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FORECASTING-BASED HYBRID MODEL PREDICTIVE CONTROLLER FOR MICROGRID ENERGY MANAGEMENT

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ABSTRACT

FORECASTING-BASED HYBRID MODEL PREDICTIVE CONTROLLER FOR MICROGRID ENERGY MANAGEMENT

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Increase in energy demand, environmental effects of conventional power generation and higher renewable energy penetration have led us to consider the topics of the smart grid, distributed generation, electrical storage, and advanced controls and optimization. In this thesis, a microgrid control problem that takes into account the stochastic nature of the solar power generation and electrical load demand, while managing the microgrid operation by an advanced control technique, namely Model Predictive Control (MPC), is studied.

First, we predict the electrical load demand and photovoltaic (PV) output power by using various forecasting methods. We apply Linear Regression, Seasonal Autoregressive Integrated Moving Average (SARIMA), and Multi-Layer Perceptron (MLP) methods to forecast generation of a building-integrated photovoltaic (BIPV) system and electrical load consumption of a building at Yaşar University, Turkey for a 24-hour horizon.

Subsequently, we design three different MPC approaches and compare their performances: (i) deterministic MPC by taking point estimations of future load and PV generation directly, (ii) stochastic MPC by using the distribution of the historical net load, (iii) a hybrid method that combines the strengths of deterministic and stochastic MPC methods. To address the stochastic nature of load demand and renewable energy generation, we employ “chance-constrained” and “two-stage (recourse)” stochastic programming in the MPC controller. In order to reduce the number of scenarios in the

two-stage method, we apply a novel Singular Value Decomposition based model of order reduction.

The novel contributions of this thesis are two-fold: (i) development of a hybrid MPC approach that combines the character of the historical data and point estimations for future horizon, and thus it outperforms better than purely deterministic or stochastic MPC approaches, and (ii) adaptation of Singular Value Decomposition technique in order to reduce the number of scenarios in two-stage stochastic programming.

Key Words: microgrids, model predictive control, forecasting, multi-layer perceptron, stochastic programming, scenario generation, singular value decomposition.

ÖZ

MİKRO ŞEBEKE ENERJİ YÖNETİMİ İÇİN TAHMİNE DAYALI HİBRİT MODEL ÖNGÖRÜMLÜ KONTROL ALGORİTMASI

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Enerji talebindeki artış, geleneksel enerji üretiminin çevresel etkileri ve daha yüksek yenilenebilir enerji penetrasyonu, bizi akıllı şebeke, dağıtılmış üretim, elektrik depolama ve gelişmiş kontrol ve eniyileme (optimizasyon) konuları üzerine düşünmeye yönlendirmiştir. Bu tezde, bir mikro şebekenin kontrol problemi, ileri kontrol tekniği olan Model Öngörülü Kontrol (MÖK) ile yönetilirken, güneş enerjisi üretiminin ve elektrik yükü talebinin rassal doğası dikkate alınarak çalışılmıştır.

İlk olarak elektrik yük talebini ve fotovoltaik (FV) çıkış gücünü tahmin etmek için farklı tahmin yöntemlerini kullandık. Türkiye'de Yaşar Üniversitesinde bulunan, binaya entegre fotovoltaik sistemin enerji üretimini ve aynı kampüste bulunan bir binanın elektrik yük tüketimini 24 saatlik zaman dilimi boyunca tahmin etmek için Doğrusal Regresyon, Mevsimsel Özbağlanımlı Tümleşik Kayan Ortalama ve Çok Katmanlı Algılayıcı (ÇKA) yöntemlerini uyguladık.

Ardından üç farklı MÖK yaklaşımı tasarlayıp, bu yaklaşımların performanslarını karşılaştırdık: (i) gelecekteki yük ve FV üretimin noktasal tahminlerini alarak deterministik MÖK, (ii) geçmiş net yük dağılımını kullanarak rassal MÖK, (iii) deterministik ve rassal MÖK yöntemlerinin güçlü yönlerini birleştiren melez (hibrit) yöntem. Yük talebi ve yenilenebilir enerji üretiminin rassal yapısını ele almak için “şans kısıtı” ve “iki aşamalı (eklenmeli)” rassal programlama yöntemlerini MÖK yaklaşımı içinde kullanıyoruz. İki aşamalı yöntemde senaryoların sayısını azaltmak için, özgün bir Tekil Değer Ayrıştırma tabanlı model derecesi azaltma yöntemi uyguladık.

Bu tezin özgün katkıları iki şekildedir: (i) gelecekteki zaman dilimleri için geçmiş verinin karakterini ve noktasal tahminleri birleştiren ve bu sayede tamamen deterministik veya rassal MÖK yaklaşımlarından daha iyi performans gösteren melez bir MÖK yaklaşımının geliştirilmesi ve (ii) iki aşamalı rassal programlamada senaryoların sayısını azaltmak için Tekil Değer Ayrıştırma tekniğinin uyarlanmasıdır.

Anahtar Kelimeler: mikro şebekeler, model öngörülü kontrol, tahmin, çok katmanlı algılayıcı, rassal programlama, senaryo üretimi, tekil değer ayrışımı.

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Ayşegül Kahraman
İzmir, 2020

TEXT OF OATH

I declare and honestly confirm that my study, titled "FORECASTING-BASED HYBRID MODEL PREDICTIVE CONTROLLER FOR MICROGRID ENERGY MANAGEMENT" and presented as a Master's Thesis, has been written without applying to any assistance inconsistent with scientific ethics and traditions. I declare, to the best of my knowledge and belief, that all content and ideas drawn directly or indirectly from external sources are indicated in the text and listed in the list of references.

Ayşegül Kahraman

Signature

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August 26, 2020

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

SYMBOLS AND ABBREVIATIONS

ABBREVIATIONS:

ACF	Autocorrelation Function
ADF	Augmented Dickey-Fuller Test
ARIMA	Autoregressive Integrated Moving Average
ANN	Artificial Neural Networks
BIPV	Building Integrated Photovoltaic
D-MPC	Deterministic Model Predictive Control
DER	Distributed Energy Resources
LM	Levenberg-Marquardt
MPC	Model Predictive Control
H-MPC	Hybrid Model Predictive Control
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MILP	Mixed Integer Linear Programming
MLP	Multi-Layer Perceptron
MSE	Mean Squared Error
P ACF	Partial Autocorrelation Function
PCA	Principal Component Analysis
PDF	Probability Density Function
PV	Photovoltaic
RMSE	Root Mean Squared Error
SMAPE	Symmetric Mean Absolute Percentage Error
S-MPC	Stochastic Model Predictive Control
SARIMA	Seasonal Autoregressive Integrated Moving Average
SoC	State of Charge

SVD	Singular Value Decomposition
Tansig	Tangent sigmoid

SYMBOLS:

N	Length of horizon (the time period)
ΔT	Sampling period in seconds
N^G	Number of generator
N^B	Number of battery storage units
k	Index of the time
i	Index of the generators
j	Index of battery storage units
C_i^{G-PC}	The unit energy production cost of generator i
C_i^{G-SU}	Startup cost of generator i
C_i^{G-SD}	Shutdown cost of generator i
C_i^{G-I}	Idling cost of generator i
C_i^{G-LC}	The cost of wear and tear / life cost of generator i
$P_i^G(k)$	Amount of power generated from generator i in time k
$\underline{P_i^G}$	Minimum power limit of generator i
$\bar{P}_i^G$	Maximum power limit of generator i
C_j^{BD-LC}	The discharge cost of wear and tear/ life cost of battery j
$\underline{P_j}^{BD}$	Minimum discharging rate of battery j
$\overline{P_j}^{BD}$	Maximum discharging rate of battery j
η_j^{BD}	Discharging efficiency of battery j
C_j^{BC-LC}	The charge cost of wear and tear/ life cost of battery j
C_j^{BD-LC}	The discharge cost of wear and tear/ life cost of battery j

$\underline{P_j}^{BC}$	Minimum charging rate of battery j
$\overline{P_j}^{BC}$	Maximum charging rate of battery j
η_j^{BC}	Charging efficiency of battery j
$\underline{E_j}^{B}$	Minimum stored energy in battery j
$\overline{E_j}^{B}$	Maximum stored energy in battery j
$C^{GR-buy}(k)$	Cost of buying energy from the grid
$C^{GR-sell}(k)$	Cost of selling energy to the grid
$P^{L}(\mathrm{k})$	Forecast of load consumption in time k
$\mathrm{P}^{\mathrm{PV}}(\mathrm{k})$	Forecast of renewable energy generation in time k

CHAPTER 1
INTRODUCTION

In the last decade, world energy consumption is increasing. According to the IEO2016 report, the buildings, which are residential and industrial, consume 20% of worldwide energy consumption completely (Conti et al., 2016). Furthermore, this consumption will continue to grow because of the rise in the number of buildings and energy-intensive facilities. These increases in energy demand cause a need to change in the traditional way of meeting energy. Between 2012 and 2040, renewable energy sources have qualified as the fastest-growing source in the world with an average 2.6 %/year rise. Under these circumstances, the use of renewable energy sources and smart grid technologies require additional interest. The fact that the electricity generation by renewable energy sources is cheaper than the main electric grid has caused the studies on this subject to become more common in the literature. Today, the decrease in their costs of renewable energy technologies indicates that these sources will be alternative to the conventional energy generation methods. In particular, photovoltaic systems are outstanding in terms of reducing costs. Since renewable energy technologies are competing against traditional fossil fuels, both the aim of decreasing carbon emissions and using clean energy at a lower cost cause reducing in fossil fuel utilization. With renewable energy has become more prevalent and increase in the number of facilities, new methods appear for generation and distribution networks. One of the promising studies relates to a small-scale local network, named “microgrid” that can operate in both grid-connected and off-grid mode.

A microgrid can integrate distributed energy generation, which has a high amount of renewable energy into the main electrical grid. The microgrid enables the integration of generated energy from different sources and can consists many components such as photovoltaics and wind turbine, Combined Heat and Power (CHP) units, fuel cells, power units, heat units, cogeneration units, micro turbines, biomass reactors, heat and electricity storage units, electric vehicles and loads (Nikos et al., 2007). These generation components are called as Distributed Energy Resources (DER). In this way, it is possible to supply electricity to the grid, purchase electricity from the grid, reduce peak loads, prevent fluctuations in the network and provide a distinguishable level of flexibility to the grid by load management. Additionally, they can reduce carbon emissions. Traditional electricity users should become more active in the electricity market and it is possible to accomplish this through a microgrid because they may take decisions related to the main grid. This situation plays an important role in microgrid technology becoming prevalent, whereas the use of renewable energy sources can be increased, then integrated into the main electric grid.

Microgrid has a comprehensive supply side that consists of many energy sources as we indicate. While allowing the integration of energies from these various alternative sources, complex and multi-objective optimization problems should be solved for multiple generation sources, consumptions, and storage devices as safely and cost-effectively. Hence, the energy management problem that we should consider to minimize the operational cost and provide all the constraints of the main grid and each individual component of microgrid occurs. The two outstanding problems relating to the microgrid are unit commitment to decide the activation of components and economic dispatch to minimize the operational cost. Many studies in the literature try to solve this management problem for making optimal decisions by trying to meet the balance between supply and demand sites under various challenges (Cagnano et al., 2020). MPC is the one of the most common strategy in order to solve optimal control problems (Rawlings, 2000). Moreover, Bemporad underlines that the MPC gives a set of optimal control decisions for a specified horizon by taking initial measurements and then applies the very first decision, refreshes the measurements and solves the problem for the horizon again that is why called as rolling or receding horizon. This procedure repeats itself; thereby, MPC turns open-loop design to the feedback loop and considers the recent changes during the solution (Bemporad, 2006). There are many studies in the literature that focus on optimal control of the microgrid by assuming have the exact knowledge of uncertain inputs, it is called deterministic model predictive control. Tenfen et al. propose the MILP solution with a deterministic approach for a microgrid problem that has three types of load; critical, curtailable, and reschedulable; additionally, the system has the integration of both PV and wind generation (Tenfen et al., 2015). Another study solves MPC for a similar microgrid frame that consists of PV, wind turbine, battery, and grid connection to minimize the bought energy from the grid.

They calculate the renewable generation by using specific equations (Patiño et al., 2014).

The MPC aims to operate the microgrid management problem efficiently and finds the optimum decision sets of each component to satisfy the load demand of users continuously. In order to manage controllable generators, main grid and battery storage operations, the amount of generation and the consumption should be known with good accuracy as possible as. The management of the decision of power and energy set points of microgrid is possible only with accurate prior knowledge about power production, consumption, and storage capacities. Although this uncertainty adds difficulty and disturbances to the management problem, it is possible to forecast solar and wind power in the renewable generation part, and thermal and electrical load in the uncertain demand part to schedule the DER and storage units for finding optimal decisions to meet supply and demand sides. In general, short-term forecasting methods for the load demand and renewable power generation presents different performances according to the data set; thus, it is not an easy duty to detect the outperformed method on the others. In the literature, some conventional statistical methods such as regression models and Box-Jenkins ARIMA (Autoregressive Integrated Moving Average) models are performing well for multi-step ahead forecasts; they are used as benchmark methods, and capable of defining the relations between the historical observations of time series successfully. Furthermore, some Artificial Neural Network models, namely Multi-Layer Perceptron (MLP), Radial Basis Function (RBF) and Recurrent Neural Networks (RNN), fuzzy logic, genetic algorithms and the hybrid frame of these methods are commonly used in the forecasting literature (Mellit & Kalogirou, 2008).

In recent years, large-scale grid-connected PV power systems have been included in microgrid applications. However, the output power is highly variable, intermittent, and mostly depends on weather conditions (radiation, humidity, temperature, wind speed, etc.). Short term forecasting of the PV output power helps to schedule the power dispatch and the power quality of the main grid in order to get further system reliability (Wan et al., 2015). PV power forecasting is very prominent research in machine learning applications and it has been studied in many different aspects for years. In general, two different approaches are applied for forecasting of the PV power output. The first one is based on essential meteorological variable forecasts such as radiation, wind speed, temperature, etc. which is used to forecast the PV output. The other approach is directly forecasting the output power of the PV system.

A study highlight the hybrid method that involves a self-organizing map (SOM), learning vector quantization (LVQ) network, support vector regression (SVR) to train the input/output data sets for the classification of previous PV power output and fuzzy inference method for 1-day ahead forecasting. The results demonstrate that this hybrid method is better than SVR and ANN, but still forecasting performance is impaired in non-sunny days (Yang et al., 2014). Leva et al. propose Artificial Neural Network (ANN) and after training and tuning of ANN, the network obtains predictions of the PV power output by supplying the weather forecasts as an input. The results are assessed according to different error definitions and compared with the measured data (Leva et al., 2017). Rana et al. present the SVR model for very short term forecasting 12 step-ahead (each time step is forecasted by separate forecaster) with 5 minutes interval data. Results pointed out the historical PV power data is enough rather than the use of meteorological inputs in this very short term forecasting (Rana et al., 2016). Ehsan et al. obtained a better predictor for 24 h-ahead PV power forecasting with verification by testing various features such as MLP architectures, algorithms, transfer functions, etc. for specific historical data in Tiruchirappalli, India (Ehsan et al., 2017). Similarly, an ANN-based approach is employed to forecast the output power of PV based on solar radiation and previous output power (Alomari et al., 2018). In the design part of the model, there are crucial factors that can affect the quality of forecasts: the architecture of the neural network, the complexity of the whole problem, and the size of the training sample. In the study of Ehsan et al., the authors design the Multi-Layer Perceptron (MLP) model while changing only one property at a time such as activation function, learning rule and a number of hidden layers to reach good forecaster structure. To achieve accurate and qualified forecasts, it is also necessary to have a large data set for training and validation (Yadav et al., 2015).

In similar to solar power output, the load consumption is also uncertain, variable, and needs to forecast. The main contributions of the short term load forecasting are helping the economic dispatch and unit commitment of generation sources, ensuring the reliable and stable operation for the power system, and providing system dispatchers (Gross & Galiana, 1987). Papalexopoulos & Hesterberg present a study that underlines the relation between outside temperature and load consumption to help to have better forecast performance. Modeling of the holidays is possible with binary variables (0-1) and it is important to declare this information to the model. If there is knowledge relates to trend, seasonality, time of a year, these serve to increase capturing accurate forecasts. Lastly, they evaluate the forecast quality of ARIMA and regression as close to each other (Papalexopoulos & Hesterberg, 1990). Catalão supports the importance of defining public holidays since these days explain to the behavior of the users. (Catalão, 2017). In addition, he mentioned that consumption is higher during weekdays than holidays, even the degree of uncertainty shows a decrease between peak hours and off-peak hours. The aforementioned study refers that the net load forecast is also possible because renewable energy generation can be classified as a negative load. However, in general, the net load forecast includes only wind power generation rather than the others such as solar and wind since it has more weightage. They accomplish their load forecasts by using temperature, hour, day, and week variables with Kernel density estimation instead of Neural Networks. A completed 24 h-ahead ANN-based load forecasting study uses 63 input neurons that are the current and previous days load, minimum and maximum temperatures of the current day, and forecasts of tomorrow, two-direction index of the weather station, and days of the week (Bakirtzis et al., 1996. A study compare Fuzzy Logic, Neural Networks, and Auto-Regressive models for a very short-term load forecast. The simulation results show that they are promising techniques except for the Auto-regressive for the short-term forecasting (Liu et al., 1996). Hippert et al. present a more comprehensive review relates to short-term load forecasting (Hippert et al., 2001). Bozkurt et al. introduce two different models by using ARIMA and ANN to forecast short-term load demand. The results indicate that ANN with 1.8% MAPE outperformed the SARIMA model with a 2.6% MAPE based on 12 test weeks. In addition, they highlight that complex model with various feature sets decrease forecast performance (Bozkurt et al., 2017).

