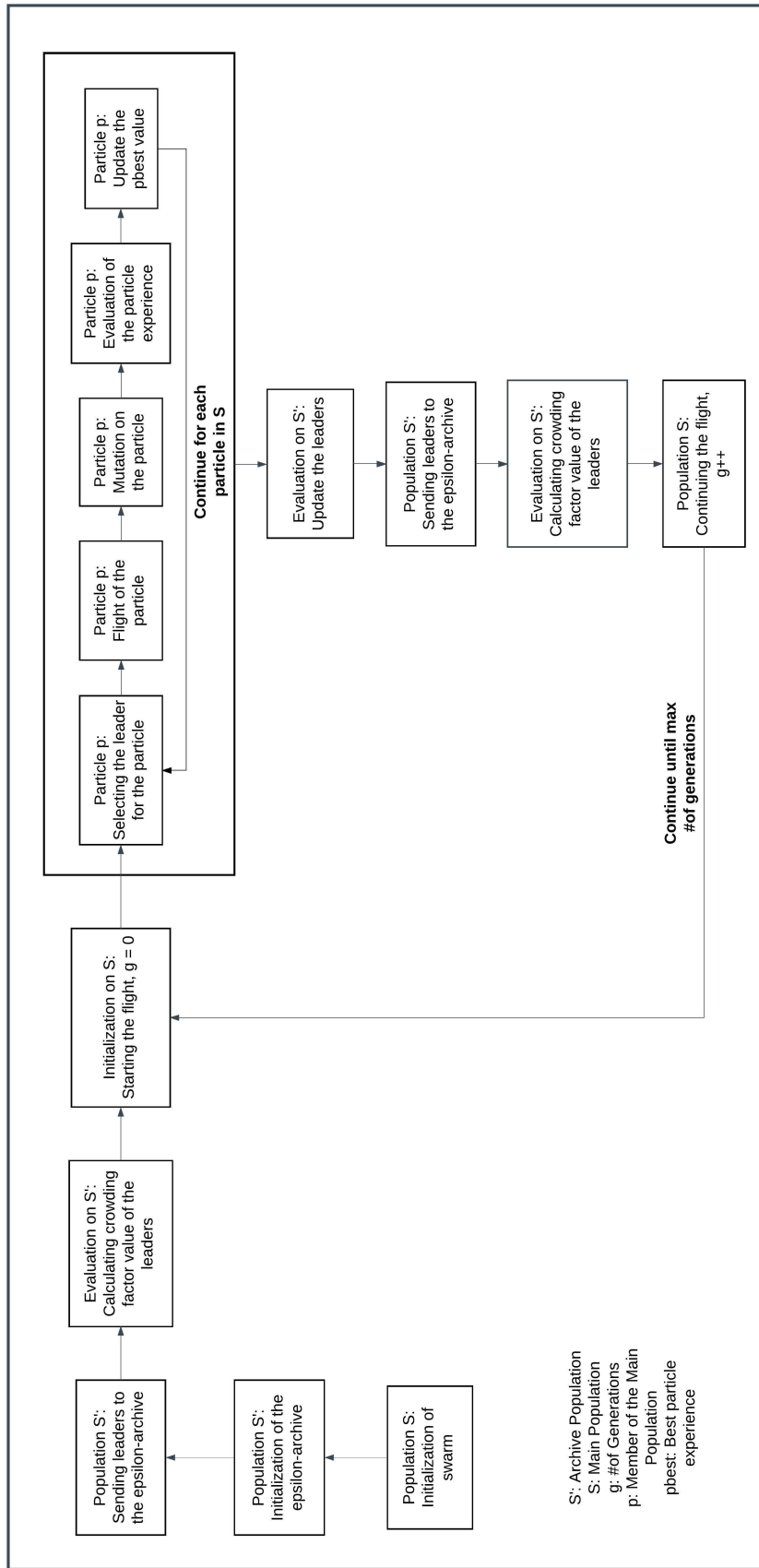


Figure 4.2: Flowchart of the OMOPSO Algorithm

4.2 Non-dominated Sorting Genetic Algorithm II

Genetic algorithms are utilized for solving a variety of multi-objective optimization problems thanks to their ability to provide good solutions in a reasonable amount of time [9]. These algorithms work according to the evolutionary principles in the optimization of both continuous and discrete valued problems. Non-dominated Sorting Genetic Algorithm II (NSGA-II), one of the genetic algorithms, has been applied to different multi-objective optimization tasks as a result of its convergence performance [32]. The procedure starts with randomly generating N members. After the generation, these members are sorted into different non-domination levels by pairwise comparisons. When the sorting task is completed, each member is assigned rank and crowding distance values which are later used in the selection. Having these properties, the members experience selection and mutation, which cause changes in the member itself [32]. In the end, the offspring population of size N is obtained. In order to store the solutions from the parent population, former and offspring populations are combined. The recently created population with $2N$ members is non-domination sorted. There should be a selection between these non-domination sorted members so as to maintain the size N . In the selection, previously assigned rank and crowding distance values are taken into account. This whole process continues until a pre-defined number of generations is reached. At the end of all steps, a Pareto set of solutions is obtained [32]. Generational loop of the NSGA-II algorithm can be found in Figure 4.3.

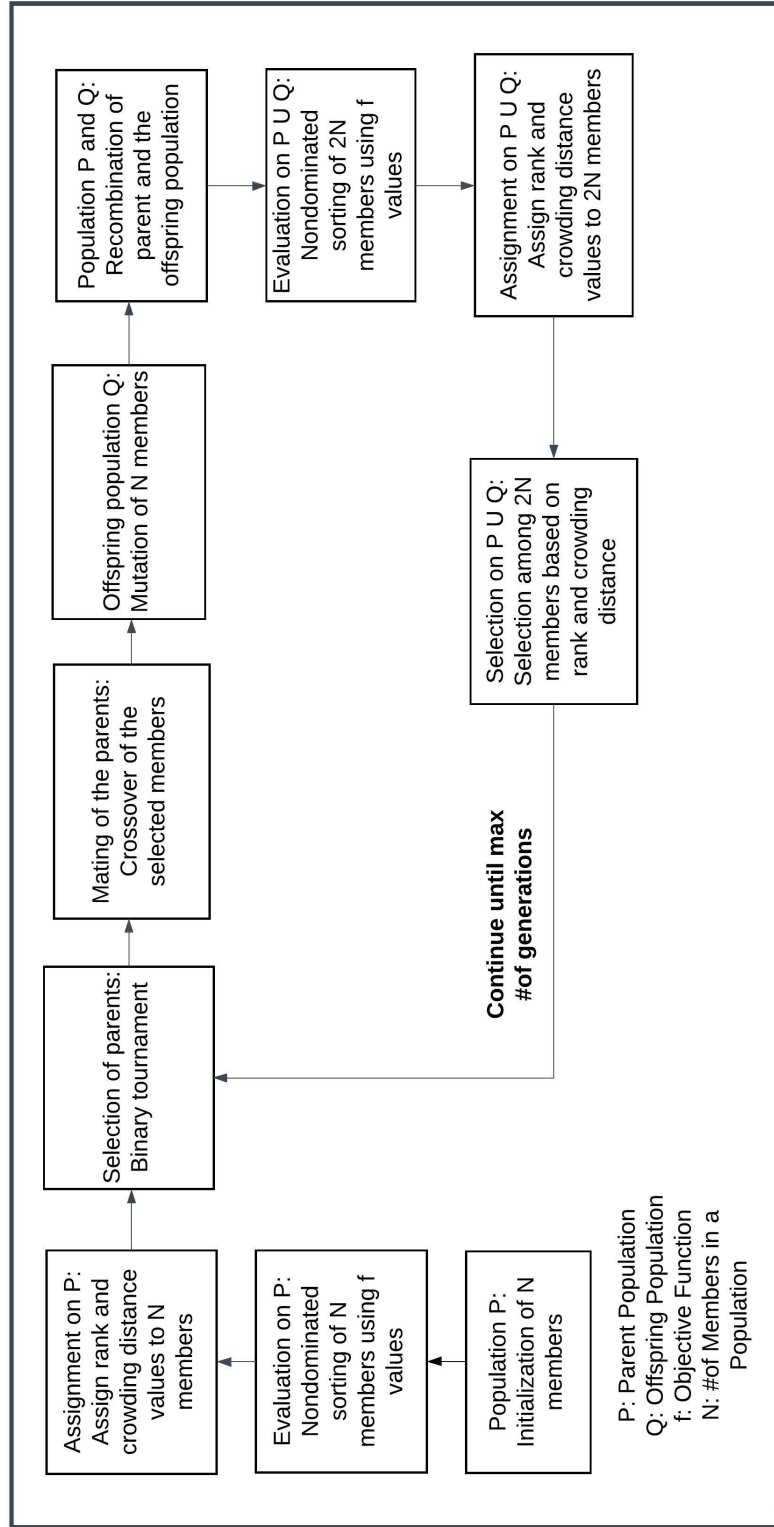


Figure 4.3: Flowchart of the NSGA-II Algorithm

4.3 Strength Pareto Evolutionary Algorithm 2

Strength Pareto Evolutionary Algorithm 2 (SPEA2) is another evolutionary multi-objective optimization technique which could approximate the set of optimal solutions in a single optimization run [9]. The algorithm is introduced by Zitzler, Laumanns and Thiele [33] so as to eliminate the potential weaknesses of its predecessor SPEA. The method is initialized by creating a population and an external archive. Following the initialization, the members both in population and archive are assigned fitness values and they are selected using these values with a tournament to fill the mating pool. The selected parents mate with each other and the resulting offspring are exposed to mutation. Since the algorithm takes the parent population into consideration while searching for the solution, the old and offspring populations are brought together. The evolution process continues until the maximum number of iterations is attained. When the process reaches the predefined number of iterations, the set of optimal solutions becomes available [33]. See Figure 4.4 for the flowchart.

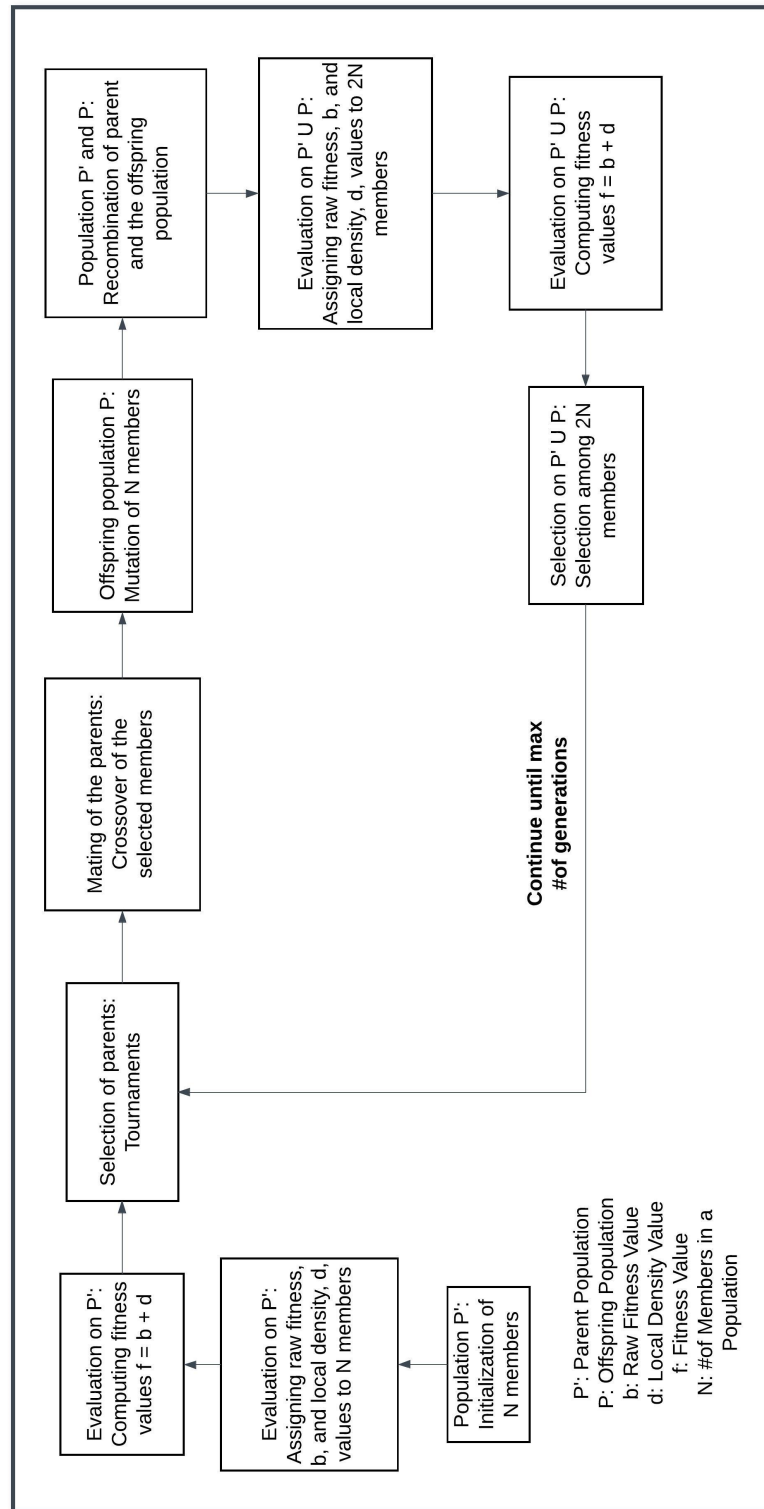


Figure 4.4: Flowchart of the SPEA2 Algorithm

Chapter 5

Performance Metrics

So as to assess the quality of Pareto fronts obtained by metaheuristics, performance metrics are introduced in multi-objective optimization literature. These measures can be categorized into three groups based on their ability to depict a certain aspect of the solution set [34].

1. Metrics which assess convergence to the known Pareto-optimal front.
2. Metrics which evaluate spread of the solutions on the Pareto-optimal front.
3. Metrics which measure combinations of solutions' convergence and spread.

In this study each Pareto front is evaluated using various metrics from the above categories. Since the true Pareto front is unknown, it is not possible to measure the convergence truly. Instead, coverage value is computed so as to compare two Pareto sets with each other. Together with the coverage metric, hypervolume measure from the third category is employed in order to assess the convergence and spread of solutions simultaneously. In addition to this assessment spacing and maximum spread values are calculated for evaluating the solutions' spread.

Spacing (S): The measure is proposed by Schott [35] and has been used to

estimate the diversity of Pareto front. In the formulation n stands for the number of solutions in frontier, d_i represents the minimum Manhattan distance between a solution i and any other solution, $\bar{d}$ is the average distance between two solutions. As S becomes zero, a more uniformly distributed Pareto front is attained.

$$S = \sqrt{\frac{1}{n-1} \times \sum_{i=1}^n (d_i - \bar{d})^2} \quad (5.1)$$

Maximum Spread (MS): Zitzler [36] introduces maximum spread metric in order to measure the spread of a given set. For this measure, greater values are preferred since they indicate a better spread of the points. The measure is calculated as follows where a_i and b_i are two solutions in Pareto frontier and n is the number of solutions.

$$MS = \sqrt{\sum_{i=1}^n \max(\|a_i - b_i\|)} \quad (5.2)$$

Coverage (C): The coverage metric, suggested by Zitzler [36] is utilized to determine whether a Pareto front dominates another. So as to make the comparison between two Pareto fronts, A and B , each solution from one front is compared with all solutions in the other front. Two points, a and b , are compared with each other at a time using the weakly dominance operator shown as $\succeq$. The coverage values of sets A and B are represented by $C(A, B)$ and $C(B, A)$. If $C(A, B)$ is equal to 1, it means all solutions in the set B are weakly dominated by A . In the opposite case, where $C(A, B)$ is 0, none of the points in B is weakly dominated by A . Since there could be interaction between two sets, both directions should be considered in the calculation.

$$C(A, B) = \frac{|\{b \in B \mid \exists a \in A : a \succeq b\}|}{|B|} \quad (5.3)$$

Hypervolume: The hypervolume measure is first proposed by Zitzler and

Thiele [37] as the size of space covered. With change in the name over the time, this metric has been applied for evaluating the Pareto solutions' convergence and spread at the same time. For this purpose, the hypervolume quantifies the volume of the dominated space which is enclosed with a reference point. Usually, the point in the reference set having the worst-case results for each of the objective is selected and by adding some delta value, which is a small number, the reference point is reached. Considering a two-objective minimization problem setting, with objective functions $f_1(x)$ and $f_2(x)$, the computed area can be seen in Figure 5.1 [38].

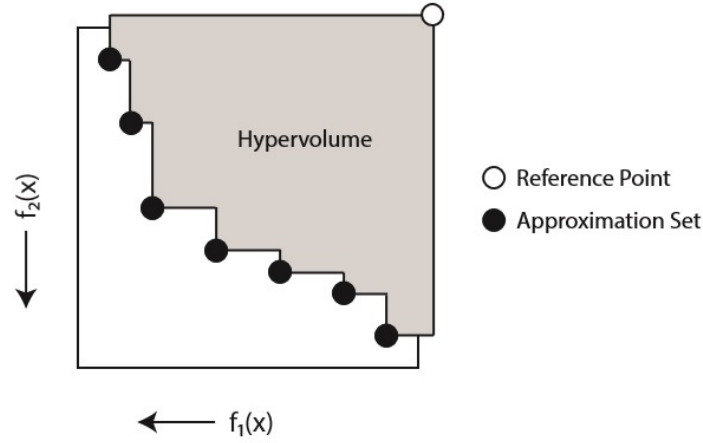


Figure 5.1: Hypervolume Measure for a Two-Objective Minimization Case

Chapter 6

Numerical Studies

6.1 Data Generation

The proposed approaches are applied to the grid-connected system located on a university campus. This campus system is considered as a medium-scale demand point in which the demand is met through renewable energy and energy purchased from the grid. In order to estimate the electricity consumption of the grid-connected system, the actual data of a campus is used. However, for the selected region only one month of hourly average electricity consumption data is acquired. So as to have the yearly data which is the total running time of the simulation, Hybrid Optimization of Multiple Energy Resources (HOMER) software is utilized. By preserving the consumption characteristics, hourly demand profiles for one year are generated. These profiles can be seen in Figure 6.1.

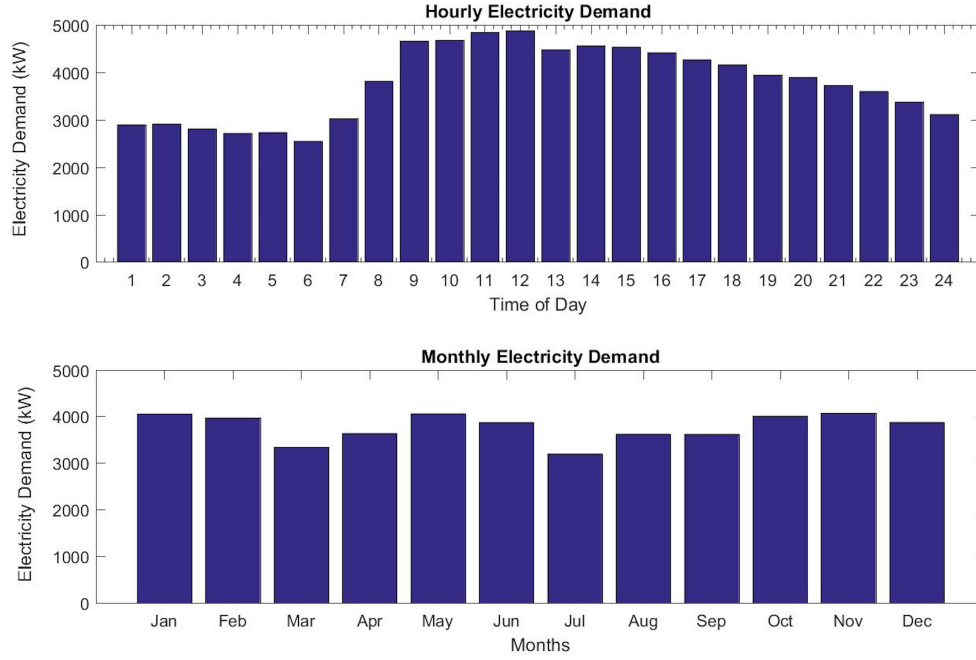


Figure 6.1: Hourly and Monthly Averages of Campus Demand

In addition to the demand data, solar and wind data are needed to make the energy calculations. The availability of renewable resources are obtained using HOMER software. Although HOMER software does not yield the data set of a given location, it provides some statistics to generate the data. For a university campus which is regarded as the medium-scale demand point, renewable energy profiles are generated using the mean wind speed value of 5.14 m/s and mean solar irradiation value of 0.17 kW/m^2 . Availability levels for solar and wind data are presented in Figure 6.2. For the details of the generated data sets, please refer to the study by Altıntaş [10].