These kinds of stochastic inputs lead to the necessity of stochastic studies in the literature, in recent years, many researchers study on these by enhancing their approaches. The necessity of the stochastic approach is clearly underlined in Birges' study (Birge & Louveaux, 2011), it is not possible to find the optimal solutions and minimize the cost without having knowledge about uncertainty.

Pacaud et al. compare heuristic, deterministic MPC, and stochastic dual dynamic programming to minimize the operational cost of microgrid management. The results claim that optimization-based solutions outperform the proposed heuristic approach. In addition, the stochastic method shows better performance than classic MPC to handle the uncertainty in the problem (Pacaud et al., 2018). Zhu and Hug underline the importance of the execution of a solution with an acceptable solution time and cost for the MPC problem with the stochastic approach (Zhu & Hug, 2014). As a solution to these, they employ the technique of optimality condition decomposition to obtain several sub-problems instead of the overall S-MPC problem. In a similar study, the formulation of the stochastic problem is completed as MINLP. The nonlinearity increases the challenge of the solution; thus, they also need to divide into master and subproblem for scheduling and power flow to find a solution easier (Su et al., 2013). Bernardini and Bemporad express a comprehensive study that combines the S-MPC formulation with discrete multiplicative disturbances (Bernardini & Bemporad, 2009).

One of the most common method to solve the microgrid management problem is two-stage (recourse) stochastic programming. In the study of Farsangi et al., the wide range microgrid problem that consists of both thermal and electrical parts are solved by using stochastic programming to illustrate the effect of demand response programs for the on-grid and islanded applications (Farsangi et al., 2018). The scenario generation is based on the discretization of PDFs to an equal specific limited scenario for every exogenous input parameter. The total number of scenarios for only the next hour is equal to the product of them. When the problem is solved for the finite horizon (24 hours specifically), it causes exponential growth. For that reason, many studies prefer to escape to handling a high number of scenarios and prefer to apply reduction techniques. There are many various scenario reduction methods in the literature. Dupačová et al. study the uncertainty of electrical load by comparing 3 different reduction algorithms namely the forward selection of scenarios, the backward reduction of scenario sets, and single scenarios. The findings support that after the elimination of 50% of the scenario set, the rest of the scenarios still have almost 90% knowledge and accuracy (Dupačová et al., 2003). Mohammadi et al. applied scenario generation by taking PDF of every uncertain part of the problem and combine with the roulette wheel. They provide the reduction of the number of generated scenarios by omitting minor probabilities and taking the one with different probabilities (Mohammadi et al., 2014). Similarly, to solve the proposed microgrid management problem by using a two-stage stochastic scenario-based method, first, the Roulette

Wheel Mechanism and Lattice Monte Carlo simulation are applied for scenario generation based on each uncertain variable. Then, they perform the simultaneous backward method as the reduction technique to complete the solution in reasonable limits (Niknam et al., 2012). In the islanded microgrid operations, storage units, conventional and renewable generators supply the desired power to the customers (Hooshmand et al., 2012). Parisio et al. completed a study on multi-objective optimization, which aims to minimize both operational costs and emissions. They constitute the microgrid problem as MILP and solve with a two-stage programming approach by taking into consideration generated 50 scenarios to eliminate the effect of uncertainty of demand and renewable energy source. In addition, they integrate the MPC frame to solve this problem with feedback mechanisms through the horizon (Parisio et al., 2013). Moreover, a similar framework is installed and performed at the Microgrid in Renewable Energy Center in Athens, Greece. Both two studies prefer to implement MILP instead of MINLP to escape computational complexity and emphasize the importance of preventing simultaneous behaviors for both batteries and the main grid as charging and discharging and as purchasing and selling (Parisio et al., 2013). A comprehensive study about the stochastic modeling and optimization works in the literature claims that computational complexity and availability of statistics of uncertain inputs are the most challenging sides for real-life implementations (Liang et al., 2014). With a similar attitude, there are some other control applications of the mentioned MPC approaches, especially for buildings. Oldewurtel et al. present a study to control indoor temperature and they showed that the S-MPC method, which uses weather prediction outperforms to classic MPC approaches (Oldewurtel et al., 2010). S-MPC is a powerful approach that combines the advance of both MPC and stochastic programming, but it should be noted that it causes the increasing of computation time seriously. For this reason, many studies implement scenario reduction techniques (Zhang et al., 2018). The implementation of two-stage stochastic models to islanded microgrid operations is also possible. In these applications, the controllable generators are the main source and leading component to compensate for the first stage decisions during the second stage (Sachs & Sawodny, 2016).

In addition, chance-constraint is an active area of research, especially in water resources management, optimization of power system operation and planning, process engineering, financial risk management, reliability-based design optimization, and control (Geletu et al., 2013). Furthermore, it is capable of controlling complex dynamic systems that have uncertainties. For this reason, a chance-constrained MPC technique is powerful to specify minimized the operational cost and finding optimal power and energy set points. Ciftci et al. present a study that implements a chance-constrained to show controlling microgrid does not need a conservative solution by taking into consideration both uncertainties of thermal/electrical load and solar generation (Ciftci et al., 2019). Sirouspour completed a study about off-line chance-constraint optimization to find the optimum decision set, especially for storage units. However, there is an assumption that is electricity prices and exogenous generation and consumption amounts are known exactly for each hour throughout the horizon (Sirouspour, 2016). To schedule the controllable electric generators, the unit commitment problem, which is formulated as a chance-constrained program, is solved (Ozturk et al., 2004). Gulin et al. show that solution by taking into account the prediction uncertainty of solar generation and load consumption gives better performance than not (Gulin et al., 2015). They apply a chance constraint to minimize operational cost and they use only the main grid to compensate for the deficit/surplus energy to keep the power balance. Moreover, there are some studies combine features of both the two-stage and chance-constrained programs for control and optimization (Wang et al., 2011).

In this thesis, we will deal with only the grid-connected applications, of course, some faults can cause possible shortages and breakdowns, the microgrid can handle by using own generators and storage units in these circumstances. Some other studies focused on risk management originating from uncertain inputs by decreasing the negative effects. The solution is given by developing risk assessment MPC in detail (Zafra-Cabeza, 2020). The maintenance, failure, and repair issues are also discussed in the literature for the microgrid management system (Prodan & Zio, 2014). Especially for the distributed generators and storage units, the life cycle and wear-tear costs should be also studied in detail. Furthermore, fault-tolerant strategies are crucial issues to ensure safe and stable operation in the control side (Prodan et al., 2015). There are some studies that relate to this, but there is still a need for comprehensive studies in these areas.

The aim of this thesis is to present optimal control strategies of the microgrid management ensures that minimize the cost spend on necessary electricity needs and optimal power dispatch by satisfying all the constraints with a reasonable solution time for the finite horizon. In particular, we want to show the usability of both stochastic and some hybrid MPC approaches to obtain efficient solutions. For this reason, we apply deterministic, stochastic, and hybrid forms of these to the same problem separately. While D-MPC does not consider the uncertainty of forecasts, S-MPC focuses on directly to the historical character of each hour. On the other hand, the combination of these, H-MPC is capable of eliminating diverges from the actual values, and the effect of inaccurate forecasts. Moreover, we evaluate the total operational costs according to how close we are to perfect prediction solutions, which is a deterministic solution of the exact knowledge on net load.

This thesis contributes to the literature of scenario generation by implementing the SVD technique to continue in a reduced dimension before we generate any scenario. Despite various scenario generation and reduction methods that have been applied in the literature, we have not met with the usage of the SVD approach in this purpose so far. According to the results, it seems that is a convenient approach to keep the solution time in a reasonable range. Furthermore, although there are some studies and contributions that already completed in the stochastic programming and control side, we present the new approach by constituting the H-MPC, which finds the power and energy set points by solving the scenario set. We develop two different approaches to generate a scenario set for a hybrid frame. First, we basically shift the previously constituted scenario set based on the deviations between point estimations and mean of the set. Second, we create a new scenario set of forecasting errors and then we add point estimations to this set. We believe that stochastic solutions based on various MPC approaches have not been currently studied within the detail and comprehensive in the literature as we presented. This thesis comprises seven chapters, including the current one. General organization details of the chapters are presented as follows:

Chapter 2 provides the identification of the microgrid problem as a system and general information related to the working principle of model predictive control. It is crucial to internalize this chapter properly since it affects and provides knowledge for the rest parts.

Chapter 3 analyzes the different forecasting approaches for both load demand and solar power generation by concerning the performance criteria that helps to detect the best forecasting performance. The best estimations for the entire horizon will be inputs of the following chapters.

Chapter 4 introduces the mathematical model of all microgrid components in detail. By introducing the microgrid components, the deterministic approach of the model predictive control is applied to solve this energy management problem explained. It takes the point estimations directly that is forecasted in Chapter 3. By using these inputs, the power and energy set points are obtained and presented for all components in the microgrid problem.

Chapter 5 deals with the stochastic nature of the presented microgrid problem in different ways and solve the control problem. To demonstrate the effect of uncertainty the problem is solved by using Worst-Case, Expected Mean, Two-Stage, and Chance-Constrained methods. However, there is an additional comparison in this part related to input definition. The definition of input sets is divided into two approaches. While the first approach is taking distribution of the net load that depends on the historical data the other takes as a hybrid by integrating distributions and the point estimations that are found in Chapter 3.

Chapter 6 gives a comparison for the Deterministic, Stochastic and Hybrid solutions of the Model Predictive Control Methods for the presented microgrid problem by using the results of theoretical benchmark namely perfect knowledge.

Chapter 7 summarizes and concludes all studies and offers possible future work in this field.

CHAPTER 2
MICROGRID ENERGY MANAGEMENT PROBLEM

A microgrid mainly consists of Distributed Energy Resources (DER) (photovoltaics, wind turbines, fuel cells and micro turbines (generators)), storage devices (batteries, fuel cells, electric cars) and loads (thermal, electrical). It operates in isolated mode, grid-connected mode, or both. If there are more than two DER, microgrid energy management is crucial when maintaining at cost-efficient operation.

2.1. Overview and General Control Strategy

The representation of proposed microgrid architecture shown in Figure 2.1, also, demonstrates the relation between generation, consumption and storage elements.

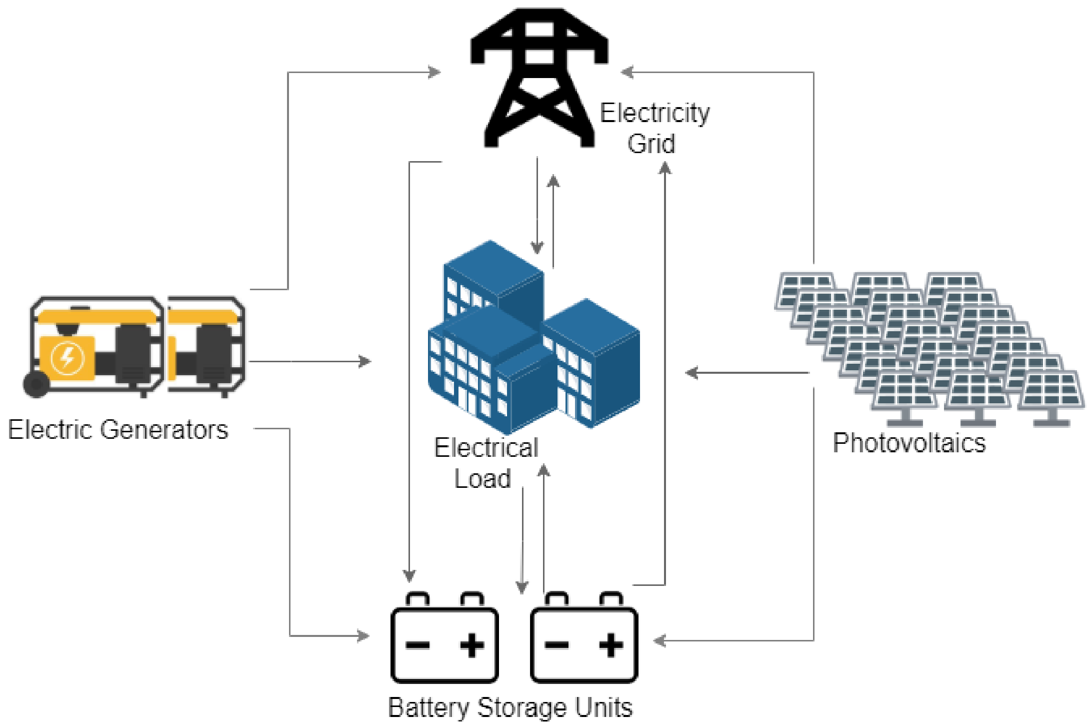

Figure 2.1. Model of microgrid problem (Redrawn by using www.draw.io site).

The proposed microgrid has only an electrical load that will be satisfied by available energy sources. The renewable generator is specified as photovoltaics, controllable generators as electric and storage units as batteries. In this frame, there is no thermal load; thus, thermal grid is not considered.

In this study, we aim to control energy generation and storage technologies by using the MPC method to optimize set points of generators and state of charge the batteries.

In addition to this, to operate the microgrid with minimum daily operation cost while meeting expected demand, we specify the main grid buy/sell decisions. Control strategies have great importance in the system design process, as they ensure stable operation of a system, robustness against undesired disturbances, and high performance.

In this method, the state of the system is taken at each control step, and then, MPC solves the problem with the help of the mathematical model. It finds out power and energy set points that keep the system within constraints and optimize system performance with its operational cost. Figure 2.2 describes the basic principles of the MPC control strategy.

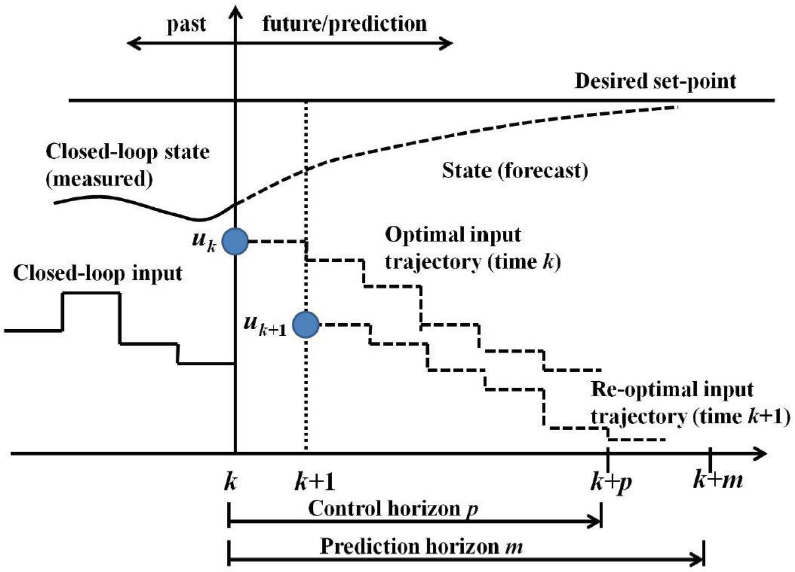

Figure 2.2. Working principle of MPC (Dai et al., 2012).

As can be seen from Figure 2.2, MPC solves the optimization problem and provides the set of best decisions over a future horizon of m. It takes the set of control decisions through the horizon at any time step k. MPC implements only the first decision of the control strategy, and discards the rest of the decisions. Then again, it takes the measurement and new data of the environment and the system, then solves the optimization with updated initial conditions in the next step (k+1). This procedure repeats itself with the shifting of the prediction horizon. It is a dynamic optimizer, capable of handling multiple inputs, can satisfy constraints, and works with the horizon. It is an appropriate and promising method for our microgrid problem.