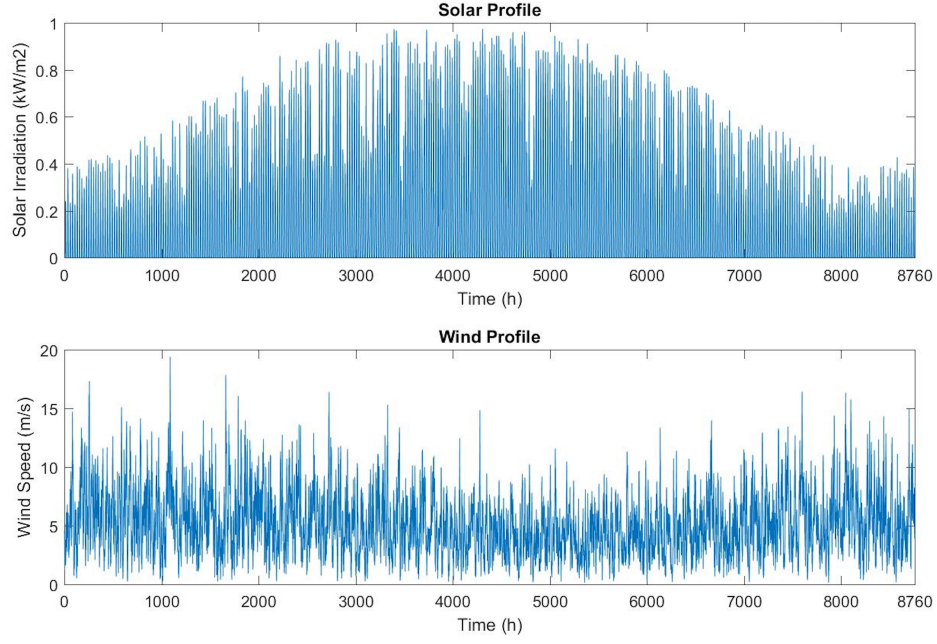


Figure 6.2: Solar and Wind Profiles for Medium Availability Level

In the grid-connected system, components are incorporated with the efficiency parameters, since they do not operate with a 100% efficiency. Examining the products available in the market, solar panel and storage device efficiencies are taken as 12% and 80%, respectively. In addition to the operation characteristics, lifetime of the system components should be considered as well. As a result, market is searched and the lifetime values are found as 10, 30, 20 years for storage device, PV panel and wind turbines respectively. With 0.05 discount rate (dr) and 30 years of panel life expectancy (L_s), the annualization factor for solar panel (α_s) is determined using the formula 6.1. Similar calculations are made for the storage item and wind turbines as well.

$$\alpha_s = \frac{dr}{1 + (1 - dr)^{-L_s}} \quad (6.1)$$

Operating the system for 30 years (L_{system}) and taking advantage of the government incentive for 10 years (L_{FT}), the formula 6.2 is applied in order to compute

the annualization factor for the selling price of solar energy (α_{ps}). Same process is repeated when the annualization factor for the selling price of wind energy is concerned. Aside from these factors, cost of the system components and the economic parameters employed in the problem are given in Table 6.1.

$$\alpha_{ps} = \frac{p^s L_{FT} + p^g (L_{system} - L_{FT})}{p^s L_{system}} \quad (6.2)$$

Table 6.1: Parameters for Numerical Study

c_b	330 \$/kWh	p^g	0.06 \$/kWh
c_s	300 \$/m ²	p^s	0.13 \$/kWh
c_w^{900kW}	1.77 M \$	p^w	0.07 \$/kWh
c_w^{2MW}	4.3 M \$	η_s	12
c_w^{3MW}	5.49 M \$	η_b	80
L_b	10 years	dr	0.05
L_s	30 years	κ	2
L_w	20 years	β	0.0004836
L_{system}	30 years	T	8760 (hours)
L_{FT}	10 years		

Market survey of these parameters can be found in Altıntaş's research [10]. Given the parameters and the data sets, GCDES and SO approaches are implemented in MATLAB 9.0 and solved using CPLEX 12.6. The source codes of metaheuristic algorithms written in JAVA environment are executed [39]. All of these solution procedures are run in a computer with Intel Xeon CPU E5-1650 3.6 GHz processor and 32 GB RAM. The resulting times are expressed in central processing unit seconds (CPU).

6.2 Comparison of Metaheuristic Algorithms

Using the numerical values mentioned in Section 6.1, three well-known algorithms, OMOPSO, NSGA-II and SPEA2, are tested for a medium solar-medium wind problem instance with nine scenario set. In order to set the generation count which is one of the parameters, algorithms are run with different number of generations. By changing the parameter each time, various sets of optimal solutions are obtained. These solutions are compared based on some popular performance metrics and their values are recorded in Tables 6.2 - 6.4. So as to provide an example for the selection of the algorithm parameter, OMOPSO algorithm is taken and its generation count is arranged accordingly using the metric results in Table 6.2.

Table 6.2: Performance Measure Results for OMOPSO Algorithm

Performance Metric / #of Evaluations	500	1000	5000	10000
Spacing	0.0154	0.0047	0.0009	0.0005
Max Spread	9.5723	14.2817	35.1018	49.8013
CPU Time(seconds)	143.95	289.08	1367.16	2818.88

Table 6.3: Performance Measure Results for SPEA2 Algorithm

Performance Metric / #of Evaluations	500	1000	5000	10000
Spacing	0.0120	0.0128	0.0039	0.0042
Max Spread	10.4554	10.1637	10.2725	10.2664
CPU Time(seconds)	141.44	290.30	1423.75	2930.03

Table 6.4: Performance Measure Results for NSGA-II Algorithm

Performance Metric / #of Evaluations	500	1000	5000	10000
Spacing	0.0122	0.0074	0.0072	0.0069
Max Spread	9.3381	10.1065	10.0013	10.2081
CPU Time(seconds)	144.83	279.61	1406.53	2935.09

All of the performance metric results indicate that 5000 and 10000 evaluations should be preferred over the others. Provided that there is no significant difference

between 5000 and 10000 evaluations in terms of the other performance measures, the version which takes less CPU time, 5000 is chosen. Tunings of the other algorithms are completed following the same steps here and in the end 5000 generations is accepted as the parameter to be used in all of the three algorithms.

Using 5000 generations, statistical analyses are conducted. For this purpose each metaheuristic algorithm is run for 10 times and their results are compared based on the hypervolume measure. This metric is selected since it evaluates both convergence and spread of the solutions. Minimum, mean and maximum values of this measure are listed in Table 6.5. In order to understand which algorithm performs the best, hypothesis testing is conducted. While checking if there is a significant difference between OMOPSO, NSGA-II and SPEA2 Kruskal-Wallis and Mann-Whitney U tests are applied [40]. The results of these tests clearly show that OMOPSO is the best performing algorithm for the given problem. When the other two algorithms are compared with each other, no significant difference is found. Therefore OMOPSO algorithm is utilized for obtaining the set of Pareto solutions in our bi-objective stochastic optimization of the grid-connected system.

Table 6.5: Hypervolume Metric Results for Algorithms

Algorithm	Hypervolume			Count	Indifferent
	Min.	Median	Max.		
OMOPSO	0.579	0.581	0.582	10	-
NSGA2	0.571	0.576	0.578	10	SPEA2
SPEA2	0.570	0.578	0.579	10	NSGA2

6.3 Comparative Analysis

In this part, three solution methods (GCDES, SO, OMOPSO) are compared with each other by taking the stochasticity of a location's renewable resources into consideration. In order to handle the stochasticity aspect of the problem, a scenario-wise approach is utilized. For solar data, scenario sets are formed via

perturbation of the profiles shown in Figure 6.2. Choosing the parameter as 5%, the procedure of [41] is followed in the scenario sets' generation. For wind data, techniques introduced by [42] and [43] are used to create the scenario sets. In the literature, the Weibull distribution is commonly used to generate synthetic wind speed data [44]. In that technique, different states are constructed and wind speed is generated using a Markov transition matrix, which is constructed using the Weibull distribution. Wind speed values are centered around the given mean value and the correlation between time units is handled by a decreasing exponential function.

For each of our low, medium, high solar and wind cases, three scenario sets are generated. While generating the scenario sets, it is assumed that renewable energy sources' data are independent from each other. Statistics of the scenario sets are given in Table 6.6.

Table 6.6: Attributes of Generated Scenarios

Level	Solar Irradiation (kW/m ²)								
	Scenario Set 1			Scenario Set 2			Scenario Set 3		
	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

Level	Wind Speed (m/s)								
	Scenario Set 1			Scenario Set 2			Scenario Set 3		
	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

The GCDES, SO and OMOPSO algorithms are run for nine different locations (combinations of high, medium and low resource availability levels) using nine different scenario sets (combinations of three solar and three wind scenario

sets), of the data of which are introduced in Section 6.1. The outputs of these computational experiments can be found in Table 6.7. In the comparison part, GCDES approach's results are left out due to the fact that the approach fails to conclude the experiment in a predesignated amount of time for all nine cases and hence, delivers only a few solutions. When these solutions are evaluated using the mentioned metrics, it is observed that GCDES approach performs moderately compared to the other methods. In addition to the nine scenario output of the medium - medium case, incorporating demand uncertainty and therefore increasing the number of scenario sets lowers the performance of GCDES greatly where no solution is delivered in the end for some cases. Hence, from this point on we will continue our analysis with SO and OMOPSO approaches only.

Table 6.7: Outputs of the SO and OMOPSO Approaches for Nine Scenarios

Solar Level	Wind Level	SO				OMOPSO			
		# Solns	Soln Time(s)	Start GP ^a	End GP ^b	# Solns	Soln Time(s)	Start GP ^a	End GP ^b
High	High	7	13085	35.9%	4.7%	121	1468	37.9%	5.4%
Medium	High	8	12491	37.9%	1.5%	347	1463	37.9%	1.6%
Low	High	7	8323	37.9%	5.1%	165	1438	37.9%	5.4%
High	Medium	4	3319	53.5%	35.5%	397	1400	100.0%	36.5%
Medium	Medium	11	36043	100.0%	48.7%	1136	1367	100.0%	49.6%
Low	Medium	9	49073	100.0%	52.7%	336	1412	100.0%	53.2%
High	Low	4	3964	53.5%	37.1%	422	1464	100.0%	36.4%
Medium	Low	11	4310	100.0%	48.9%	703	1452	100.0%	48.7%
Low	Low	9	3912	100.0%	58.7%	995	1460	100.0%	59.7%

^a Percentage of demand satisfied by the grid of the first Pareto solution found.

^b Percentage of demand satisfied by the grid of the last Pareto solution found.

The results indicate that OMOPSO algorithm is able to achieve a variety of solutions with less computational effort compared to the SO approach. Although this table gives valuable insights about the performances, it is necessary to conclude the comparison by looking at the other performance measures discussed in Chapter 5.

With the three measures implemented, performances of the approaches can be seen in Table 6.8. While comparing SO and OMOPSO, it is clear that there are significant differences between the performances of the two algorithms. For the S measure, OMOPSO has numbers which are almost one-tenth of the SO. A

Table 6.8: Performance Metrics of the SO and OMOPSO Approaches for Nine Scenarios

Solar Level	Wind Level	SO				OMOPSO			
		S	MS	C(GCDES, SO)	C(OMOPSO, SO)	S	MS	C(GCDES, OMOPSO)	C(SO, OMOPSO)
High	High	0.3	2.9	0.0%	0.0%	0.035	11.9	0.0%	14.9%
Medium	High	0.3	3.1	0.0%	12.5%	0.005	20.4	0.0%	5.8%
Low	High	0.3	2.9	0.0%	14.3%	0.008	13.7	0.0%	13.3%
High	Medium	0.1	2.2	0.0%	25.0%	0.005	21.3	0.0%	0.3%
Medium	Medium	0.1	3.4	9.1%	90.9%	0.002	34.5	0.0%	0.0%
Low	Medium	0.2	3.1	11.1%	77.8%	0.008	18.5	0.0%	0.0%
High	Low	0.1	2.2	0.0%	0.0%	0.004	22.0	0.0%	3.8%
Medium	Low	0.1	3.5	9.1%	54.5%	0.004	26.8	0.0%	1.4%
Low	Low	0.1	3.1	11.1%	66.7%	0.002	31.8	0.0%	0.6%

similar ratio is observed among the MS values. Despite high weakly domination ratios in some cases, OMOPSO performs better in terms of the C metric as well. The results of the medium–medium case can be seen graphically in Figure 6.3. Nine-Scenario PFs of the SO and OMOPSO approaches for the remaining cases are found in Appendix A.

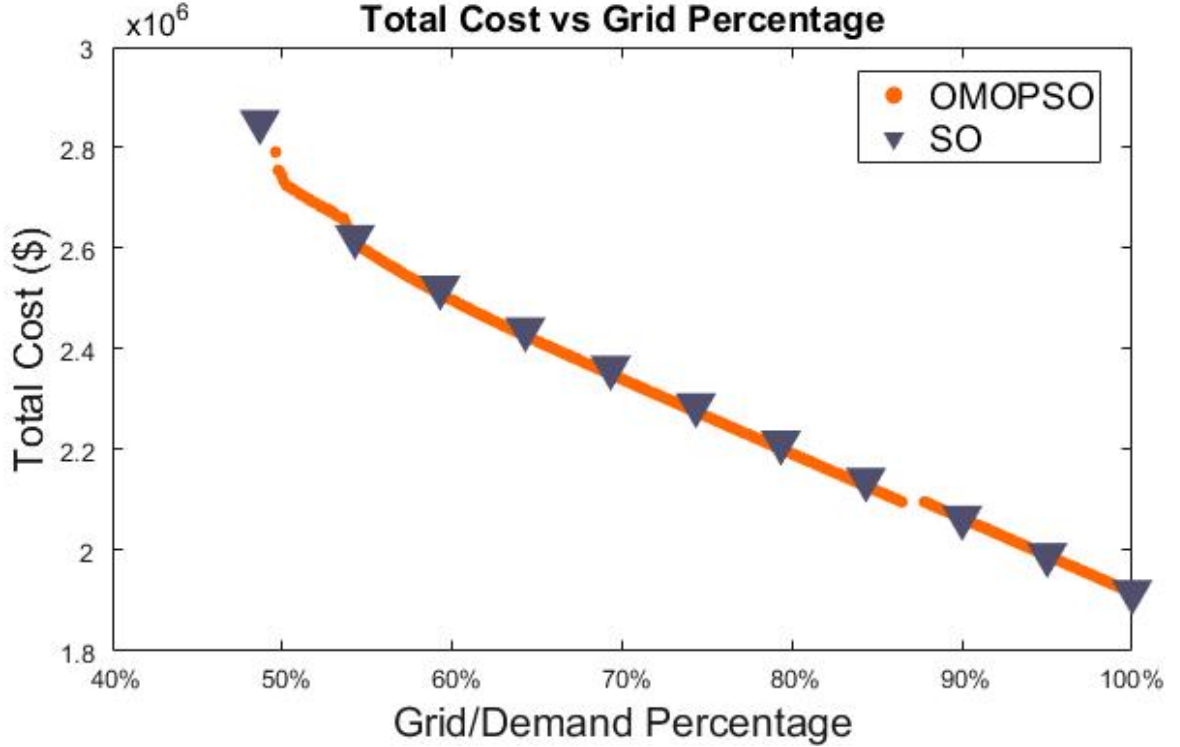


Figure 6.3: Nine-Scenario Pareto of the SO and OMOPSO Approaches for the Medium Solar-Medium Wind Case

Completing the nine-scenario experiments, we now examine the performances of the algorithms in the cases where demand uncertainty is included. Using medium solar-medium wind case and by generating three and five scenario sets for demand, the number of scenario sets is increased to 27 and 125 respectively. The outcomes of this study can be seen in Table 6.9. By looking at this table, we can conclude that OMOPSO returns a diverse set of solutions which performs better in all of the metrics in a shorter amount of time. For the graphical results of the other cases, please refer to the Appendix B.

Table 6.9: Outputs of the SO and OMOPSO Approaches for 27 - 125 Scenarios

#Scens	SO					OMOPSO				
	#Solns	Soln Time (s)	S	MS	C(OMOPSO, SO)	#Solns	Soln Time (s)	S	MS	C(SO, OMOPSO)
27	12	40178	0.131	3.6	83.3%	716	6033	0.003	27.1	0.4%
125	11	976980	0.100	3.4	81.8%	1056	24781	0.004	33.0	1.0%

So as to observe the contribution of including demand uncertainty in the problem setting, value of stochasticity (VSS) is computed. For calculating this value, first expected outcome of expected solution (EEV) is found. While finding this outcome, a deterministic model in which mean values of random parameters are employed is solved. Together with this computation, solutions of the stochastic problem, which correspond to the recourse problem (RP) in the formulation, are used. The formula for calculating VSS in a minimization case can be seen below.

$$VSS = EEV - RP \quad (6.1)$$

Note that we consider a bi-objective problem, hence we compare objective function vectors of EEV and RP solutions. For that reason we perform a Pareto analysis, as seen in Figure 6.4. The graph demonstrates that solutions of the stochastic problem might dominate the deterministic case's results since they give lower values for objective functions. Although some solutions of the RP are dominated by the EEV problem, this can be attributed to the fact that metaheuristic algorithms are utilized in finding solutions. VSS for other cases can be obtained following the same procedure here.

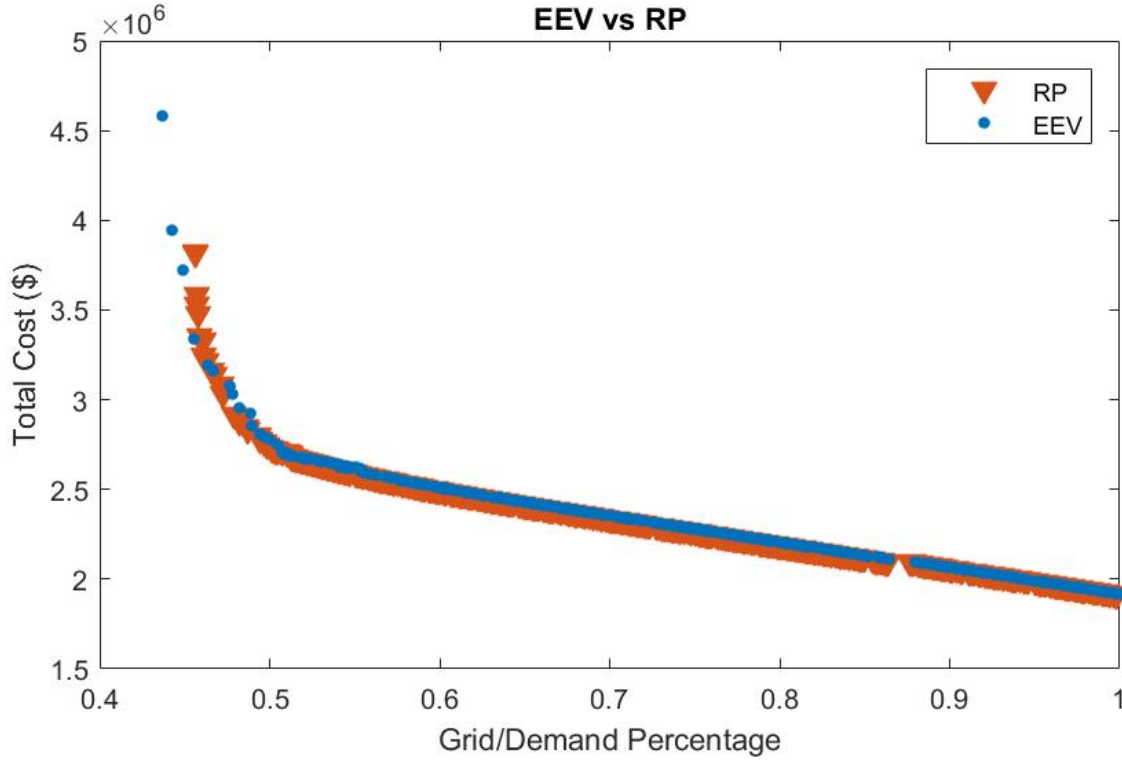


Figure 6.4: Comparison of Outputs of EEV and RP for Medium Solar-Medium Wind Case

6.4 Sensitivity Analysis

In order to see the effect of the price parameters on the solutions, a sensitivity analysis is performed. Although, one instance of the problem, which is the medium solar – medium wind case is considered for the analysis, the same procedure could be carried out for the other cases as well. Moreover, nine-scenario setting is preferred for the study because of the fact that it requires less computational effort and shorter amount of time. Initially, a solution is chosen from the PF which has a grid percentage value of 60% so as to bound the CO₂ level. The price parameters are then halved and doubled one at each time while keeping the others at their base levels. For each of the resulting case, the problem is solved with the solution approaches, SO and OMOPSO, and the outcomes are recorded in Tables 6.10 - 6.11 respectively.