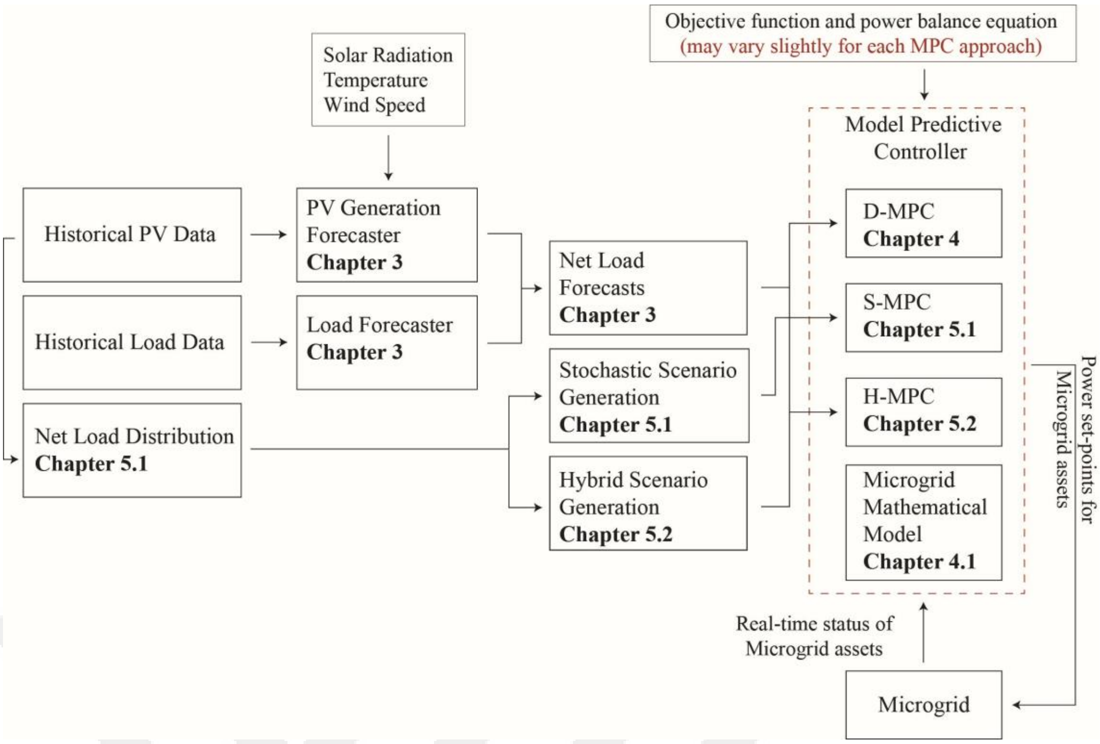

Figure 2.3. General representation and relation of the chapters for the energy management problem of the microgrid.

In Figure 2.3, we illustrate our approaches to the solution of the microgrid problem with the general flow of this thesis. D-MPC does not take into account the stochastic nature of PV generation and load demand. It uses a single set of future forecast values to compute optimal decisions. On the other hand, S-MPC acknowledges that the PV generation and load demand exhibit stochastic behavior and uses their uncertainty to obtain a possible set of future that may help the escape of suboptimal performance. D-MPC takes obtained net load as point estimations without any change. On the other hand, if we prefer to use distributions based on historical data of net load, then we apply S-MPC. Lastly, we may prefer to study with H-MPC, which is the combination of distribution and point estimations. The most important distinctness in these formulations the objective function and power balance equation takes shape according to the preferred MPC type.

2.2. System Description

Solar power is a huge energy source in the world. However, solar systems are an intermittent and exogenous energy source; it is difficult to obtain their future power generation. In our microgrid problem, we select a study on a real PV system that we can collect the related data and system information.

The PV generation data set used in this study is collected from a Building Integrated Photovoltaic (BIPV) system that was installed at Yaşar University, in Izmir, Turkey under the scope of REnewable ELectricity COOPeration (REELCOOP) project. This system has a 7.44 kWp nominal power and consists of 48 PV modules. PV output power is in 15 minutes interval and climatic features such as radiation, temperature, wind speed, humidity, etc. are in a 1-second interval. The location and view of the installation of a BIPV system are shown in Figure 2.4 and Figure 2.5, respectively.

Figure 2.4. A location of the BIPV installation in Yasar University campus.

Figure 2.5. The BIPV system at Yaşar University, Izmir, TURKEY.

Measurement data provides useful insight to forecast the power output of the PV system. Using recorded measurements generally is a prior preference since the meteorological center has the regional information, which cannot usually give shading effects and local knowledge of the system.

On the other hand, electrical load demand is also an uncertain component in the input side. The amount of electricity consumption is highly correlated with the type of building such as residential, commercial or type of it such as school, university, or hospital since it defines its energy consumption characteristics.

The load data set is taken from one of the buildings at Yaşar University; thus, both solar power and electrical load have similar local characteristics. We also proceed with all the forecasting studies for the same length and same period by arranging both two inputs hourly intervals.

We want to prove that micro grids are essential constitutions for large campus areas that can really meet all of the energy needs. Since we respect the privacy of personal information and the original power range of recorded data set is relatively low for a campus site, we prefer to multiply both sets of data by different coefficients. The importance of knowing actual demand is related to the solution of the control problem mainly focus on minimizing the operational cost but more importantly supplying the necessary demand. In this case, we actually trying to solve the net load forecasts that are equal to the electrical load forecasts minus solar power generation forecasts for optimal and economical dispatch planning.

Both PV output power and load consumptions are completely stochastic and local variables. In Chapter 3, we will apply different forecasting methods to find the approaches that give the best estimations performance of load and generation for our data sets and their results are in detail. Without realistically knowing the expected load, we cannot efficiently manage microgrid decisions.

CHAPTER 3
RENEWABLE ENERGY AND LOAD FORECASTING

In this chapter, within the scope of the thesis, both the electrical energy to be produced from the renewable energy source PV and the consumption of electricity of consumer fed by the local grid are needed. The optimal control of the microgrid is possible with accurate knowledge about these mentioned stochastic inputs. The reason for this request is ensuring better control of the microgrid. We decide the power and energy set points that mainly based on the forecasted net load, which is equal to the difference between electrical load demand and PV power generation. We can reach a more accurate decision set by decreasing the forecasting errors; therefore, we can minimize the operation cost and find optimal power dispatch since we do not take decisions in the wrong direction.

For the energy consumption and generation forecasting, the main applied models are Seasonal Auto-Regressive Integrated Moving Average (SARIMA), Linear Regression and Multi-Layer Perceptron (MLP) and the details are given for both problems with the results obtained in each section.

3.1. Performance Criteria

The performance accuracy of the forecasting techniques can be evaluated by the different criteria. Mean Squared Error (MSE) is a measure of how good the training and testing success of the minimization methods. However, since MSE is a quadratic error, it is not in the same unit as the forecasted data. Although Root Mean Squared Error (RMSE) is in the same unit as the forecasted data, it is sensitive to outliers in the forecast errors, but not as much as MSE because of taking the square root of the sum of squares of these errors. Therefore, there are various criteria have developed to better evaluate how good the estimate is. These are Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Symmetric Mean Absolute Percentage Error (SMAPE). We give the formulas of the mentioned criteria in Table 3.1.

In this thesis, we specify MSE as forecast error to be minimized since it provides the possibility of using gradient-based algorithms according to parameters as the minimization algorithm. Another reason for choosing MSE as an error criterion is that if the error distribution is normal, the parameter values that give the smallest value of the MSE are the most appropriate parameter values in terms of maximum likelihood in forecasting models. Despite these two important facts, it is necessary to measure the accuracy and performance of the forecasting methods with the other error criteria that are given in Table 3.1 is appropriate for the nature of the problem in addition to the minimized MSE.

Table 3.1. Forecast criteria of error/success.

Performance Criteria	Formula
MSE	$\frac{1}{N}\sum_{s=1}^{L}(\hat{x}_s - x_s)^2$
RMSE	$\sqrt{\frac{1}{N}\sum_{s=1}^{L}(\hat{x}_s - x_s)^2}$
MAE	$\frac{1}{N}\sum_{s=1}^{L}\lvert\hat{x}_s - x_s\rvert$
MAPE	$\frac{100}{N}\sum_{s=1}^{L}\frac{\lvert\hat{x}_s - x_s\rvert}{\lvert x_s\rvert}$
SMAPE	$\frac{100}{N}\sum_{s=1}^{L}\frac{\lvert\hat{x}_s - x_s\rvert}{(\lvert\hat{x}_s\rvert + \lvert x_s\rvert)/2}$

Both solar power and electrical demand have yearly historical data records. To be clear and equal for all the methods in the performance comparison part and increase the generalization ability of the forecast performances, we prefer to apply 5-fold cross-validation to detect the parameters of each model by focusing on general error. The implementation of cross-validation may vary in the literature. In Figure 3.1, we illustrate the implementation details.

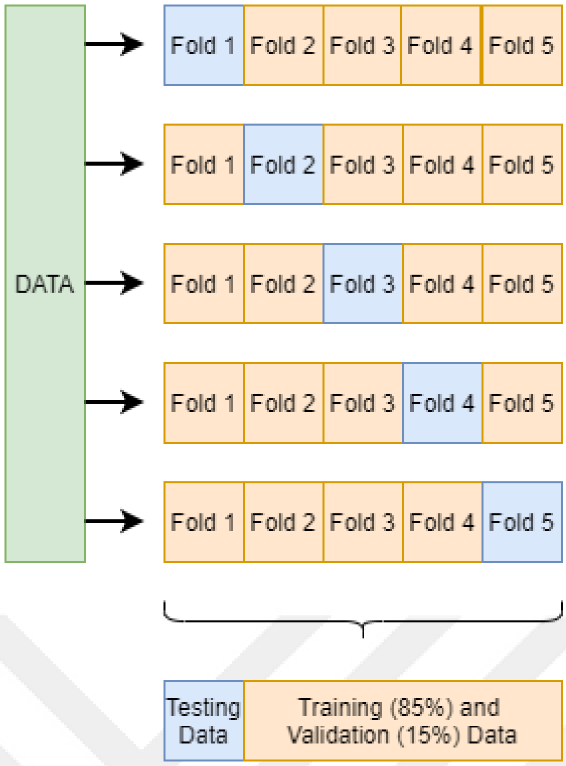

Figure 3.1. Representation of k-fold cross-validation. The data set is divided into 5 parts. In each part, we reserve the test set first, then the rest of it is split into the training and validation if necessary.

We usually choose k as 5 or 10, but there is no certain rule related to this, it depends on the data set and application (Kuhn & Johnson 2013). The increase of k causes a decrease in size between training and test sets. Thus, we can expect to decrease in bias, but it may incline the computation time.

We try to find properly tuned parameters that give minimum MSE error. This means that an average MSE of 5-divided test set throughout the year, not by chance for the limited part of the year. We apply the same approach for all the forecast methods.

3.2. Linear Regression

Linear regression is a convenient way to forecast quantitative terms. It is a naive approach based on supervised learning, it learns by constituting an algebraic linear mapping from input to output. This method has been used for a long time because it is uncomplicated, analytically solvable and appropriate to make significant comments. Many methods and statistical approaches can be conceivable as an extension or generalization of the linear regression (James, 2013). Thus, it is important to start by using this method, make crucial inferences and continue by using other methods that are more complex. For the linear regression, there is approximately a linear relation than can find by analytically between output 'Y' and input 'X'. Additionally, there are constant unknown β parameters represents intercept and slope, respectively.

$$Y \approx \beta_0 + \beta_1 X \tag{1}$$

The prediction can be done by using training data set and established β_0 and β_1. The forecasted $\hat{y}$ is equal to equation (2).

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x \tag{2}$$

As general,

$$y_i \approx \hat{\beta}_0 + \hat{\beta}_1 x_i, \quad i = 1,2,\dots,N \tag{3}$$

Second part of the equation (3) is equal to $\hat{y}_i$ for $i = 1,2,\dots,N$ and the difference between y_i called as residual. We can write residual term for every i as $e_i = y_i - \hat{y}_i$. The summation of the square of residuals gives a residual sum of squares $e_1^2 + e_2^2 + \cdots + e_n^2$, and the division with N equals to equation (4), which represents MSE.

$$MSE = \frac{1}{\mathrm{N}}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 = \frac{1}{\mathrm{N}}\sum_{i=1}^{N}\left(y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i\right)^2 \tag{4}$$

Since we are trying to forecast as close as possible to the actual result, equation (4) also represents the expression that should be minimized based β_0 and β_1. We call it the least square approach that minimizes this by choosing β_0 and β_1.

As we mentioned before, we divide data into 5 parts, every one of them includes training and test set. Minimization of error is based on the test, but the focus should be given to both training and testing errors. There is a relation between model complexity, variance, and bias. In general, with the rise of complexity, while variance is increasing, bias is decreasing. To have a small error, the model should able to catch the appropriate data points –should have a good fit for data-. Thus, our predictions get close to actual ones, the bias that we can think as a measure of how we are close to defining the unknown function. If the model is taken too sophisticated, then when we use the test data, error may rise sharply under even minor change and it means variance is too large. By taking into consideration these relations and results, making comments about the result is the setting of models can complete. If there is more than one input, instead of using two β parameter, we specify p different β as given equation (5). An extension of the single linear regression model, namely multiple linear regression, is preferred to represent the relationship between a dependent variable and several independent variables instead of one (Brown, 2009).

$$Y \approx \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + +\beta_p X_p \tag{5}$$

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + +\hat{\beta}_2 x_2 + \cdots + +\hat{\beta}_{\mathrm{p}} x_p \tag{6}$$

$$MSE = \frac{1}{\mathrm{N}} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 = \frac{1}{\mathrm{N}} \sum_{i=1}^{N} \left(y_i - \hat{\beta}_0 - \sum_{j=1}^{p} \hat{\beta}_j \, x_{ij} \right)^2 \tag{7}$$

The minimized term is given by equation (7) by choosing $\hat{\beta}_0, \hat{\beta}_1, \dots, \hat{\beta}_{\mathrm{p}}$. The calculation and representation of multiple regression are much easier by using vectors and matrices since finding all $\hat{\beta}$ terms to minimize MSE. The inverse of $X^T X$ exists only if the columns of X are full rank. We organize the expression based on this assumption. Then, $X^T X \beta = X^T y$ can be arranged into the final version as $\beta = (X^T X)^{-1} X^T y$.

We define the historical and current values of the time series as dependent and independent variables. We apply two models that are one independent (single) and more than one independent variable (multiple) for both generation and consumption. For the linear regression, while we are adjusting the previous day as an independent variable for single, we integrate additional variables for the multiple and we illustrate the list of these variables in Table 3.2.

Table 3.2. Independent variable sets of Linear Regression method to find PV power generation and load consumption.

	PV Power Generation	**Load Power Consumption**
Single	Previous day PV power	Previous day load power
Multiple	Previous day PV power Solar Radiation Air Temperature Wind Speed Hour of day	Previous day load power Previous week load power Average load of previous day Average load of previous week Hour of day Day of the week Weekdays/ Weekend

In general, multiple linear regression shows better performance since has extensive knowledge according to the one that has only one independent variable. Here, we add meteorological inputs; radiation, temperature, and wind speed. These factors highly affect the power generation of the PV system; therefore, it helps us to reach successful estimates since we use their forecasting before a day. The following Figure 3.2 supports our expectations. It shows the hourly forecasting results of one of the most naive approaches taking into consideration averages of test folds. The implementation of the only previous day as a variable is not enough that is why multiple variables have lower SMAPE. In addition, the forecasting load demand of a very specific building has its own characteristics. Thus, the error level is rising in the load power forecasting by the comparison of solar power performance.

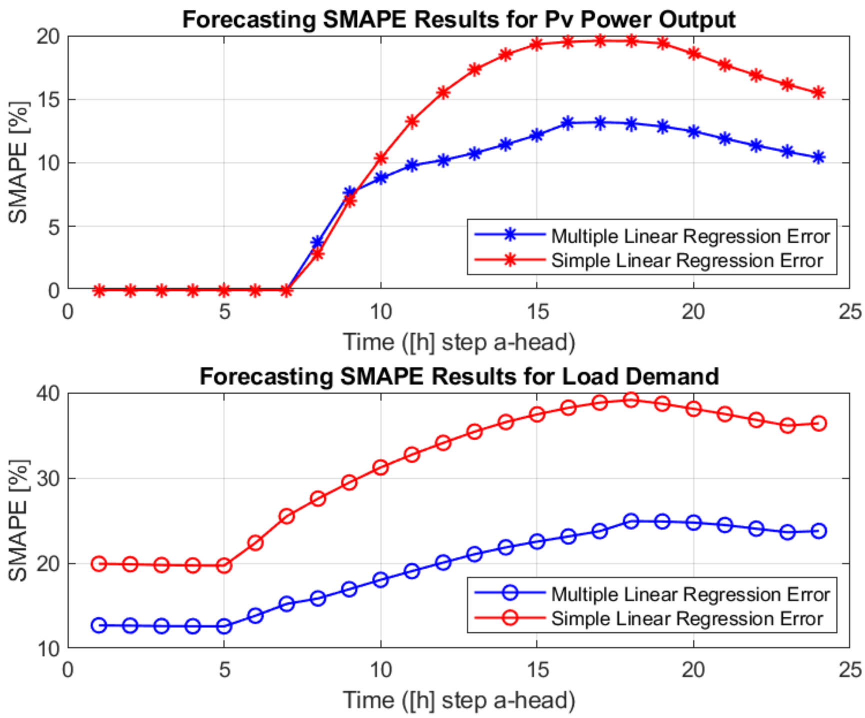

Figure 3.2. Hourly SMAPE results for forecasting of PV power and load consumption through the year for linear regression.