Table 6.10: Sensitivity Analysis Results of SO Approach

	Base Case	c_b		c_s		c_w		p^w	p^s
	100%	200%	50%	200%	50%	200%	50%	200%	200%
Cost	2510187	2510187	2510187	2997726	1684329	2592661	1946417	2510373	2553399
Grid P.	59.30%	59.30%	59.30%	58.72%	58.52%	59.99%	58.72%	58.85%	51.51%
A_b	0	0	0	0	0	0	0	0	0
A_s	50104	50104	50104	20010	97608	89713	20010	31989	76666
A_w^{900kW}	0	0	0	0	0	0	0	0	0
A_w^{2MW}	0	0	0	0	0	0	0	0	0
A_w^{3MW}	1	1	1	3	0	0	3	2	1

Table 6.11: Sensitivity Analysis Results of OMOPSO Approach

	Base Case	c_b		c_s		c_w		p^w	p^s
	100%	200%	50%	200%	50%	200%	50%	200%	200%
Cost	2497306	2496815	2497882	3233194	1969693	2908045	2156122	2495758	2478357
Grid P.	59.99%	59.99%	59.94%	59.97%	57.89%	59.95%	59.99%	59.98%	59.99%
A_b	3.87	0	0	0	0	0	8.96	0	3.35
A_s	48368	48336	48482	34620	65212	58636	31547	48389	48336
A_w^{900kW}	0	0	0	0	0	0	1	0	0
A_w^{2MW}	0	0	0	1	1	1	1	0	0
A_w^{3MW}	1	1	1	1	0	0	1	1	1

One important observation which can be made on the tables is that the solar area and number of wind turbines change significantly whereas no difference is observed regarding the storage capacity in almost all of the cases. By taking this finding into account, it can be concluded that energy storage is not a cost effective option for the medium-medium instance of the GCDES problem.

Chapter 7

Conclusion

With the increasing trend in switching from centralized to decentralized energy systems, this study investigates the sizing problem of a GC decentralized energy system. This system contains renewable sources such as solar and wind together with connection to the grid. In addition to these parts, storage unit is put into the system due to the intermittent natures of the resources. Placing a higher priority on the renewable energy components, system operates according to a specific policy in order to meet the energy requirement.

Given the system setting, a decision maker tries to find the optimal sizes of the system components. The decision maker facing this problem takes both cost and the environment into consideration. Consequently, total cost and CO₂ emission of the system are considered as the two objectives. While minimizing these two objectives, renewable resources introduce uncertainty to the system, which makes the problem stochastic in nature. In this formulation, various availability scenario sets of the solar and wind sources are considered in order to incorporate stochasticity in the models.

For the solution of the mentioned problem, a simulation-optimization method is proposed by Altıntaş [10] in order to capture the stochastic nature with less computational effort. In this algorithm, two versions of the mathematical model

and a simulation module are established so as to obtain a Pareto set. These modules provide input for each other and as a result of this joint operation, a solution with a cost and CO₂ emission value is reached. Moving on the Pareto front iteratively, a subset of the Pareto solutions is generated. Although SO approach is able to handle the stochastic and bi-objective aspects of the problem to a certain degree, it fails to return solutions in a reasonable amount of time when uncertainty is included in the system. Because of this reason, we introduce another method, which is based on metaheuristic algorithms.

In the metaheuristic approach, there are two modules, simulation and optimization, which provide input for each other. First, solutions are randomly generated in the optimization module, then they are conveyed to the simulation module in order to perform the simulation. After the simulation is completed, each solution is given a cost and carbon emission value which are used in the Module 1 for the optimization purposes. The optimization module could use any metaheuristic algorithm. In this study, we use OMOPSO, NSGA-II and SPEA2, since these algorithms are reported to perform well for other problem settings in the literature. The joint work of the optimization and simulation modules results in a set of Pareto solutions.

OMOPSO, NSGA-II and SPEA2 algorithms are employed in the optimization of a medium-scale system such as a university campus so as to observe performance. Together with the demand data, solar and wind data generated through HOMER software are given as inputs. While running the algorithms, number of generations is needed to be set. By changing this parameter every time different sets of solutions are obtained and they are compared with each other using some performance metrics. Based on these comparisons, a better value for the parameter is acquired. Given this parameter, each one of OMOPSO, NSGA-II, SPEA2 is run on a computer and their resulting Pareto fronts are evaluated with the hypervolume metric. The statistical tests demonstrate that OMOPSO is the best performing algorithm, whereas no significant difference is found between NSGA-II and SPEA2. After OMOPSO is selected, metaheuristic and simulation-optimization approaches are assessed using problem instances with 9 scenario sets firstly. Once this experiment is completed, uncertainty in demand data is taken

into account. By creating three scenario sets of the demand data, a total of 27 scenario sets is obtained. For the last numerical comparison, the number of scenario sets is increased from three to five and a total of 125 scenario sets is used in the study. All of these tests indicate that OMOPSO algorithm outperforms the SO method based on the well-known performance metrics.

For the future research, different objectives such as maximizing reliability, minimizing unmet load could be incorporated into the system. With these newly introduced objectives, different investment options could be investigated. In addition to this option, uncertain parameters could be included. For example, instead of using deterministic values of electricity purchase and selling prices, one can let them be determined in a dynamic market environment, which makes the parameters highly uncertain. Increase in the number of objectives and stochasticity would make the system a better representative of the real life, yet this time the problem would be harder to solve. As a result, different solution approaches could be developed in order to tackle the computational issues.

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Appendix A

Nine-Scenario Pareto of the SO and OMOPSO Approaches

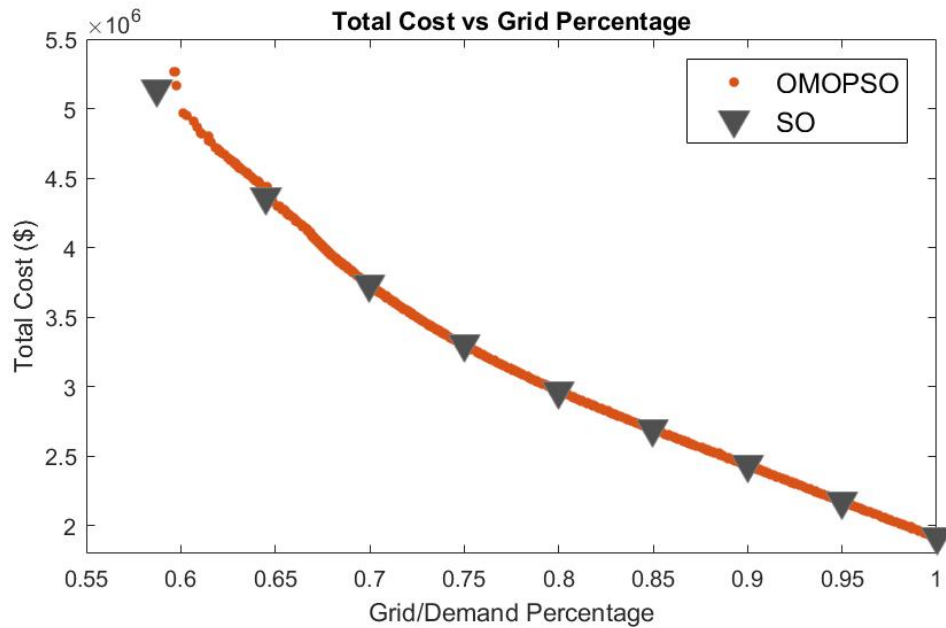


Figure A.1: Nine-Scenario Pareto of the SO and OMOPSO Approaches for the Low Solar-Low Wind Case

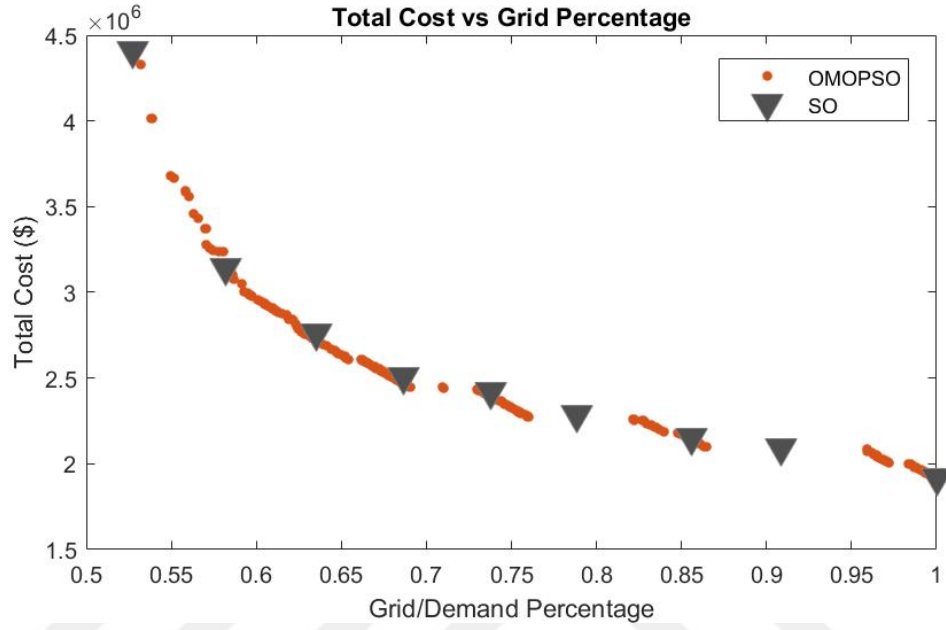


Figure A.2: Nine-Scenario Pareto of the SO and OMOPSO Approaches for the Low Solar-Medium Wind Case

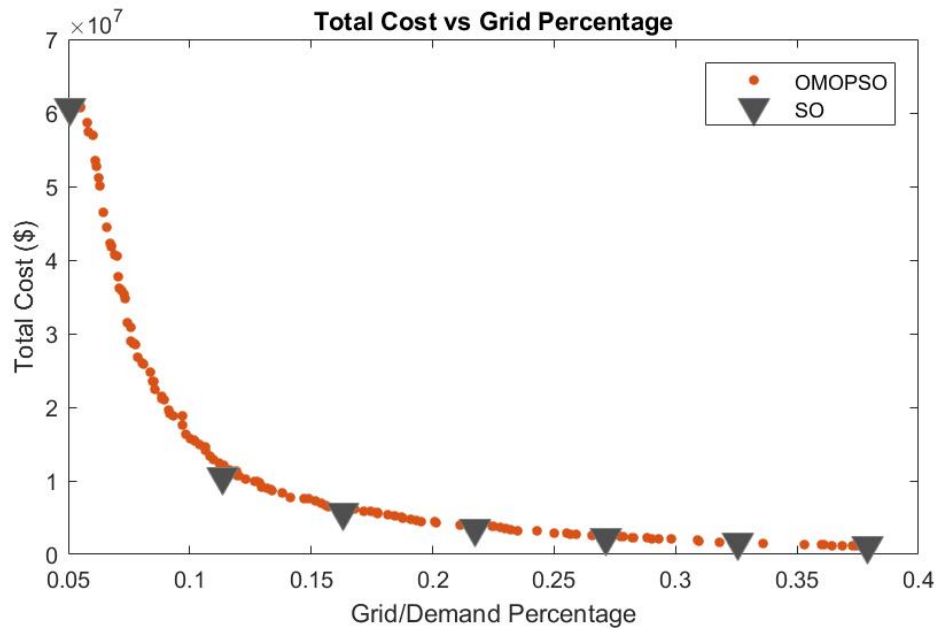


Figure A.3: Nine-Scenario Pareto of the SO and OMOPSO Approaches for the Low Solar-High Wind Case

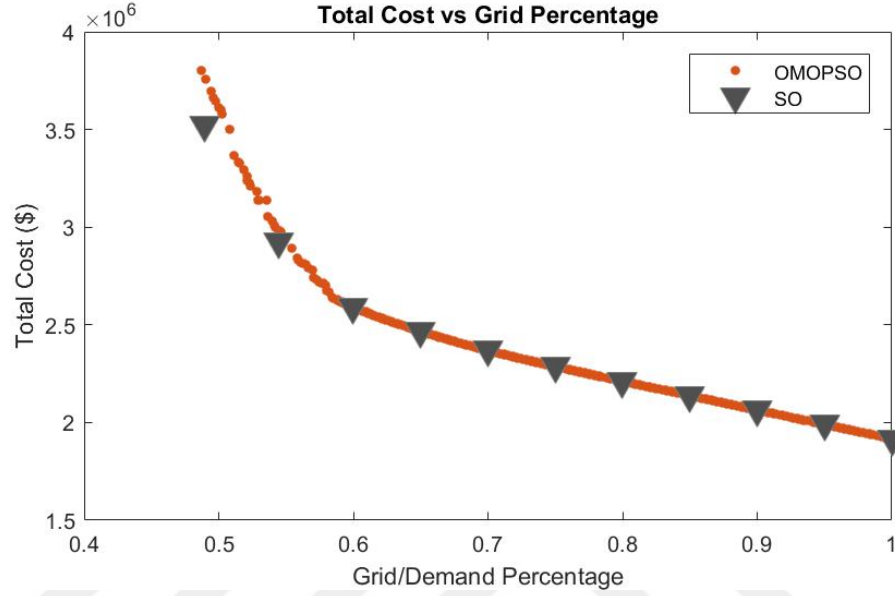


Figure A.4: Nine-Scenario Pareto of the SO and OMOPSO Approaches for the Medium Solar-Low Wind Case

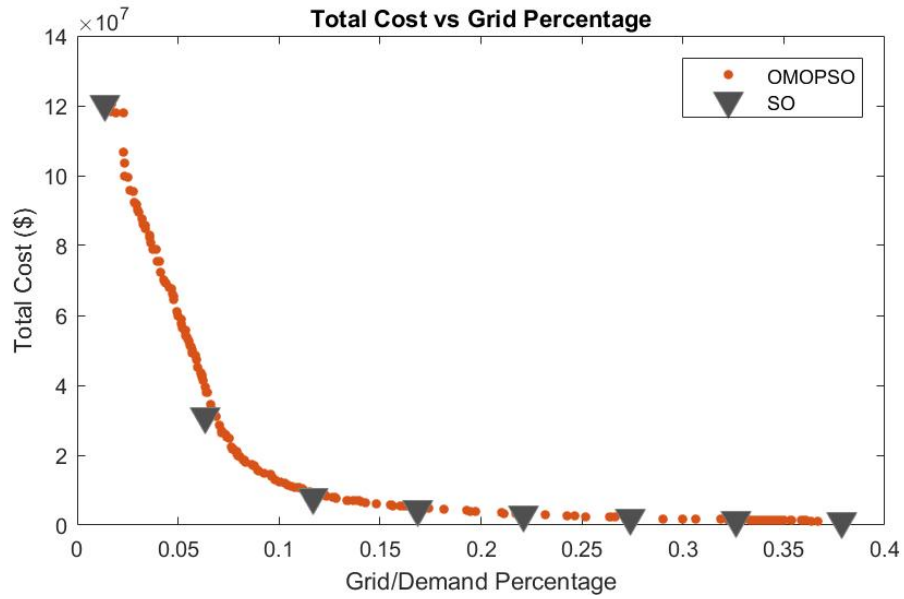


Figure A.5: Nine-Scenario Pareto of the SO and OMOPSO Approaches for the Medium Solar-High Wind Case

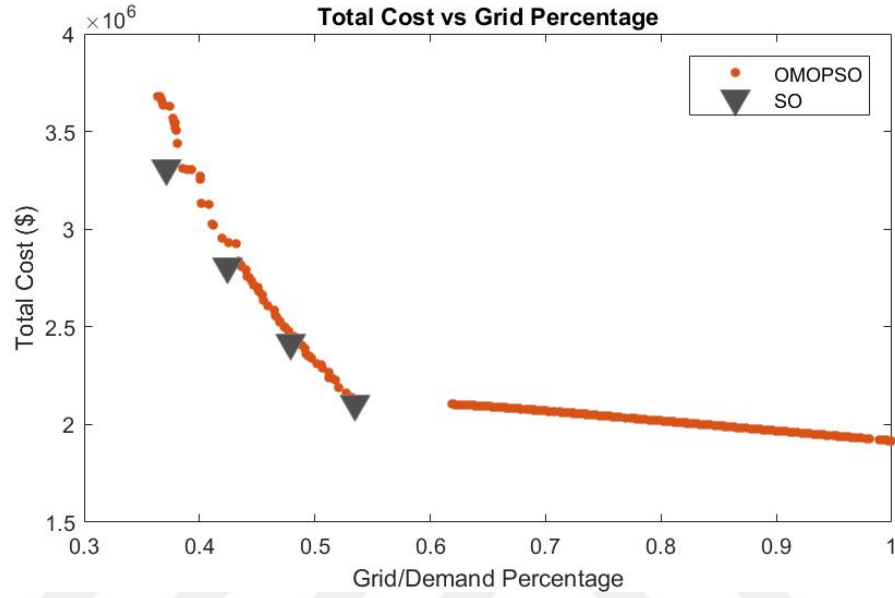


Figure A.6: Nine-Scenario Pareto of the SO and OMOPSO Approaches for the High Solar-Low Wind Case

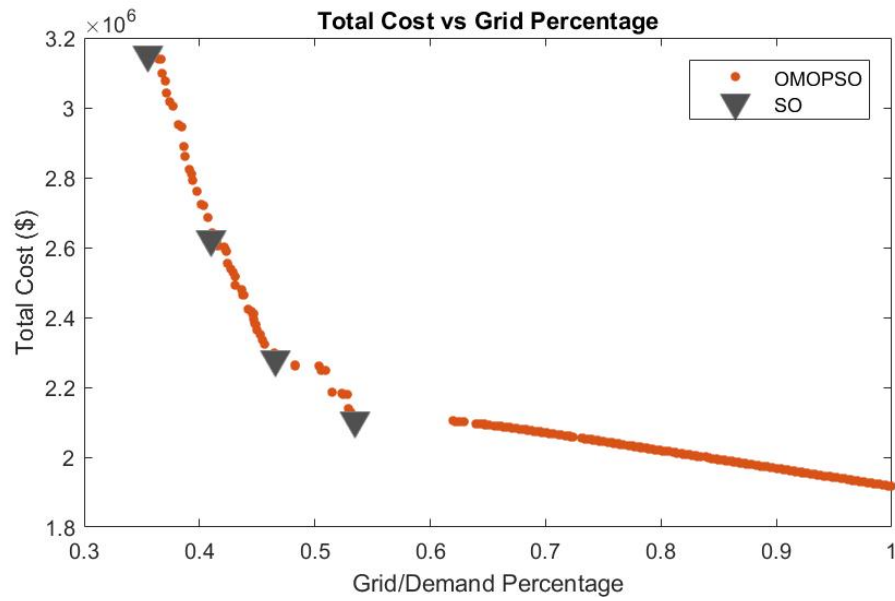


Figure A.7: Nine-Scenario Pareto of the SO and OMOPSO Approaches for the High Solar-Medium Wind Case