Table 3.3. Averages of different performance criteria for Linear Regression.

		MAE (kW)	MSE (kW^2)	RMSE (kW)	MAPE (%)	SMAPE (%)
Single	PV Generation	46.69	9958.81	61.22	15.32	11.13
	Load Demand	191.29	77601.76	233.11	54.65	31.29
Multiple	PV Generation	24.03	2439.09	30.34	8.81	7.66
	Load Demand	106.02	35725.40	156.94	27.21	19.36

Table 3.3 summarize the average error criteria for each implementation. Although the linear regression is a benchmark, the results are promising, especially for multiple regression.

3.3. SARIMA

Both electrical load demand and PV power generation are time series; it is quite common methods for predicting the future. Parametric Seasonal Autoregressive Integrated Moving Average (SARIMA) models are an extended version of Autoregressive Integrated Moving Average (ARIMA) and correspond to the seasonality of the mode. These are one of the most convenient parametric approaches to forecasting time series.

SARIMA models are multiplicative models. The form of SARIMA is $(p, d, q)\ x\ (P, D, Q)_S$ where (p, d, q) is relevant to the non-seasonal part and $(P, D, Q)_S$ is about seasonal part of the model. p is the order of autoregressive and it can be explained with the function of p different historical values, $x_{t-1}, x_{t-2}, x_{t-3,} \dots, x_{t-p}$. p is the necessary p^{th} past step from the current time in the past to forecast the next value. Order of d refers to the degree of differencing and it helps to make time-series stationary if it is non-stationary. q is the moving average order and it is related to past forecast errors instead of past values (Hyndman & Athanasopoulos, 2017). S indicates the seasonality of the model. Seasonal terms are quite similar to the non-seasonal terms, only they backshift with the seasonal term. We can write the representation of SARIMA as equation (8) (Taneja et al., 2016):

$$\phi_{\mathrm{p}}(\mathrm{B})\Phi_{\mathrm{P}}(\mathrm{B}^{\mathrm{S}})(1-\mathrm{B})^{\mathrm{d}}(1-B^{S})^{D}\mathrm{x}_{\mathrm{t}} = \theta_{\mathrm{q}}(B)\Theta_{Q}(B^{S})\varepsilon_{t} \quad (8)$$

where ϕ, θ, and d are non-seasonal autoregression, moving average and differencing operator, Φ, D and Θ are the seasonal operators of these. B represents the backshift, s is seasonal lag, ε_t is error variable and x_t is a current value of the time series.

We illustrate time series, Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) of the solar generation and electrical load demand in Figure 3.3 and Figure 3.4. Although in the first place there is no apparent tendency in the way of non-stationary movements (increasing or decreasing trend), the reasonable decision is applying Dickey-Fuller or Augmented Dickey-Fuller Test (ADF) to ensure that time-series needs a differencing operation or not. For instance, an interval in the load consumption has quite low levels in the process corresponding to the summer months. The specification of trend in the series also means deciding on the term d. When ADF test statistics are outside tabulated critical values, ADF test returns maximum (0.999) or minimum (0.001) p-values. If the p-value less than 0.05, we can reject the null hypothesis and can assume the series is stationary. The ADF test shows that our generation and consumption series do not need to any differencing process since p values have a really small value that is not bigger than 0.001.

In general, it is difficult to specify autoregressive and moving average parameters since there is not a precise solution method. Thus, we employed ACF and PACF plots to adjust boundaries and get intuition. While cross-correlation is a measure of the correlation between forecasted and actual values of time series, autocorrelation measures the linear relationship between lagged values of a time series. ACF indicates the relation between x_t and x_{t-p}, for different p. On the other hand, PACF shows the relation between x_t and x_{t-p} after eliminating the impact of the lags $1, 2, 3, \ldots, p-1$.

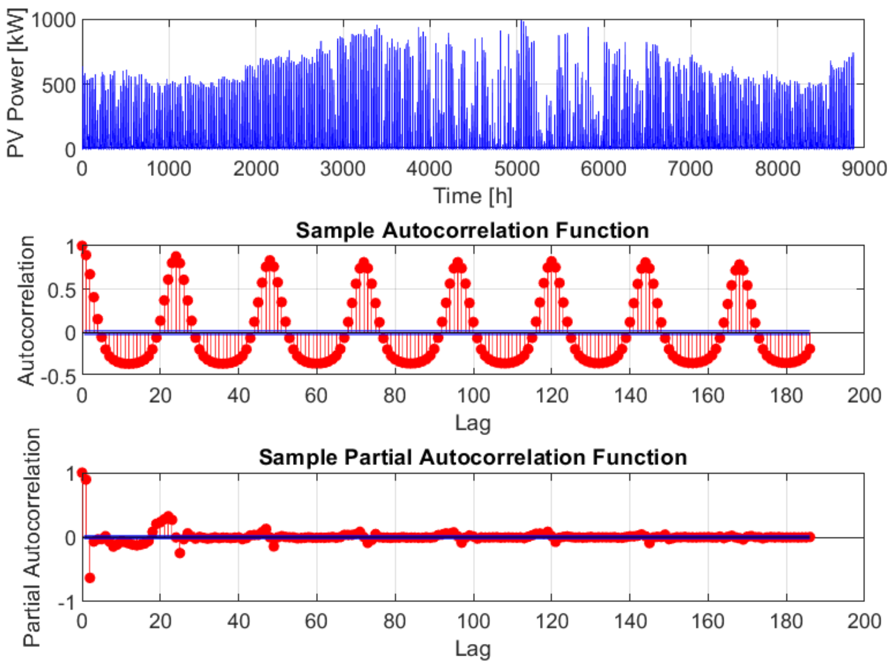

Figure 3.3. Yearly PV power generation, ACF and PACF of the solar power generation without applying the difference operation (d = 0).

In Figure 3.3, some lags are higher than for the others. Especially every 24th lag has a prominent spike; this is due to the seasonal pattern. There are no other repetitive peaks, which means this related time series data tend to indicate an only daily seasonality (Hyndman & Athanasopoulos, 2017). In the ADF test, we stated that there is no need to take seasonal ($D = 0$) and non-seasonal ($d = 0$) differences because the time series is stationary. We proceed exhaustive search in the MATLAB environment, within the limits determined according to the ACF and PACF graphics; p and q $\in \{1,2,3,4\}$, while P and Q Seasonal terms, on the other hand, the given in the set $\{1,2,3,4,23,24,25,26\}$, which are given by limiting the lag points of seasonality. We find the best model that has minimum MSE that express also the parameters of SARIMA by taking an average of each MSE in the cross-validation parts. One of the reasons for such a search for ARIMA is to find out how suitable the model is for this PV power-forecasting problem.

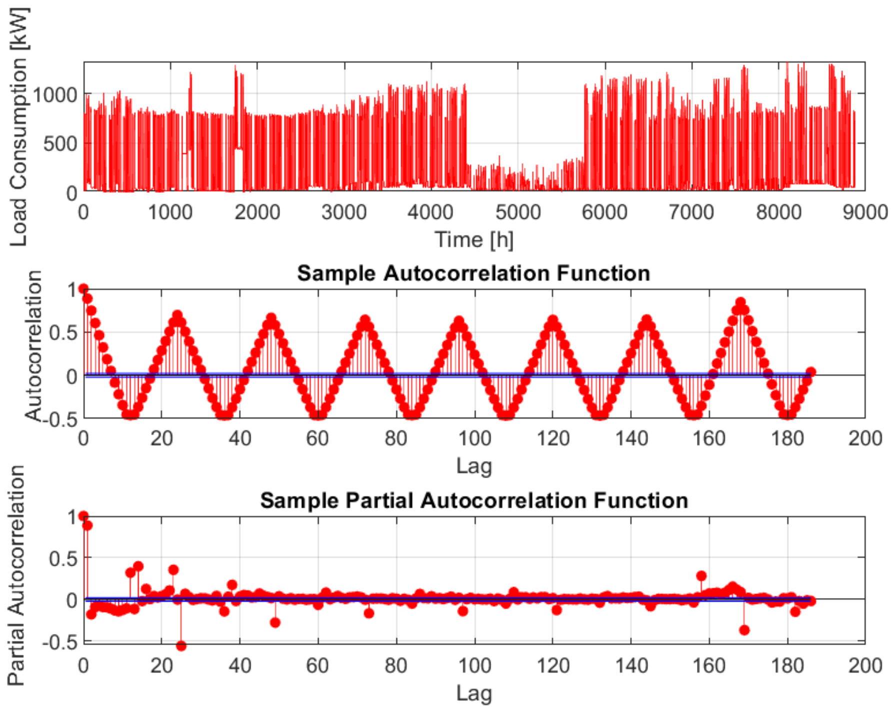

Figure 3.4. The time series, ACF and PACF of the electrical load consumption without applying the difference operation (d = 0).

On the other hand in Figure 3.4, we record 168th lag has a noticeable spike in addition to each 24th lag, which means electrical demand relates both 24th hour (daily characteristic) and 168th hour (weekly characteristic). We select the rest of the parameters with the exhaustive search around the scope of ACF and PACF plots. We search for p ∈ {1, 2, 3, 4}, q ∈ {1, 2, 3}, and P and Q, in the given set $L = \{11, 12, 13, 23, 24, 25, 35, 36, 37, 47, 48, 49, 167, 168, 169\}$. Table 3.4 illustrates the most convenient models for PV and load series after the evaluation of many combinations for these parameters.

Table 3.4. Parameters of the proposed models for the SARIMA(p,d,q)(P,D,Q)s.

	Non-seasonal			Seasonal		
	AR Lags	d	MA Lags	SAR Lags	D	SMA Lags
PV Power Output	1	0	1	1,2,3,4,23	0	1,2,3,4,23,24
Load Demand	1,2,3	0	1	All L set	0	All L set

We show the SMAPE results of the hourly averages that we find at the end of cross-validation for both series. Although we select many seasonal lags for the demand, still the error is more than the PV generation. It is an expected result since electrical demand is highly characteristic and needs a model that can work with complex relations.

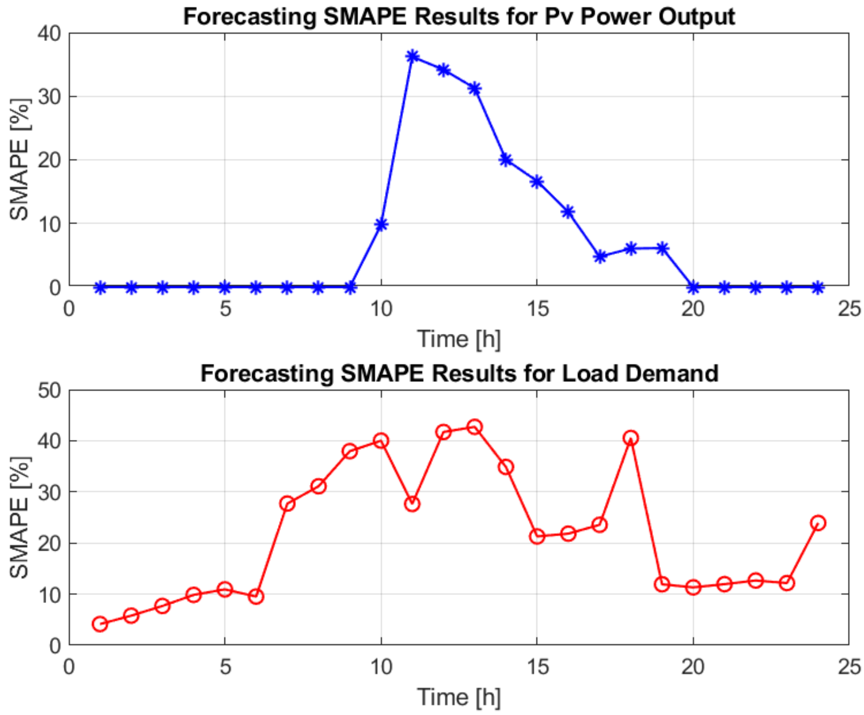

Figure 3.5. SMAPE results for forecasting of hourly PV power and load consumption through the year for SARIMA.

Table 3.5. Averages of different performance criteria for SARIMA.

	MAE (kW)	MSE (kW^2)	RMSE (kW)	MAPE (%)	SMAPE (%)
PV	36.37	7559.69	47.87	16.46	7.37
Load	104.60	35848.45	151.47	30.18	21.78

We calculate the performance criteria of the given SARIMA models using yearly data since we divide the series into 5 different test sets that has 72 days in each. We represent the average performance indicators for electrical generation and consumption in Table 3.5. SARIMA is a good model to choose if especially we have only time series and do not have any other additional features.

3.4. MLP Model

Artificial Neural Networks (ANN) are one of the common Machine learning techniques. There are various types of ANN, but within the scope of this study, we deal with only the Multi-Layer Perceptron (MLP). MLP is a multilayer algebraic ANN model. Figure 3.6 represents the general representation of the MLP structure with two hidden layers.

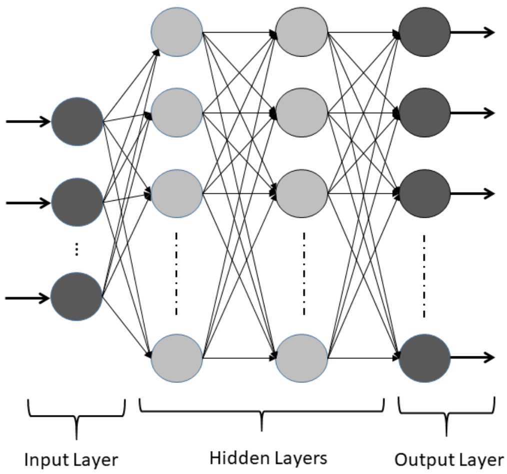

Figure 3.6. The Multi-Layer Perceptron (MLP) structure with two hidden layers.

The first layer of the MLP is the input layer, it accepts input values directly from the raw data or features that are obtained by selection/extraction methods from the raw data and it has the output layer that gives the outputs. Between the input and output layer, there are one or more hidden layers that are not directly connected to them. The process units called neurons, in each layer they are connected to all cells in the previous layer and in the following layer. The outputs of the neurons in the previous layer perform a feed-forward connection process by feeding only the neurons in the next layer. These connections have weights and neurons transmit a weighted sum through the activation function to the output. There are some common activation functions in the field and we list them in Table 3.6.

Table 3.6. Common activation functions (Hu & Hwang, 2002).

Activation Function	Formula
Sigmoid	$f(u) = \frac{1}{1 + e^{-u/T}}$
Hyperbolic tangent	$f(u) = \tanh\left(\frac{u}{T}\right)$
Linear	$f(u) = au + b$

In this thesis, the hyperbolic tangent sigmoid transfer (Tansig) function, which is a continuous-valued bipolar sigmoid function, is selected as the activation function of the MLP model used in the input and hidden layers. We use a linear activation function (Purelin) in the output layer since the real-time output is required because the time series prediction is actually a regression problem. We formulate forecasting problem for the time series of PV power output and load consumption; 1) historical and current values of the time series and 2) the features that are derived from the time series.

We try both approaches for MLP models and give the details of the network with their results. MLP can learn by examples called supervised learning if there is enough input-output data set and maps the input to the output handling these historical. MLP can be trained and it can learn to produce acceptable outputs for input data that are not in the training set, ANNs are considered similar to the human neurological system as they have the ability to learn. The representation of supervised learning algorithm; $\{(x^s, y^s)\}_{s=1}^{N}$, where x^s and y^s represent inputs and (desired) outputs, respectively.

In training, we perform the Levenberg-Marquardt backpropagation algorithm, which is a gradient-based minimization algorithm of the least value of the MSE (forecasting) error. The reason for using the Levenberg-Marquardt algorithm is that it provides regularization. This adds a generalization capability without adding a generalization term to the MSE that is desired to be minimized for increasing the generalization ability of the network, by applying a kind of Gradient-Newton method. It combines Newton Method's fast local convergence and Gradient Descent's prevention of instability through suitable step-size parameter selection. The designing of an MLP model that must be performed before the implementation of the selected LM learning algorithm, determining the number of layers, neurons in each hidden layer, size of the input layer, and what the features are, is a crucial process.