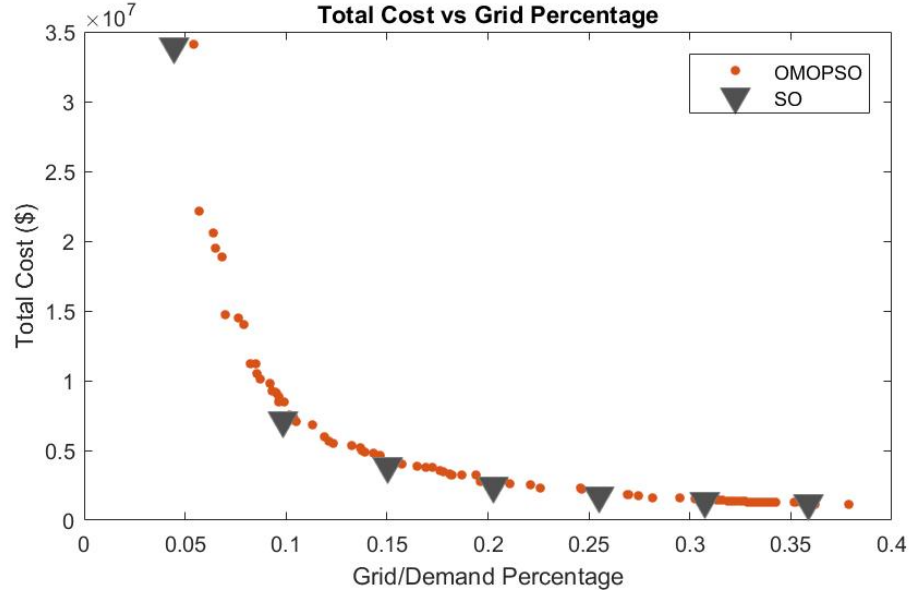


Figure A.8: Nine-Scenario Pareto of the SO and OMOPSO Approaches for the High Solar-High Wind Case

Appendix B

27-Scenario Pareto of the SO and OMOPSO Approaches

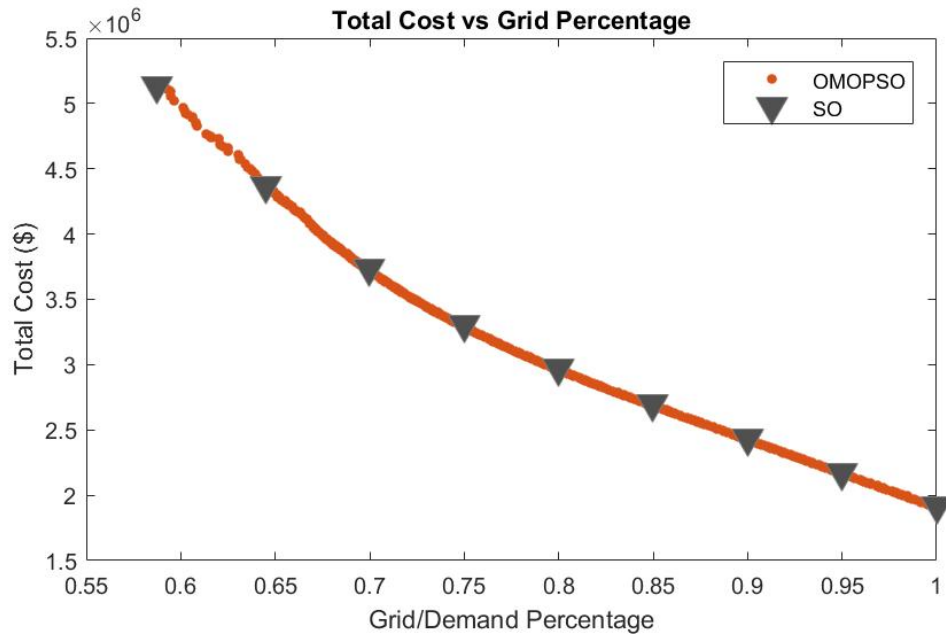


Figure B.1: 27-Scenario Pareto of the SO and OMOPSO Approaches for the Low Solar-Low Wind-Medium Demand Case

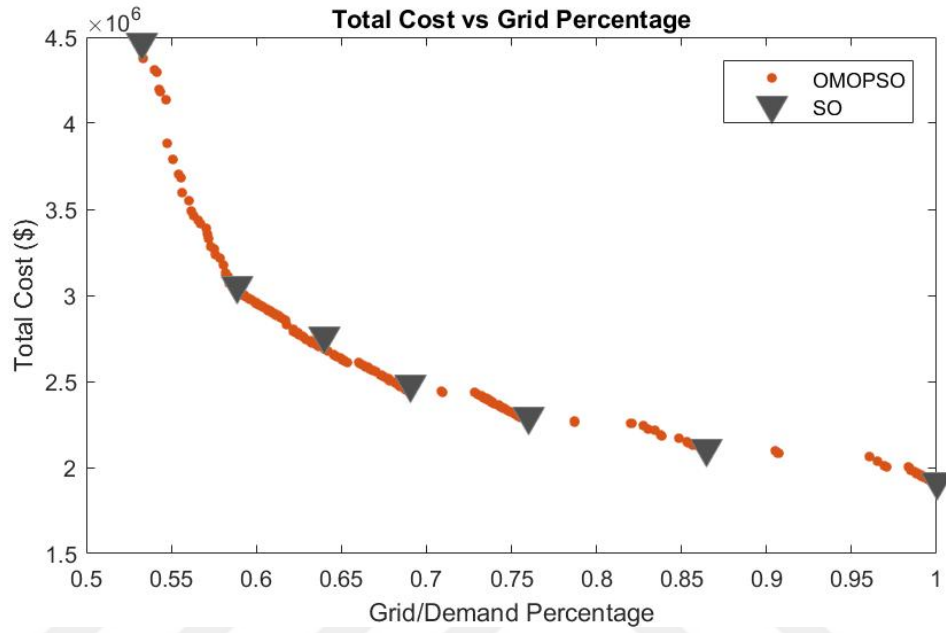


Figure B.2: 27-Scenario Pareto of the SO and OMOPSO Approaches for the Low Solar-Medium Wind-Medium Demand Case

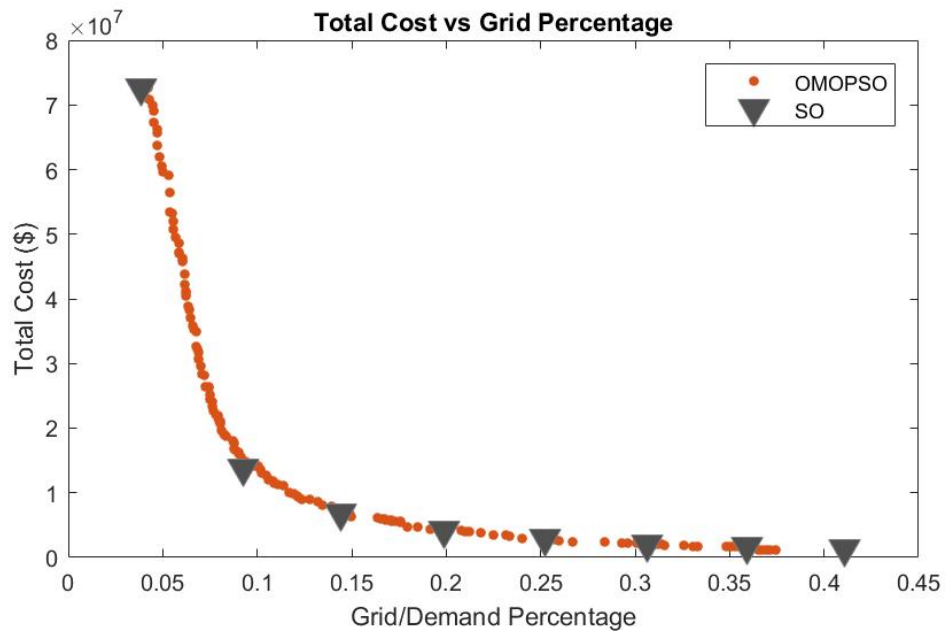


Figure B.3: 27-Scenario Pareto of the SO and OMOPSO Approaches for the Low Solar-High Wind-Medium Demand Case

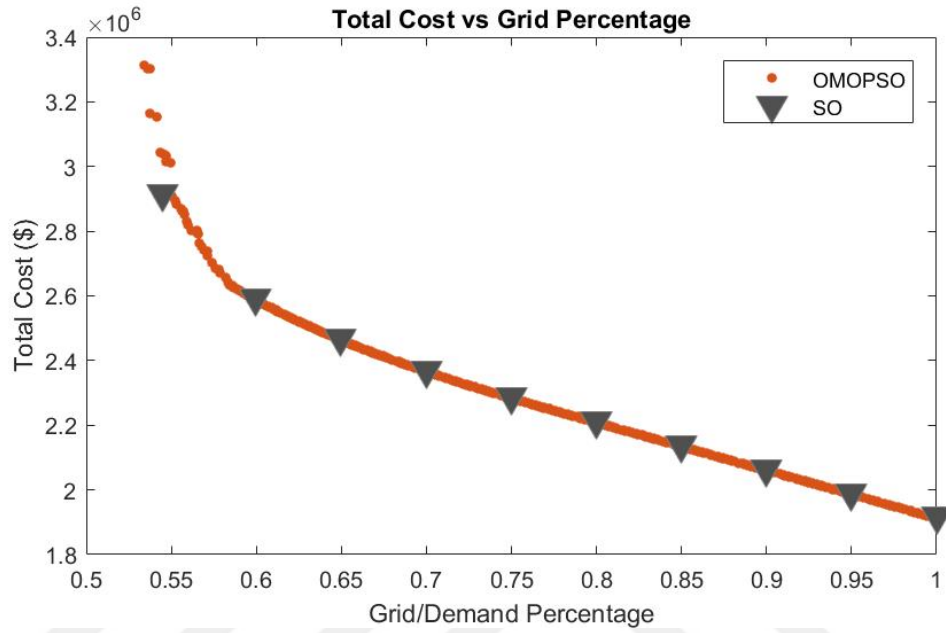


Figure B.4: 27-Scenario Pareto of the SO and OMOPSO Approaches for the Medium Solar-Low Wind-Medium Demand Case