We employ two different input sets and network architectures for MLP. The first one has an input layer that takes previous 24-hour generation amounts of the PV system, and the output layer gives the forecasts of 24 h PV power output for the next day. We demonstrate the representation of the first model in Table 3.7.

Table 3.7. The size of the input layer and the creation of the features for the PV power forecasting. While the upper part summarizes the entrance of the inputs to the network, the lower illustrates the outputs.

k	**k+1**		**k+n**
x1	x25	…	x(n*24+1)
x2	x26	…	x(n*24+2)
x3	x27	…	x(n*24+3)
…	…	…	…
x24	x48	…	x((n+1)*24)

k+1	**k+2**		**k+n**
X25	X49	…	X((n+1)*24+1)
X26	X50	…	X((n+1)*24+2)
X27	X51	…	X((n+1)*24+3)
…	…	…	…
X48	X72	…	X((n+2)*24)

On the other hand, the second approach forecasts related hours using the prediction of solar radiation, temperature, wind speed, solar PV output at the same time at yesterday, and time of the day. We list of features in Table 3.8.

As we can see from Table 3.8, the second model has more and more features than the first; therefore, we expect that the PV Model-II brings successful forecasts, as it is informative about the behavior and character of the PV module.

Table 3.8. Feature set of MLP to forecast PV power generation.

Model	Features
PV Model-I	Previous day PV power
PV Model-II	PV power on the previous day at the same hour Solar Radiation Air Temperature Wind Speed Hour of day

One of the challenging side related to MLP is designing the network architecture, especially the number of neurons in hidden neurons. There is no any strict rule to specify, instead, we define de interval and complete the exhaustive search that minimizes the MSE error upon the average of the test sets. Table 3.9 lists the number of neurons in each hidden layer that minimizes the MSE in these models.

Table 3.9. Details of number of neurons in each hidden layer for each model.

Forecasting Model	number of neurons in the first hidden layer	number of neurons in the second hidden layer
PV Model-I	13	6
PV Model-II	9	15
Load Model-I	18	3
Load Model-II	2	9

We also try two different feature set for demand estimation. The first one is similar mostly with the first approach of solar power forecasting, except for the effective addition of the knowledge of which day we are trying to forecast.

In a similar manner to the PV generation, we apply two different and promising feature set. The first load model has load consumption on the previous day, load on the previous week, day of the week, and the information about the day (weekday or weekend). Table 3.10 represents the configuration of the network and the entrance of the first load model.

Table 3.10. The size of the input layer and the creation of the features for the electrical demand forecasting. While the upper part summarizes the entrance of the inputs to the network, the lower illustrates the outputs.

k	**k+1**		**k+n**
x1	x25	…	x((n*24)+1)
x2	x26	…	x((n*24)+2)
x3	x27	…	x((n*24)+3)
…	…	…	…
x24	x(49-168)	…	x((n+1)*24+1-168)
x(25-168)	x(50-168)	…	x((n+1)*24+2-168)
x(26-168)	x(51-168)	…	x((n+1)*24+3-168)
x(27-168)	x(52-168)	…	x((n+1)*24+4-168)
…	…	…	…
x(48-168)	x(72-168)	…	x((n+2)*24-168)
Tuesday	Wednesday	…	Wednesday
1	1	…	1

k+1	**k+2**		**k+n**
X25	X49	…	X((n+1)*24+1)
X26	X50	…	X((n+1)*24+2)
X27	X51	…	X((n+1)*24+3)
…	…	…	…
X48	X72	…	X((n+2)*24)

Table 3.11. Feature set of MLP to forecast load consumption.

Model	**Features**
Load Model-I	Previous day load consumption Previous week load consumption Day of the week Weekdays/Weekend
Load Model-II	Load consumption on the previous day at the same hour Load consumption on the previous week at the same hour Average load consumption of previous day Average load consumption of previous week Hour of day Day of the week Weekdays/ Weekend

Table 3.11 provides detailed expressions of the feature set of load forecasting models. In the second load model, the definition of features is not far from the first model; however, we model the architecture of the entrance in the input layer differently.

We conclude the last forecasting model by using the numbers of neurons in Table 3.9 and feature set in Table 3.8 and Table 3.11 for PV power generation and electrical load consumption, respectively. As we indicated before, forecasting of load demand of a specific building needs detailed information, even in that case, we may not foresee the many situations. Figure 3.7 shows the hourly average forecasting results of each time series by comparing the proposed approaches. In the upper part, hourly errors show the meteorological features bring better forecasting performance. 24 steps ahead forecasting is a quite challenging process, error rates rise by the increasing number of steps. The below part represents the electrical demand, even though we integrate additional explanatory features to the second model, we still cannot come up with a decreased level of error. Despite all these, the second model for both PV and load forecasting approaches capture relatively small errors than any other method that we applied and presented in this thesis. Figure 3.7 that demonstrates the average of test sets also supports this outcome.

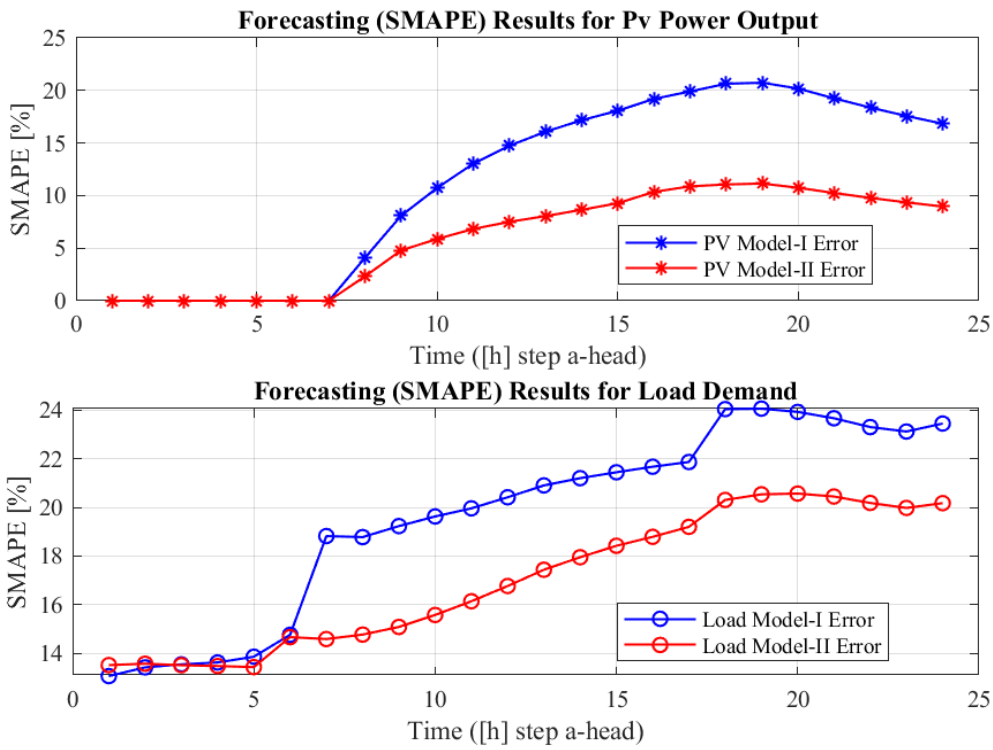

Figure 3.7. Hourly SMAPE results for forecasting of PV power and load consumption models through the year for MLP.

The SMAPE performance shows a decrease as the number of steps ahead increases. There are major advantages to the MPC frame. Although it gives a solution set for the entire horizon, we implement only the very first hours and solve it repeatedly throughout the horizon. Thus, even there is a high percent error of forecast before we implement all sets we can regulate the system and prevent large deviations by solving problems repeatedly for each hour.

In Table 3.12, we present the results of the performance criteria for each model. We can see conclude that feature selection is crucial to reach accurate estimation. The RMSE is highly small in the PV Model-II. We do not achieve this amount of progress in the Load Model-II because of challenging characteristics, but still, we obtain better results within the comparison of Load Model-I.

Table 3.12. Averages of different performance criteria for each model by using MLP.

	MAE (kW)	MSE (kW^2)	RMSE (kW)	MAPE (%)	SMAPE (%)
PV Model-I	42.16	8359.60	52.70	18.69	11.17
PV Model-II	18.54	1645.90	25.27	6.48	6.07
Load Model-I	94.20	29595.00	140.06	28.55	19.66
Load Model-II	77.09	25347.94	126.36	21.77	17.05

It is important to remark that these results are promising and possible to improve. However, the forecasting of time series needs longer historical data as possible (Leva et al., 2017). We apply these techniques to only one-year data, we believe in longer than a yearly data will show a smaller error than this performance.

3.5. Performance Comparison of the Considered Methods

We summarize all the forecasting work for the electric load demand and PV power output that are completed in this chapter and we compare their performance. Figure 3.8 illustrates the 24-hour ahead average SMAPE for all hourly loads and electricity generation through a year. As we can see, the most promising technique is MLP model-II for both applications.

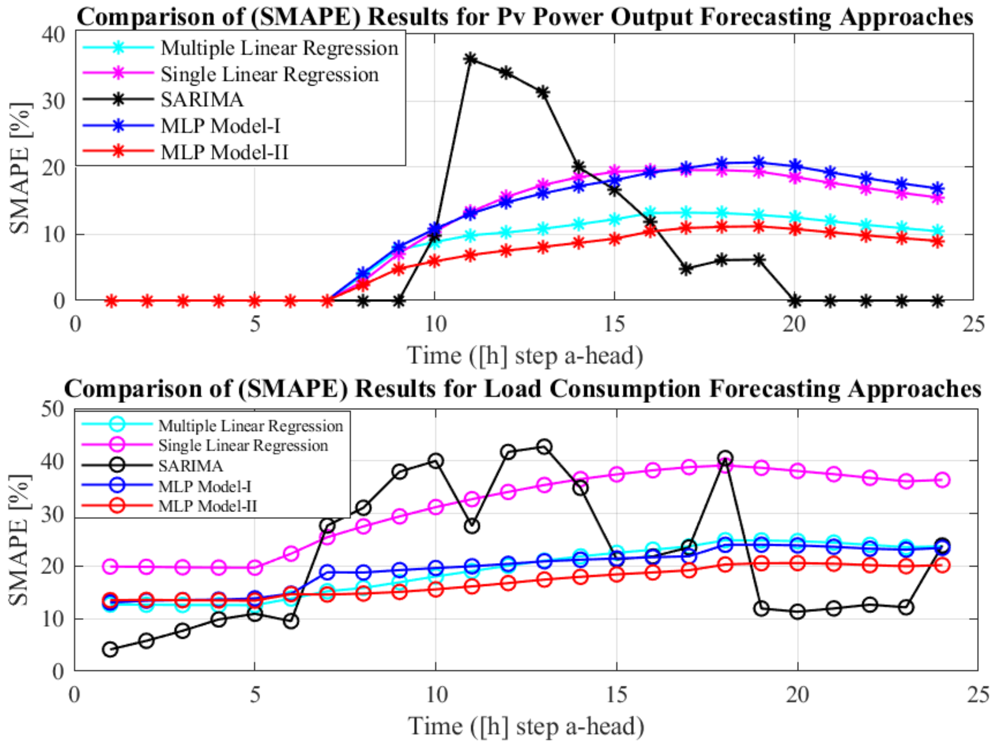

Figure 3.8. Comparison of hourly average SMAPE results of every forecasting approaches.

As discussed until this point, single regression is a benchmark model, with the increasing number of variables multiple regression presents improved performance. SARIMA method is an extension of the linear method and it is not capable of deal with non-linear relations, especially load forecasting in this study. The applied MLP methods show various performance; actually, we wanted to show the importance of features and design of a network. Table 3.13 and Table 3.14 presents the average of each performance criterion, and the developed MLP model has better forecasting performance than the others do. As we can read from the tables, RMSE is around 25 kW and 140 kW for solar power and electric demand. The SMAPE is 6.07% and 17.05% that we also desired to reach smaller than 10% for the PV model and 20% for the demand model.

Table 3.13. Performance criteria for different PV power forecasting models.

	MAE (kW)	MSE (kW^2)	RMSE (kW)	MAPE (%)	SMAPE (%)
MLP Model-I	18.54	1645.90	25.27	6.48	6.07
MLP Model-II	42.16	8359.60	52.70	18.69	11.17
SARIMA	36.37	7559.69	47.87	16.46	7.37
Multiple Regression	24.03	2439.09	30.34	8.81	7.66
Single Regression	46.69	9958.81	61.22	15.32	11.13

Table 3.14. Performance criteria for different electrical load forecasting models.

	MAE (kW)	MSE (kW^2)	RMSE (kW)	MAPE (%)	SMAPE (%)
MLP Model-I	77.09	25347.94	126.36	21.77	17.05
MLP Model-II	94.20	29595	140.06	28.55	19.66
SARIMA	104.60	35848.45	151.47	30.18	21.78
Multiple Regression	106.02	35725.40	156.94	27.21	19.36
Single Regression	191.29	77601.76	233.11	54.65	31.29

We apply the same model over a whole year, but while doing this we take advantage of 5-fold cross-validation to increase the generalization ability over the yearly data. We train each set and measure its performance, in the end, we choose the minimum MSE of an average of these five sets. We believe this forces the model to generalize over the year and present reliable and consistent results. Even though the MLP outperformed the other methods, there is still room for improvement of its general performance, mainly because it is possible to add new features, work with longer historical data and try new architectures. We use the MLP forecasting of this chapter as point estimations in Chapter 4, also operate these estimations and forecast errors in the second part of Chapter 5. All the information related to microgrid problem formulation and its deterministic solution is in Chapter 4.

CHAPTER 4
DETERMINISTIC MODEL PREDICTIVE CONTROL (D-MPC)

In this chapter, we present the objective function, and constraints of the mathematical model of a microgrid with their related explanations and details. Next, we implement the Deterministic Model Predictive Control (D-MPC) approach that is one of the advanced methods of real-time detailed control by feeding the point forecasts from Chapter 3. In the end, we give corresponded total cost of taken set point decisions in order to provide insight the daily operation of the microgrid by D-MPC is a cost-effective manner or not. D-MPC uses point estimations of electrical load demand and PV power generation to ensure that optimal power dispatch of the microgrid management and defines power and energy set points by including unit commitment solution of the battery storage units and electric generators.

4.1. Microgrid Mathematical Model

The operational constraints are essential for the components of the microgrid consisting of the generator, battery, electric grid and net fixed load demand for defining the boundaries of the problem.

The main problem is related to both the minimization of the operation cost of microgrid energy management and deciding the unit commitment of generator and battery usage. This commitment problem requires binary integer variables for some of the battery and electric generator decisions. However, the addition of integer variables makes the problem non-convex and increase the dimension.

k is the index of the time, while i representing the number of the generator N^G, j represents the number of battery storage units N^B.

$k \in \{1, 2, \dots, N\},\ i \in \{1,2, \dots, N^G\},\ j \in \{1,2, \dots, N^B\}$

We give all the decision variables and modeling details of system components. These components remain the same throughout all chapters of the thesis.

4.1.1. Electric Generators

There are N^G generators in the microgrid, $\underline{P_i}^G$ and $\bar{P}_i^G$ are known minimum and maximum power outputs, $P_i^G(k)$ is established amount of power that produced from generator in time k . The decision variables of the electric generators are $P_i^G(k)$, $z_i(k)$, $\alpha_i(k)$ and $\beta_i(k)$.

$P_i^G(k) = \text{amount of power generated from generator i in time k}$

$$z_i(k) = \begin{cases} 1, & generator \text{ i is operational } at\ time\ period\ k \\ 0, & otherwise \end{cases}$$

$$\alpha_i(k) = \begin{cases} 1, & generator\ i \text{ starts up } at\ time\ period\ k \\ 0, & otherwise \end{cases}$$

$$\beta_i(k) = \begin{cases} 1, & generator\ i\ shutdowns\ \ at\ time\ period\ k \\ 0, & otherwise \end{cases}$$

The constraint (9) applies based on $z_i(k)$ that, represents generator is operational or not:

$$z_i(k)\,.\,\underline{P_i}^G(k) \leq\ P_i^G(k) \leq\ z_i(k)\,.\,\bar{P}_i^G(k)\ , \forall i, \forall k \tag{9}$$

The starting and shutting down the generator give rise to additional costs. We can write the following equations to express the effect of the changing status of generators ($\alpha_i(k)$ and $\beta_i(k)$) on cost.

$$\alpha_i(k) = \mathrm{z_i(k)}.\,(1 - z_i(k-1)), \forall i, \forall k \tag{10}$$

$$\beta_i(k) = \big(1 - z_i(k-1)\big).\, z_i(k-1), \forall i, \forall k \tag{11}$$

However, equations (10) and (11) makes the problem non-linear. The problem has already become computationally challenging due to integer variables. In order to prevent the problem from getting more difficult with the integration of the non-linear solution, we prefer to linearize this and any quadratic constraints that will come. Another motivation to continue by linear programming is the previous experiences that have shown that a piecewise affine term that results in a Mixed Integer Linear Programming (MILP), is more efficient than a quadratic solution (Parisio, 2011). Thus, we choose to keep along with MILP as a solution to this problem. MILP is very similar to linear programming but includes a combination of both continuous and integer variables.

We can write the following constraints (12), (13), and (14) for the identifying status of startup and shutdown of generators instead of quadratic constraints (10) and (11) to keep the problem as linearized.

$$z_i(k) - z_i(k-1) = \alpha_i(k) - \beta_i(k), \forall i, \forall k \tag{12}$$

$$\alpha_i(k) \leq 1 - z_i(k-1), \forall i, \forall k \tag{13}$$

$$\beta_i(k) \leq z_i(k-1), \forall i, \forall k \tag{14}$$

As the fuel consumption rate varies between the upper and lower limits of generators, the general approach is to determine the fuel cost of electrical generators is to associate it with the fuel flow chart (Biyik, 2014). The general representation is as equation (15):

$$F_i^G(k) = C_i^f \left(k_{0_i} + k_{1_i}.P_i^G(k)\right) \Delta T, \forall i, \forall k \tag{15}$$

Based on equation (15), we can conclude that there are two various costs related to generators, first one is idling cost, even if the generator is not active there is still additional cost but it is not correlated with the generator power. On the other hand, the second cost is based on the power of the generators, we can find it by the sum of unit energy production cost and life cost.

If we want to write the first part of the objective function that includes the sum of all the generator costs as in equation (16); fuel cost, life cost, starting and shutdown, and idling cost, respectively. Here, while the first part of equation (15) represents the sum of $C_i^{G-PC} + C_i^{G-LC}$, second part of the equation (15) indicates the C_i^{G-I} in equation (16).

$$M_i^G(k) = \left(P_i^G(k)(C_i^{G-PC} + C_i^{G-LC}) + C_i^{G-SU}\alpha_i(k) + C_i^{G-SD}\beta_i(k) + C_i^{G-I}z_i(k)\right), \forall i, \forall k \tag{16}$$

4.1.2. Battery Storage Units

The decision variables of the battery storage units are $P_j^{BD}(k)$, $P_j^{BC}(k), E_j^B(k), b_j^x(k)$ and $b_j^y(k)$.

$P_j^{BD}(k) =$ amount of power charged to the system by battery j in time k

$P_j^{BC}(k)$ = amount of power discharged from the system by battery j in time k

$E_j^B(k)$ = state of charge (SoC) in battery j in time k

$$b_j^x(k) = \begin{cases} 1, & battery\ is\ charging\ at\ time\ period\ k \\ 0, & otherwise \end{cases}$$

$$b_j^y(k) = \begin{cases} 1, & battery\ is\ discharging\ at\ time\ period\ k \\ 0, & otherwise \end{cases}$$

Constraint (17) and (18) refer to the limits of instantaneous power that the batteries can discharge from and charge to the system, and constraint (19) express the energy limits that can be stored in the batteries.

$$\underline{P_j}^{BD} \leq P_j^{BD}(k) \leq \overline{P_j}^{BD}, \forall j, \forall k \tag{17}$$

$$\underline{P_j}^{BC} \leq P_j^{BC}(k) \leq \overline{P_j}^{BC}, \forall j, \forall k \tag{18}$$

$$\underline{E_j}^{B} \leq E_j^{B}(k) \leq \overline{E_j}^{B}, \forall j, \forall k \tag{19}$$

Constraint (20) indicates the relation between State of Charge (SoC) of batteries and power that they can discharge from and charge to the system with respect to their charge and discharge efficiencies.

$$E_j^B(k+1) = E_j^B(k) + P_j^{BC}(k).\eta_j^{BC}.\Delta T - \frac{P_j^{BD}(k)}{\eta_j^{BD}}\Delta T, \forall j, \forall k \tag{20}$$

Constraint (21) is preventing charge and discharge at the same time in the battery storage units.

$$P_j^{BD}(k).P_j^{BC}(k) = 0, \forall j, \forall k \tag{21}$$

Since we study MILP, we should avoid obtaining quadratic constraints equation (21). Thus, we choose to linearize this expression by using auxiliary 0-1 decision variables and regulate it, as is equation (21′). b_j^x and b_j^y represent the charging and discharging status of batteries and equation (21′) prevents to occur these events at the same time.

$$b_j^x(k) + b_j^y(k) \leq 1, \forall j, \forall k \tag{21′}$$

We can write the second part of the objective function as in equation (22) that includes the life cycle cost of battery storage units related to the amount of charge and discharge power.

$$M_j^B(k) = \left(P_j^{BC}(k)C_j^{BC-LC} + P_j^{BD}(k)C_j^{BD-LC}\right), \forall j, \forall k \tag{22}$$

4.1.3. Main Electric Grid

The decision variables of the main electric grid are $P^{GR-buy}(k)$, $P^{GR-sell}(k)$, $y^x(k)$ and $y^y(k)$.

$P^{GR-buy}(k) =$ amount of power bought from the grid in time k

$P^{GR-sell}(k) =$ amount of power sold to the grid in time k

$$y^x(k) = \begin{cases} 1, & \textit{buying power from grid at time period } k \\ 0, & \textit{otherwise} \end{cases}$$

$$y^y(k) = \begin{cases} 1, & \textit{selling power to grid at time period } k \\ 0, & \textit{otherwise} \end{cases}$$

Here, constraint (23) tries to avoid taking buying and selling decisions at the same time.

$$P^{GR-buy}(k).\, P^{GR-sell}(k) = 0\,, \forall k \tag{23}$$

As we prevent the nonlinearity of the constraints by using equation (21′), similarly we also arrange equation (23′) instead of equation (23) by using auxiliary 0-1 decision variables $y^x(k)$ *and* $y^y(k)$.

$$y^x(k) + y^y(k) \leq 1, \forall k \tag{23′}$$

Eventually, we can write the last part of the objective function as in equation (24) that includes the total cost of interactions between the consumer and the electric grid because of bought or sold power.

$$M^{GR} = \left(P^{GR-buy}(k)C^{GR-buy}(k)\right) - \left(P^{GR-sell}(k)C^{GR-sell}(k)\right), \forall k \tag{24}$$

We complete the writing of the mathematical model of the main components. After all, the formula of the linear objective function is completed for finite horizon N starting from t and given in equation (16). However, the objective function and the power balance equation may change based on solution methods although the rest of the component formulas keep the same and we give as equation (25).

$$\sum_{k=t}^{t+24}\left(\sum_{i=1}^{N^G} M^G(k) + \sum_{j=1}^{N^B} M^B(k) + M^{GR}(k)\right), \forall i, \forall j, \forall k, \forall t \tag{25}$$

In this part, we explained the model details of the microgrid problem. We will solve this problem in the next part, but to solve this we should use the input parameters that fed by Chapter 3 of the MPC.

4.2. D-MPC Formulation for Microgrid Energy Management Problem

In this thesis, the proposed microgrid problem includes two distributed generators, two battery storage units and a photovoltaic (PV) system with the electrical loads only. Each generator and battery have different characteristics from each other such as their costs, capacities, powers, and sizes. Besides, the microgrid is connected to the main grid to ensure that buying the required energy and selling surplus energy.

At this point, we have details of the microgrid problem, mathematical model, and best forecasts of stochastic inputs that are demand consumption and PV system output by the various methods (see Chapter 3). These forecasted values come as point estimates to become the input of D-MPC. The deterministic model assumes there is no uncertainty for these inputs and takes all the point estimates as it comes. The main advantage of the D-MPC approach compared to stochastic approaches is its simplicity, but the results are inflexible since they highly depend on the forecasts without allowing the realization of any uncertainty.

Within the scope of this chapter, we perform the D-MPC approach that optimizes the performance of microgrid energy management. In the D-MPC approach, the final status of system dynamics is specified by measuring state variables (load, SoC, and fuel cost, etc.) at every control step through the horizon. We formulate our problem as MILP to obtain power set points of all the components for an energy management problem that we give the details of the mathematical model. A MILP solver aims to minimize the objective function, which is $f^T x$ under some constraints.

$$\min_{x} f^T x \ subject\ to \begin{cases} Ax \leq b \\ A_{eq}x = b_{eq} \\ x = \begin{bmatrix} x_c \\ x_b \end{bmatrix} \\ x_{min} \leq x \leq x_{max} \\ x_c \in \mathbb{R}^{n_c}\ and\ x_b \in \{0,1\}^{n_b} \end{cases} \tag{26}$$

where f represents the cost, x is a set of decision variables. While x_c variables are real, x_b (binary) variables can take only 0 or 1, that is one reason why we prefer to use MILP. The objective function is $f^T x$ which represents the operational cost and our aim is minimizing it by obtaining a feasible x vector.

A stands for inequality constraint matrix, b inequality value vector, A_{eq} equality constraint matrix and b_{eq} value vector, respectively. x_{min} and x_{max} represent the upper and lower limits of the variables. We have already listed model constraints and boundaries of the problem. However, like underlined in before, we prefer to explain and add the power balance equation and overall objective function here for D-MPC. The obvious reason to do this is the objective function and power equation will slightly get different shapes according to MPC approaches, will not stay the same for all procedures. We arrange the proposed microgrid description according to the mathematical model and give the all details of the problem in Table 4.1 and Table 4.2.

Table 4.1. Model parameters of generators and batteries.

Variables	Unit	Lower Bound	Upper Bound
$P_1^G(k)$	kW	0	150
$P_2^G(k)$	kW	0	80
$P_1^{BC}(k)$	kW	0	50
$P_2^{BC}(k)$	kW	0	40
$P_1^{BD}(k)$	kW	0	60
$P_2^{BD}(k)$	kW	0	50
$E_1^B(k)$	kWh	120	600
$E_2^B(k)$	kWh	100	500

MPC optimizes the operation cost by keeping these bounds. Here, we underline the minimum energy of batteries is equal to 20% of their upper limit, which means they not allowed to become zero.

Table 4.2. Model details of batteries.

Variables	Value
$E_1^B(1)$	180
$E_2^B(1)$	150
η_1^{BC}	0.95
η_2^{BC}	0.90
η_1^{BD}	0.85
η_2^{BD}	0.87

Table 4.3 presents the detailed costs that affect the operational cost of the controllable generators and storage units.

Table 4.3. Microgrid costs in detail.

Type of Cost	**Parameters**	**Cost ($/kWh)**	
		Generator1	Generator2
Fuel	C_i^{G-PC}	0.6	0.8
Starting	C_i^{G-SU}	2.5	1.5
Shutdown	C_i^{G-SD}	2	1
Idling	C_i^{G-I}	1.15	1.2
Life/Wear	C_i^{G-LC}	0.05	0.04
		Battery1	Battery 2
Charging	C_i^{BC-LC}	0.02	0.01
Discharging	C_i^{BD-LC}	0.025	0.015

The main grid tariff may change from day to day and hour to hour. It can be forecasted also, but within the scope of this thesis, we assume to have full access to knowledge of grid buy/sell day-ahead costs before starting the optimization. Table 4.4 and Table 4.5 show the hourly tariff of the electric grid costs.

Table 4.4. Day-ahead market costs for buying energy from electric grid.

Hour	**00-01**	**01-02**	**02-03**	**03-04**	**04-05**	**05-06**	**06-07**	**07-08**
Day-ahead Cost ($/kWh)	0.70	0.70	0.70	0.70	0.70	0.90	0.90	0.90
Hour	**08-09**	**09-10**	**10-11**	**11-12**	**12-13**	**13-14**	**14-15**	**15-16**
Day-ahead Cost ($/kWh)	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90
Hour	**16-17**	**17-18**	**18-19**	**19-20**	**20-21**	**21-22**	**22-23**	**23-00**
Day-ahead Cost ($/kWh)	0.90	1.20	1.20	1.20	1.20	1.20	0.70	0.70

Table 4.5. Day-ahead market costs for selling energy to electric grid.

Hour	**00-01**	**01-02**	**02-03**	**03-04**	**04-05**	**05-06**	**06-07**	**07-08**
Day-ahead Cost ($/kWh)	0.49	0.49	0.49	0.49	0.49	0.63	0.63	0.63
Hour	**08-09**	**09-10**	**10-11**	**11-12**	**12-13**	**13-14**	**14-15**	**15-16**
Day-ahead Cost ($/kWh)	0.63	0.63	0.63	0.63	0.63	0.63	0.63	0.63
Hour	**16-17**	**17-18**	**18-19**	**19-20**	**20-21**	**21-22**	**22-23**	**23-00**
Day-ahead Cost ($/kWh)	0.63	0.84	0.84	0.84	0.84	0.84	0.49	0.49

We ensure that the electrical power is in balance in the microgrid at any time instant and equation (27) forced to keep the power balance between demand and generation.

$$P^{GR-buy}(k) - P^{GR-sell}(k) + \sum_{i=1}^{N^G} P_i^G(k) + \sum_{j=1}^{N^B} P_j^{BD}(k) - P_j^{BC}(k) + \mathrm{P^{PV}(k)} = P^L(\mathrm{k}), \forall i, \forall j, \forall k \tag{27}$$

Now, $P^L(\mathrm{k})$ and $\mathrm{P^{PV}(k)}$ are the forecasts of load consumption and PV power generation, respectively. We continue with $\mathrm{P^{NL}}(k)$ by replacing $P^L(\mathrm{k}) - \mathrm{P^{PV}(k)}$ to represent net load. Their dimensions are Nx1. According to our problem, N is the horizon and equal to 24 hours, N^G and N^B are the numbers of the electric generator and battery units, and we know both they equal to 2. If we arrange equation (27) and write specifically for this problem, we obtain equation (28).

$$P^{GR-buy}(k) - P^{GR-sell}(k) + \sum_{i=1}^{2} P_i^G(k) + \sum_{j=1}^{2} P_j^{BD}(k) - P_j^{BC}(k) = P^{NL}(k), \forall i, \forall j, \forall k \tag{28}$$

The objective function of an optimization model for the problem of microgrid energy management is also equals to the sum of all cost equations that we mentioned in equation (25) in closed form, the objective function is as follows:

$$
\begin{aligned}
\min \sum_{k=1}^{24} \Bigg(\sum_{i=1}^{2} \Big(& P_i^G(k)(C_i^{G-PC} + C_i^{G-LC}) + C_i^{G-SU}\alpha_i(k) + C_i^{G-SD}\beta_i(k) \\
& + C_i^{G-I} z_i(k) \Big) \\
& + \sum_{j=1}^{2} \big(P_j^{BC}(k) C_j^{B-LC} + P_j^{BD}(k) C_j^{B-LC} \big) \\
& + \Big(P^{GR-buy}(k) C^{GR-buy}(k) \Big) - \Big(P^{GR-sell}(k) C^{GR-sell}(k) \Big) \Bigg)
\end{aligned} \tag{29}
$$

The first cost term in the objective function represents the costs associated with electrical generators. It shows the summation of life cost and fuel cost based on utilization, generator startup, and shutdown costs, respectively. Next term expresses modeling the wear cost of battery storage units due to charge and discharge. The third term is the total cost of the electrical power bought from the grid. The last term refers to the total profit of the power sold to the grid. Since this term indicates income, it is written as a negative sign to the objective function, which we are trying to minimize. The only way to generate income from this problem is to sell energy to the main electric grid, especially during high tariffs. Like load demand and renewable generation, the cost of selling to the grid and buying from the grid are also stochastic and non-measurable inputs. However, we assume that these prices are known based on the day-ahead market. D-MPC solves our problem for the $N = 24$. Finally, the obtained problem is solved using "intlinprog" function solver via MATLAB to minimize operational cost.

D-MPC ignores the possibility of any stochasticity in the objective function and the constraints. There is no necessity dealing with random variables in here because we know net load as pointwise. However, it includes uncertainty that is why we prefer to study also S-MPC and H-MPC to observe results and differences. Before implementing these methods in Chapter 5, we present the results of D-MPC in the next part.

4.3. D-MPC Simulation Results

We summarize the results and MPC decisions of the deterministic approach in this part. We illustrate in Figure 4.1 both the 24-hour ahead net load forecasts that we find taking the difference between forecasted load demand and PV power in Chapter 3 for a specified day and realized net load profile.