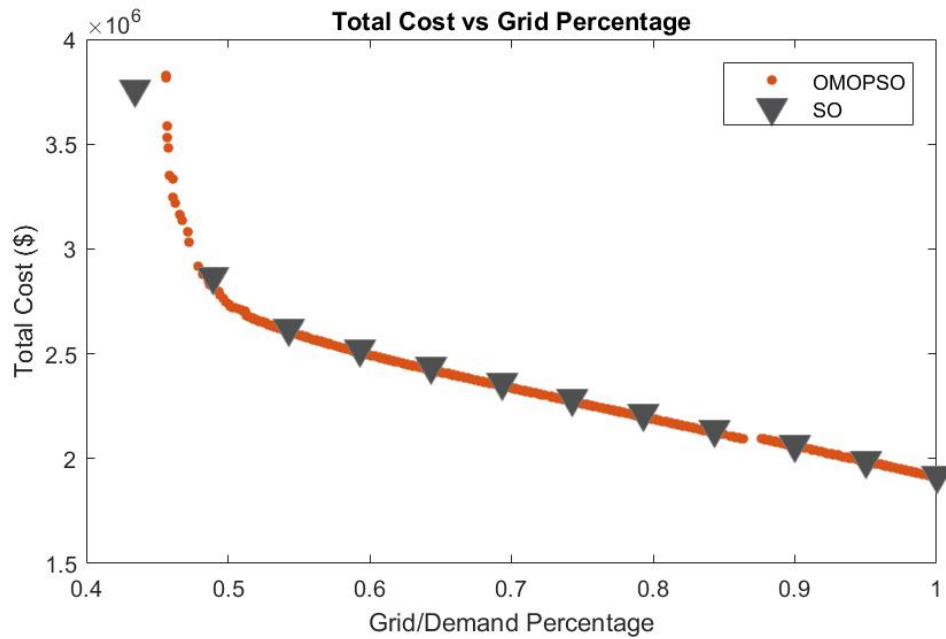


Figure B.5: 27-Scenario Pareto of the SO and OMOPSO Approaches for the Medium Solar-Medium Wind-Medium Demand Case

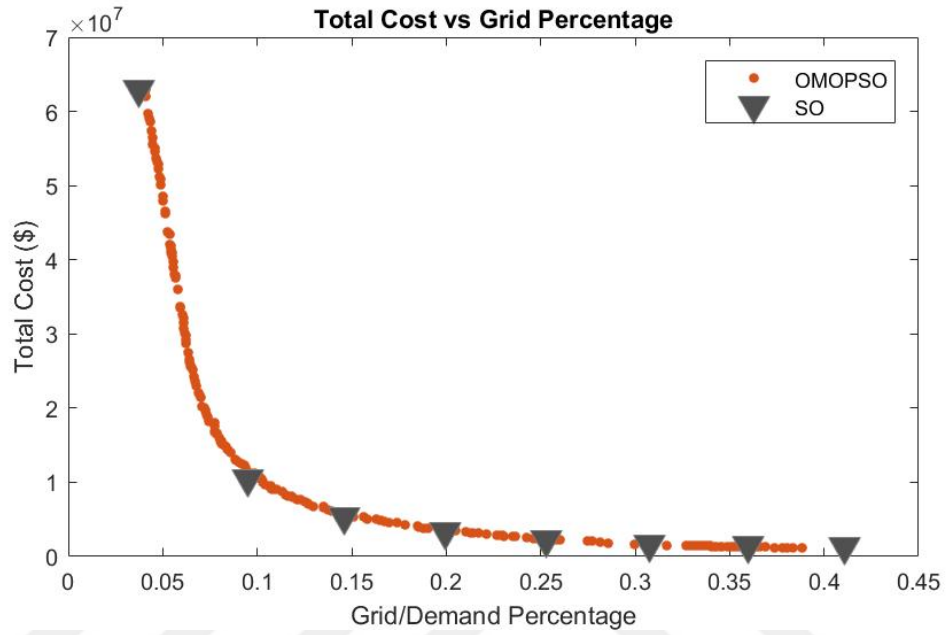


Figure B.6: 27-Scenario Pareto of the SO and OMOPSO Approaches for the Medium Solar-High Wind-Medium Demand Case

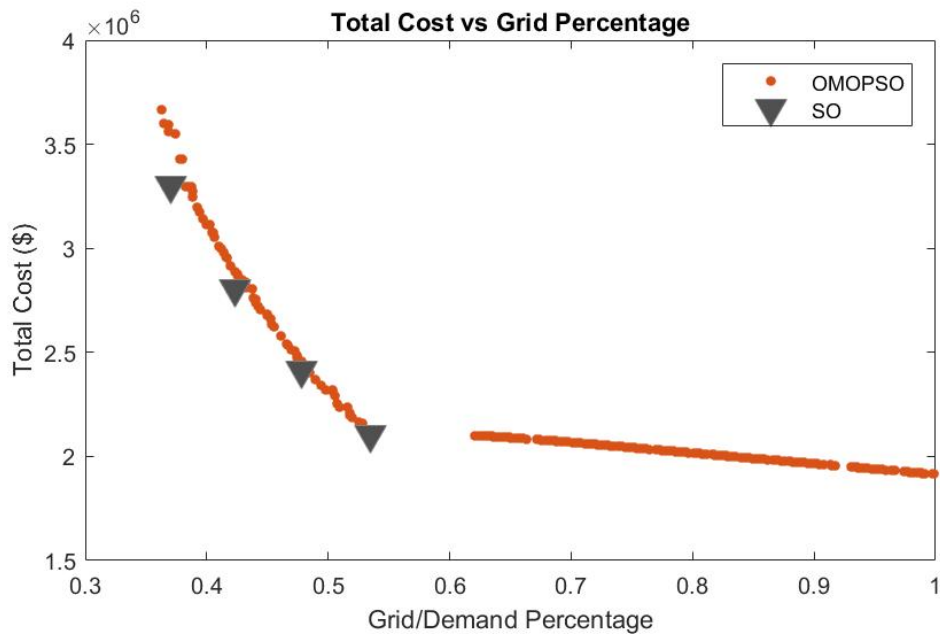


Figure B.7: 27-Scenario Pareto of the SO and OMOPSO Approaches for the High Solar-Low Wind-Medium Demand Case

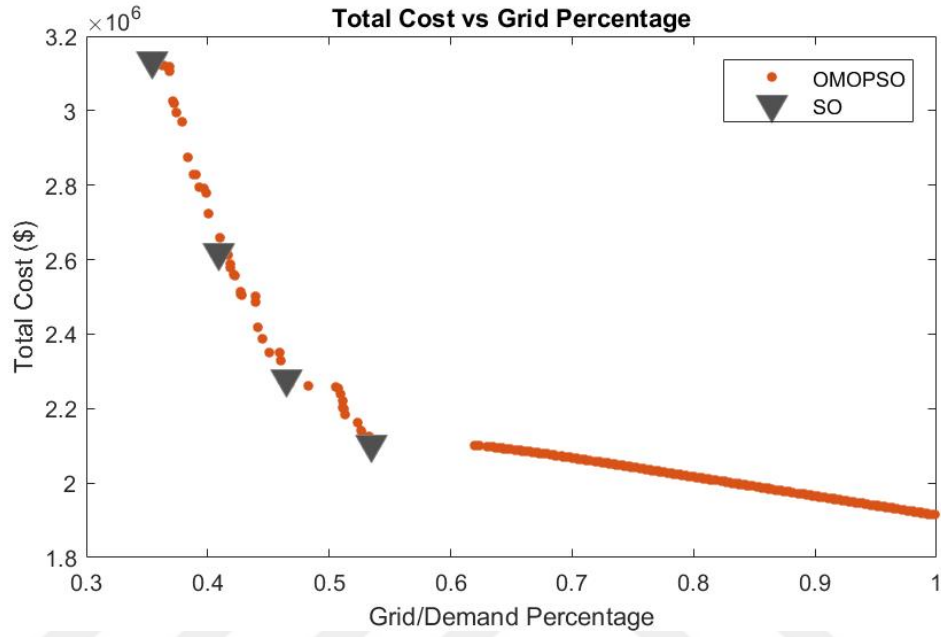


Figure B.8: 27-Scenario Pareto of the SO and OMOPSO Approaches for the High Solar-Medium Wind-Medium Demand Case

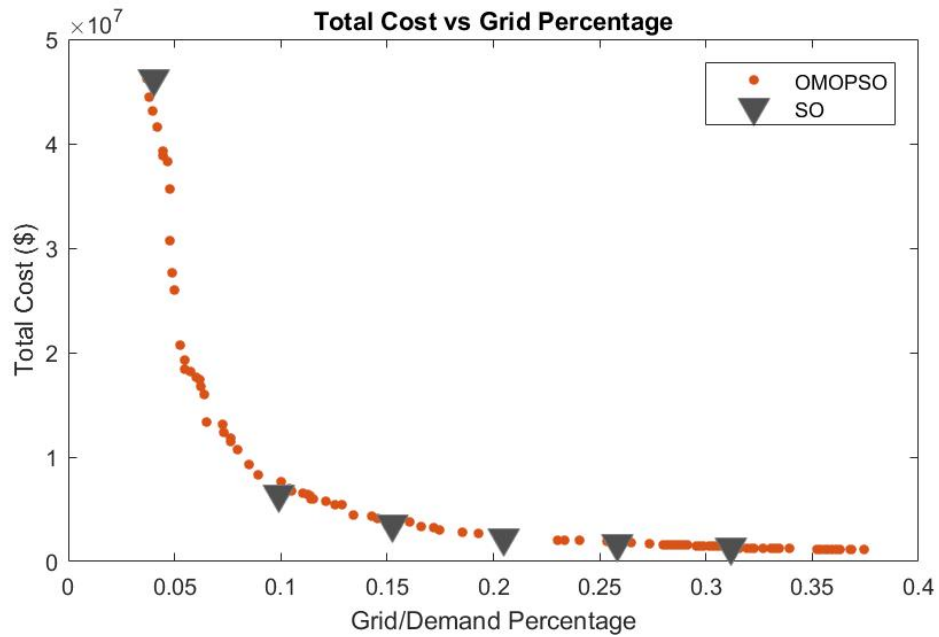


Figure B.9: 27-Scenario Pareto of the SO and OMOPSO Approaches for the High Solar-High Wind-Medium Demand Case