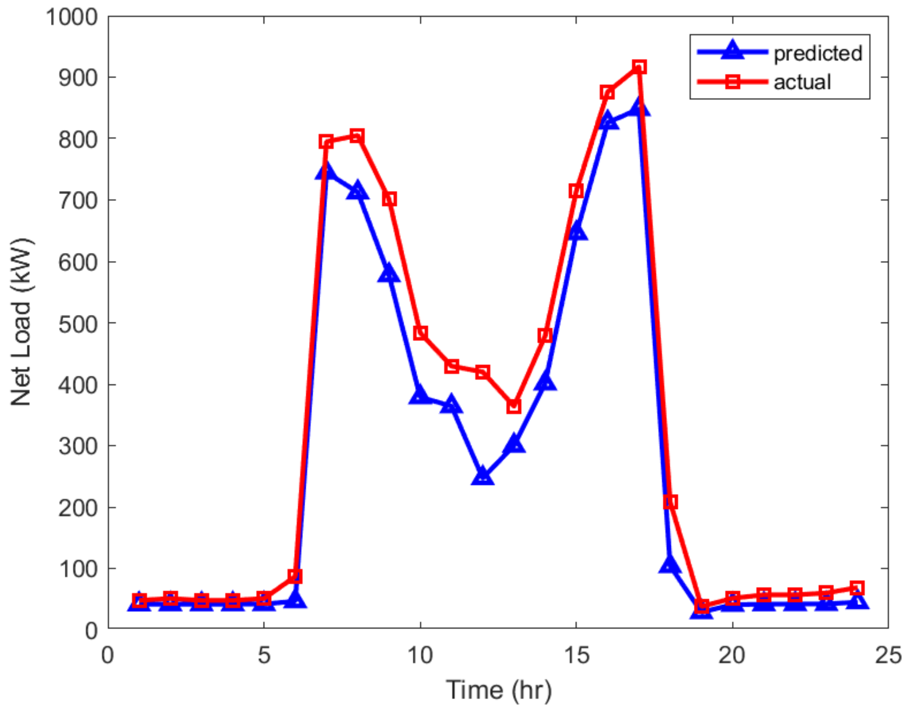

Figure 4.1. Forecasted (based on MLP method) and realized net load profile over 24 hours.

D-MPC performs control for the 24-time step by assuming the daily net load profile as in Figure 4.1. MPC aims the minimization of the operational cost of the microgrid; therefore, it decides each component such as charge and discharge of batteries, usage of generators, and trade of the main grid to meet the estimated net electric demand.

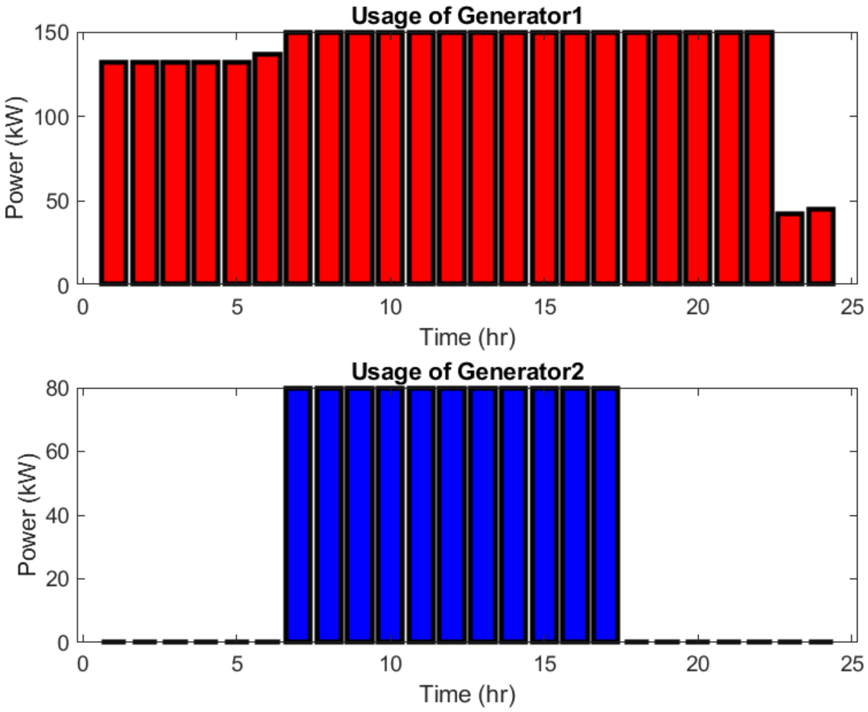

Figure 4.2. Electric generators power production over 24 hours (the upper limit of generators are 150 kW and 80 kW for Generator I and II).

In Figure 4.2, we present the power generated by the controllable generators. Due to electric generators have the start-up and shutdown cost, the controller tends to operate them continuously when they employed despite the idling cost. In addition, D-MPC usually uses the larger capacity generator since the priority is meeting the electric need of the microgrid and generally do not use the second generator during lower demand. The next component is battery storage units that are beneficial components in these systems since they give the opportunity to charge during lower costs and discharging later during higher costs. Figure 4.3 displays the initial charge in batteries and variations in energy levels with charging and discharging decisions along the horizon. Figure 4.4 shows the electricity price of the next 24 hours and the grid decisions. By taking into consideration Figure 4.3 and Figure 4.4, the decisions of storage units corroborate the expectation by charging between midnight and 6 am that is the range with the lowest demand as well as cheaper electricity price than the daylight and discharge the batteries during peak loads and higher prices.

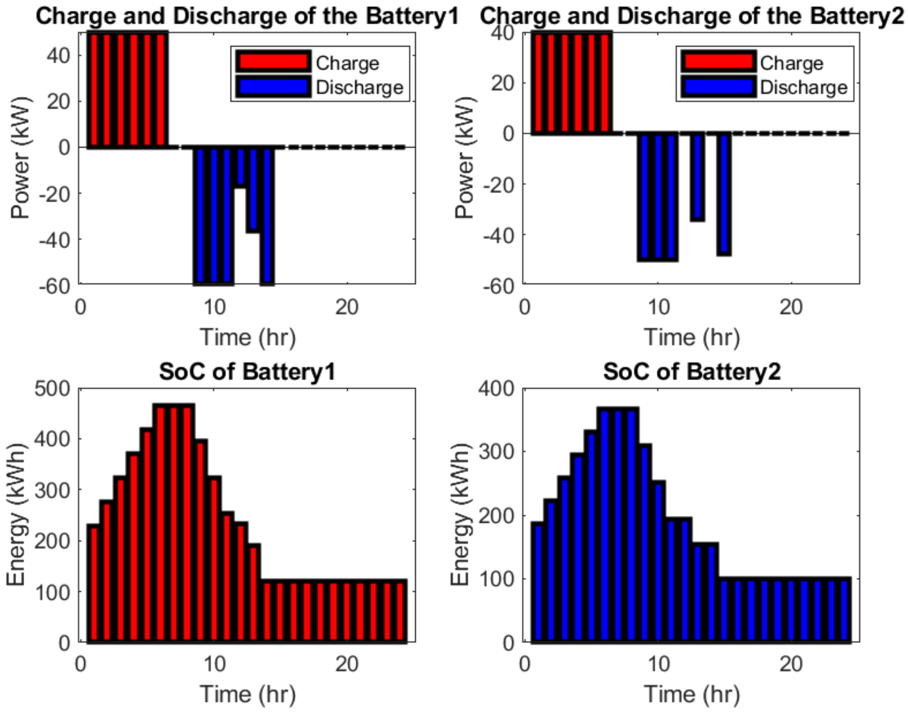

Figure 4.3. SoC of the battery storage units with charging and discharging decisions.

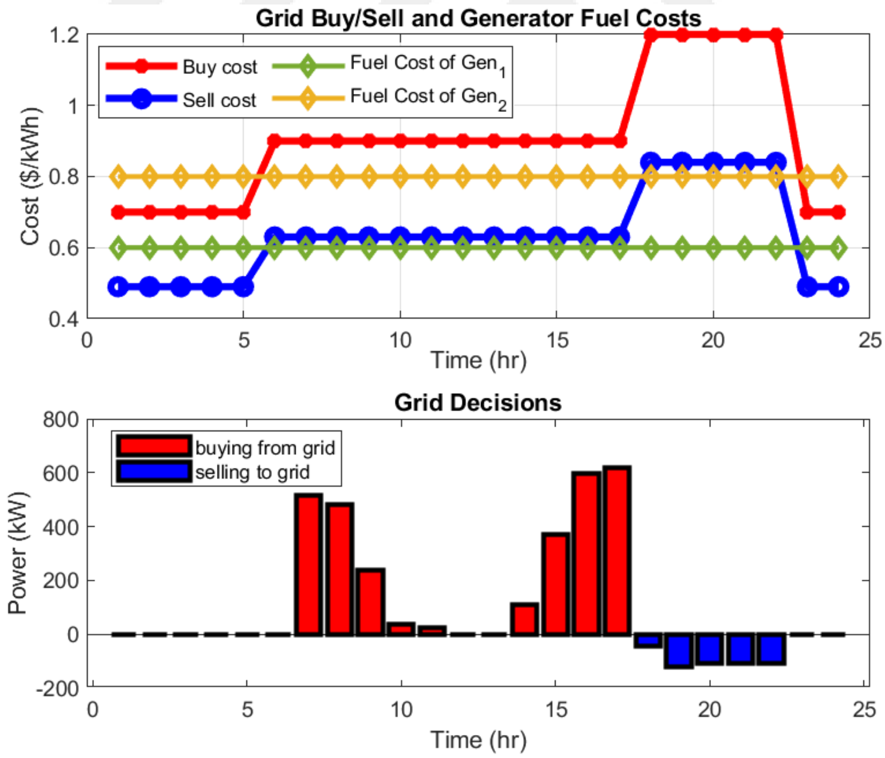

Figure 4.4. Amount of power bought/sold between grid and consumer according to deterministic method.

To summarize all the previous results of the microgrid components, we constitute Figure 4.5. We can see the effort of the controller to meet the demand with the minimum amount of operation cost. If we apply every decision through the day, the total cost is equal to $5217.70. However, in a real application, we know we implement the first hour decisions, then refreshing the MPC with respect to the new measurements.

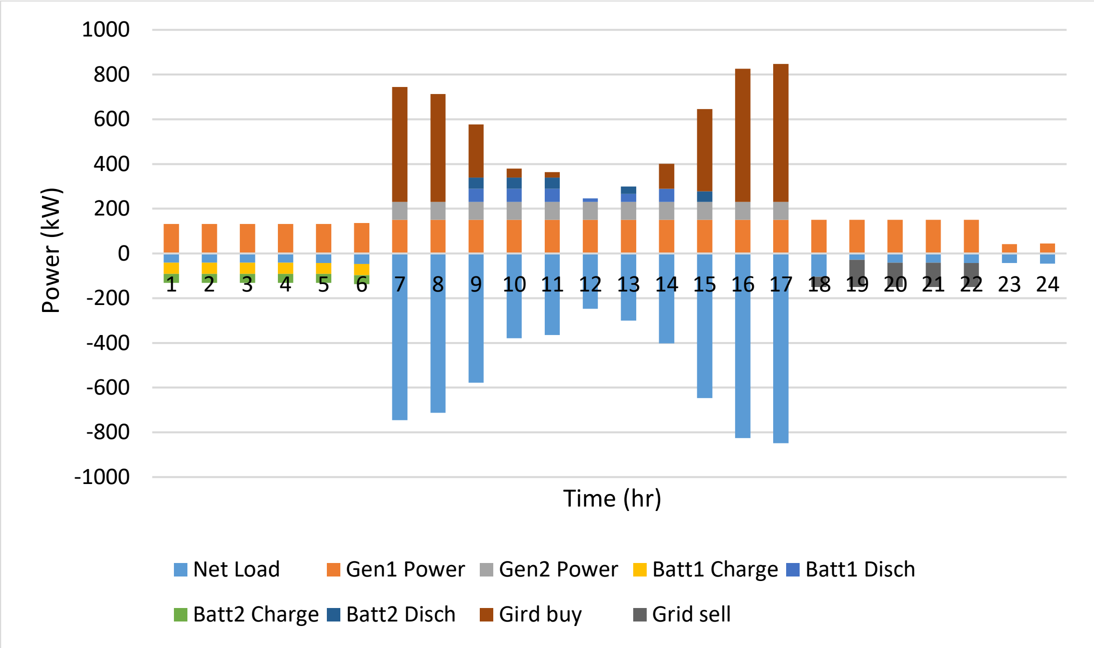

Figure 4.5. Microgrid decisions through the horizon according to D-MPC.

Although we specify the uncertain inputs by forecasting methods, it still corresponds to the naive approach since these point estimations are accepted as is. The deterministic approach does not consider the uncertainty of forecasts. The solar power and electrical load are the uncertain and highly characteristic series, if the forecasting result is far from the actual, the controller will take a set of decisions in the wrong direction. This situation may end with unnecessarily high operation costs or energy consumption more than need. For these reasons, we believe that we should add stochastic consideration. In the following chapter, we study both the stochastic based on historical data and the hybrid approach of point estimations and historical knowledge.

CHAPTER 5
STOCHASTIC MODEL PREDICTIVE CONTROL (S-MPC)

A problem may include a number of random variables because of uncertainties. In our problem, electrical demands depend on uncertain consumer behaviors; PV power generation depends on solar radiation, wind speed, and temperature, which are uncertain parameters. In addition, grid costs also depend on uncertain market conditions, but we prefer to take these costs from the electric market directly.

There is a set that includes all possible outcomes, by collecting different random events from this, a new class is constituted. We can write for every event is an element of the class with its probability P. The combination of set, class, and probability refers to probability space. Each random event comes with probabilities between 0 and 1.

On the contrary to the D-MPC, the strong future of the Stochastic Model Predictive Control (S-MPC) is handling model uncertainties. Ensuring the stability of the system and keeping the balance have importance in microgrid applications. This chapter explains the main approaches to be perused when developing an S-MPC for stochastic programming. We employ the S-MPC by using the distribution of the historical net load and apply model reduction. The principal components in the historical data are identified by using an Singular Value Decomposition (SVD) analysis on the historical data. To the best of our knowledge, this is the first study that generates the scenarios from the reduced-order transformed data. Moreover, we develop a novel approach that combines the strengths of deterministic and stochastic MPC methods by integrating point estimations and the distribution of net load. In this approach, we not only generate scenarios based on historical net load set but also perform scenario generation by using forecast errors.

5.1. S-MPC based on Distributions

Stochastic programs may consist of one or more uncertain variable. There may be several random variables such as electricity prices, demand by consumers, energy generation by renewable generators based on mainly weather conditions in real life problems. The random vector is defined with ξ. We can represent the functional form as $\xi(w)$.

If the Probability Density Function (PDF) of random vector "ξ" is known, then the procedure where repeats itself and character are also known. Distribution of ξ can be estimated from historical data also. We are conscious that it is possible to create many scenarios based on the distribution of the random vector. We prefer to deal with only the distribution of net load in this thesis.

In contrast with taking pointwise forecasted values as we did in D-MPC, now we focus on the distribution. Our aim is to optimize the total cost and to do this we also solve the expectation of random components of the problem based on the various solution approaches. We investigate Stochastic Programming Methods under the four main approaches: Worst-case, expected value, two-stage (recourse) and chance constraint (probabilistic) method.

5.1.1. Worst-Case and Expected Value Method

Actually, Worst-Case handles the worst possible combination under all uncertainties. Net load demand is the only uncertainty component that we do not know through the horizon. Then, worst-case analysis and takes all decisions to satisfy this highest load by assuming this demand will come true with probability 1. The objective function is completely the same with equation (29) in Chapter 4.1, but the power balance constraint takes the maximum load demand instead of point estimations for every hour and the P^{NL} the same as in Chapter 4.1 as in equation (28), refers to the possible maximum load vector.

This situation leads to a huge overestimation of the load demand, because the needed power of the microgrid may have considerably less than the expectation. Thus, the solution minimizes the possible loss but causes a big amount of waste with a low profit. We know we meet the demand with full confidence. It is safe, but a computationally expensive method to apply. As the microgrid is grid-connected, the needed power is procurable through buying energy from the main electric grid at worst. Of course, there may be a shortage, repair, or maintenance related to the grid, but we all know that are rare events. If we try to prepare for the worst depending upon historical net demand data, Figure 5.1 is an inevitable scenario. The MPC takes decisions to optimize total cost, but although its effort when the real needed power is coming, quite likely we will see huge losses in advance. Although the MPC takes decisions to optimize total cost subject to the worst-case approach, when the real needed power is updated, quite likely huge losses show.

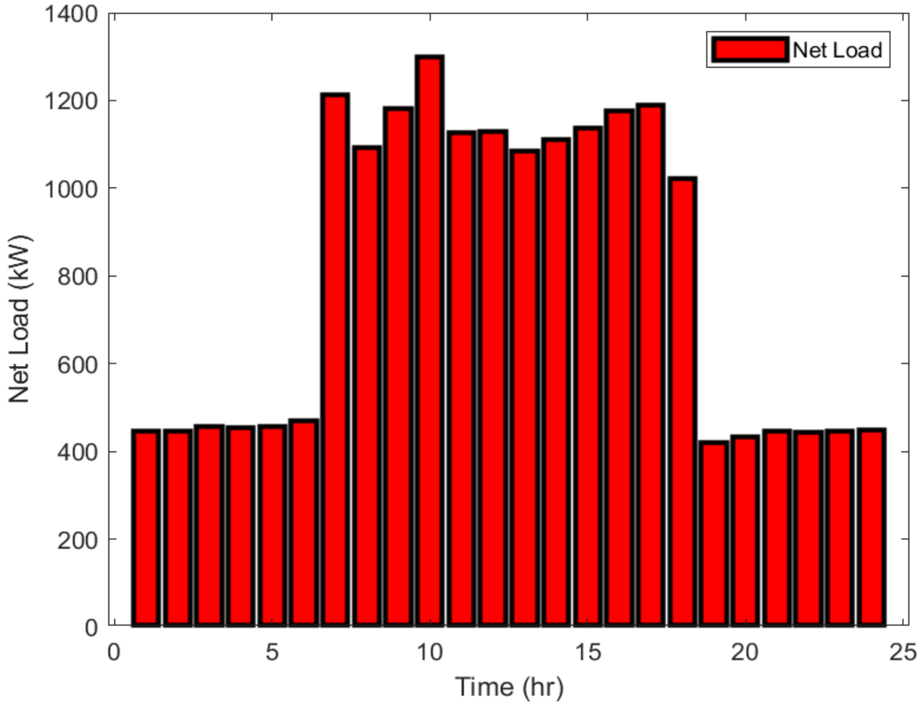

Figure 5.1. The net load for every hour based on the Worst-Case scenario method.

Since the Worst-Case method focus on the highest demand, Figure 5.1 demonstrates a distinguishably high amount of load demand and does not expect a negative load within the horizon. MPC solves the optimization and takes decisions of generators (Figure 5.2), storages (Figure 5.3), and grid usage (Figure 5.4) with respect to electricity tariff and constant costs (see Table 4.3) to meet this power for the next 24 hours.

In Figure 5.2, while the first generator that has lower fuel costs is used at all hours, the second generator is not used during the hours with relatively low power requirements.

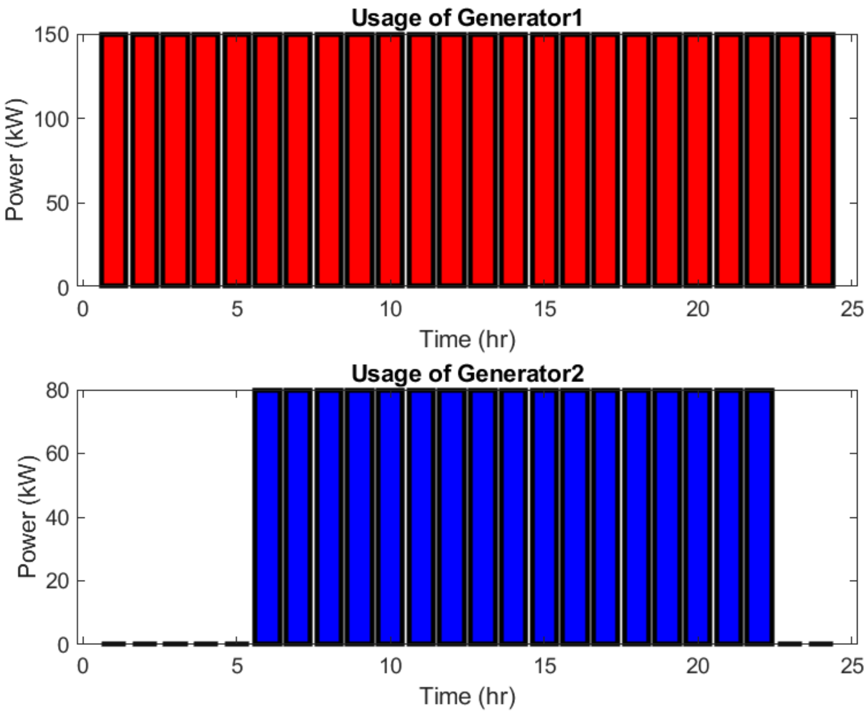

Figure 5.2. Generator decisions for the Worst-Case.

Battery decisions indicate in advance of charging them to use during high electricity costs.

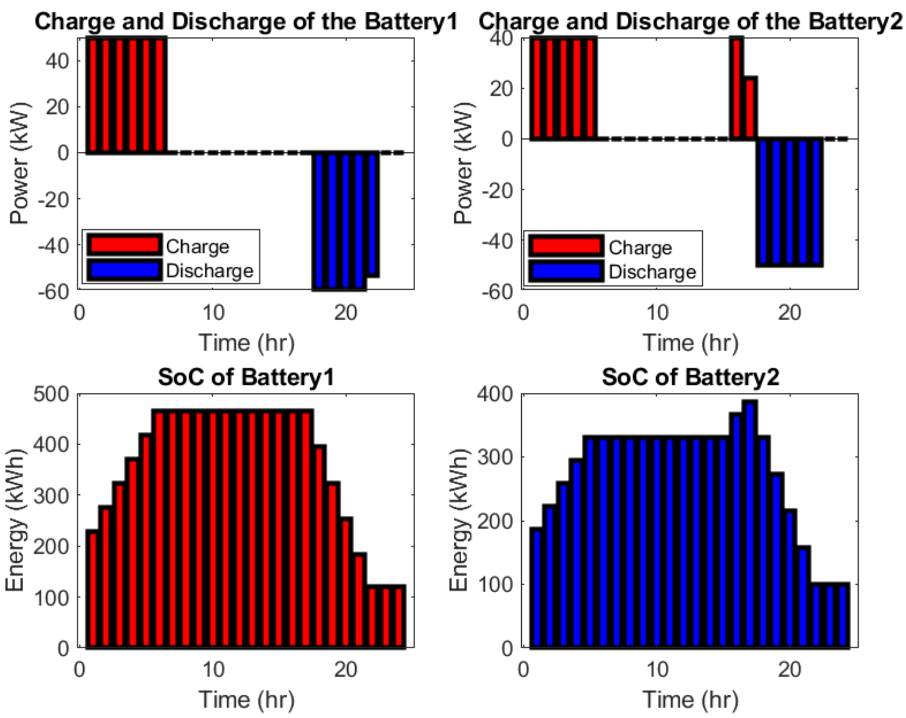

Figure 5.3. Change of SoC based on charge and discharge decisions according to Worst-Case method.

Figure 5.4 exposes which with this amount of demand, makes a profit by selling energy to the grid is not in question. It should be noted that the main objective is to satisfy the requirement load no matter what.

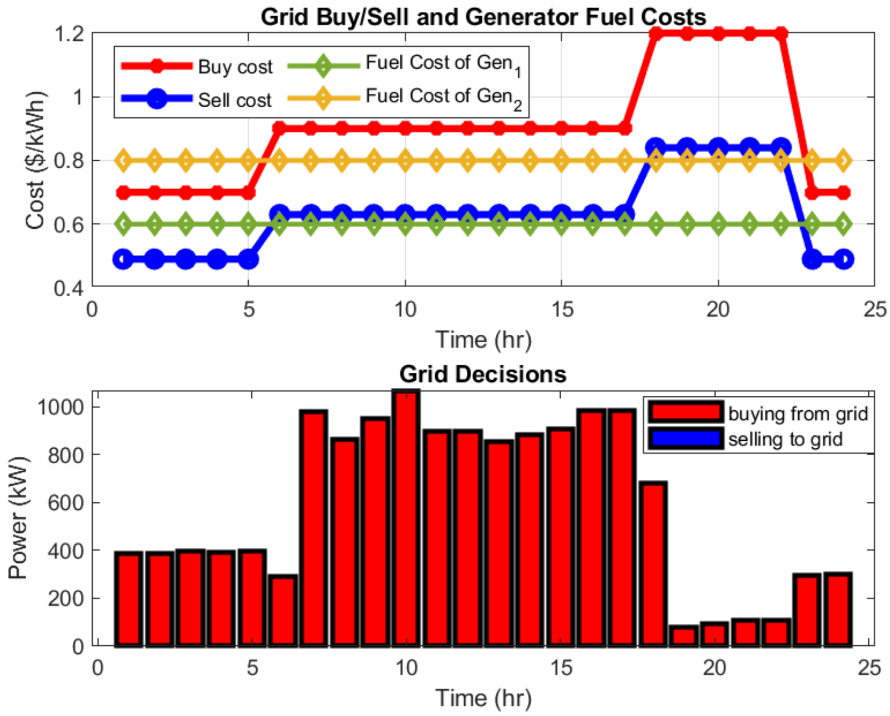

Figure 5.4. Amount of power bought/sold between grid and consumer according to Worst-Case method.

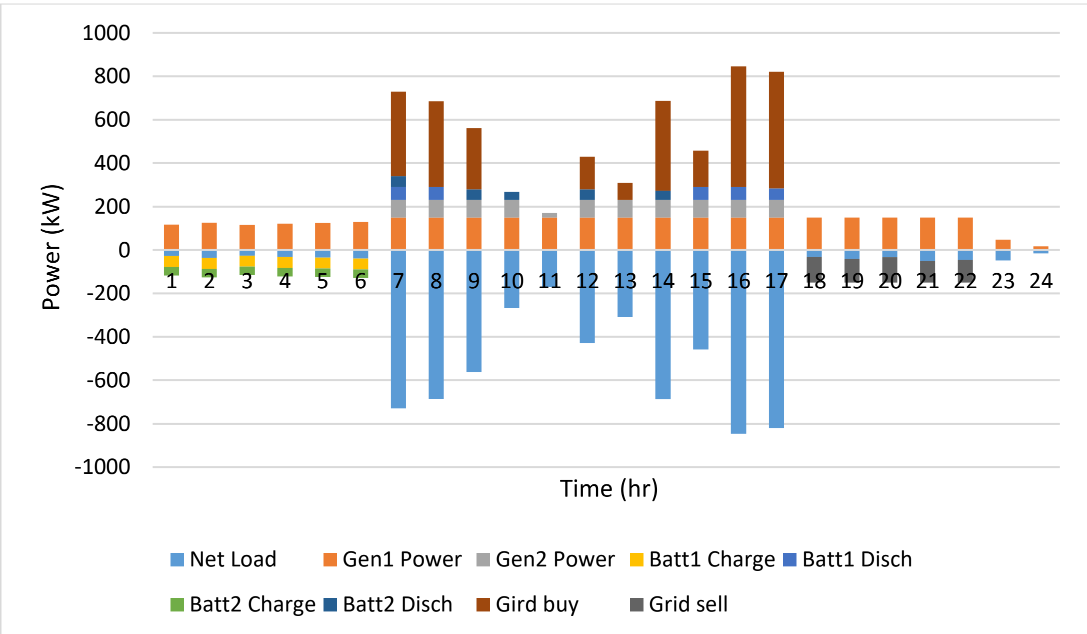

Figure 5.5. Microgrid decisions through the horizon according to Worst-Case method.

Last, we show all the decisions of the microgrid to meet the net load in Figure 5.5. The worst-case solution causes a large consumption since it is excessively close to the upper or lower bonds. Thus, it will be better to find the expectation to be close to average. The worst-case solution causes a large consumption since it is excessively close to the upper or lower bonds. Thus, we decided to escape from aggressive and unrealistic decisions by continuing with the Expected Value Method.

In the Expected Value Method, it is moderate to proceed with average without being aggressive, rather than working with upper and lower bounds. This actually solves the problem replacing uncertain input by its expected value.

We create a histogram that represents the frequency of each load value. By analyzing a histogram of yearly data, we can understand the probabilities and related values. Therefore, we can find the expectation of each hour with the product of the value and corresponded probability.

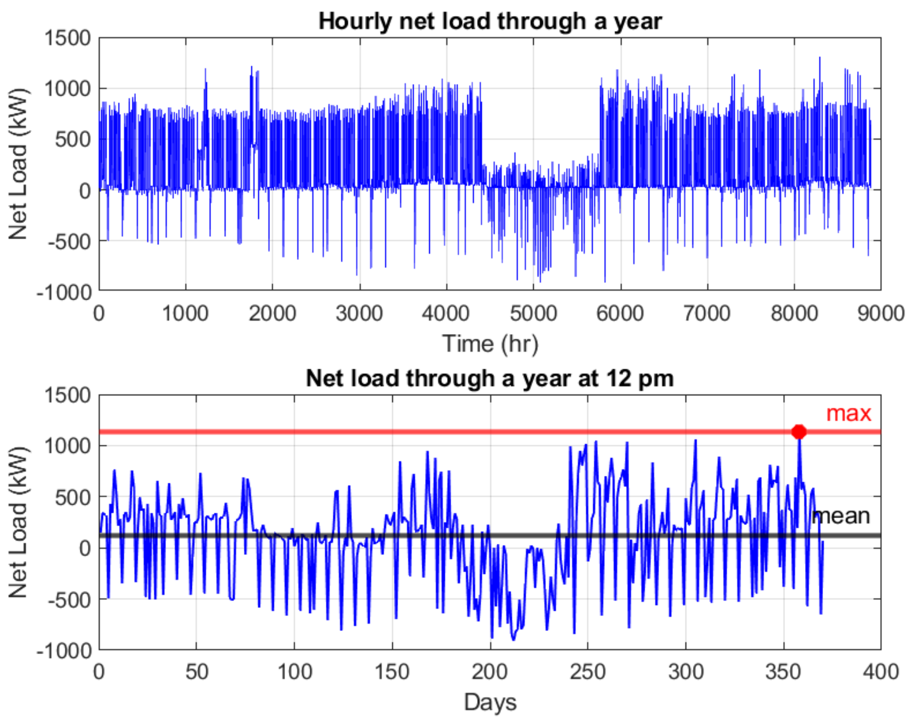

Figure 5.6. Hourly net load and the constitution of the input demand for Worst-Case and Expected Value methods at 12 pm, representatively.

To show the general approaches of mentioned methods for a representative hour in a day, we create Figure 5.6, while the first graph illustrating the net demand for all year, the second graph presents both corresponded demand by finding the maximum load and obtaining the average load for Worst-Case and Expected Value method, respectively. The difference between these hourly expectations is quite large and very helpful in showing the attitudes of both methods.

Electric demand predictions are used by deducing their expected value during the historic data to extract the behavior of users. Figure 5.7 expresses the estimation of the net load falls below half at almost all hours.

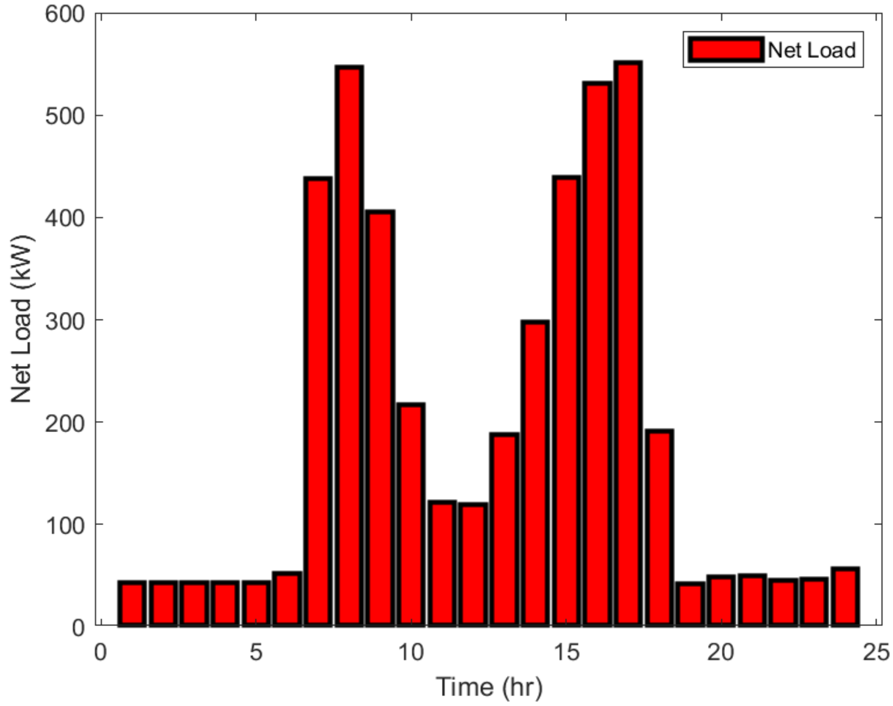

Figure 5.7. The net load for every hour based on Expected Value.

Figure 5.8, Figure 5.9 and Figure 5.10 illustrates all MPC decisions for each microgrid components.

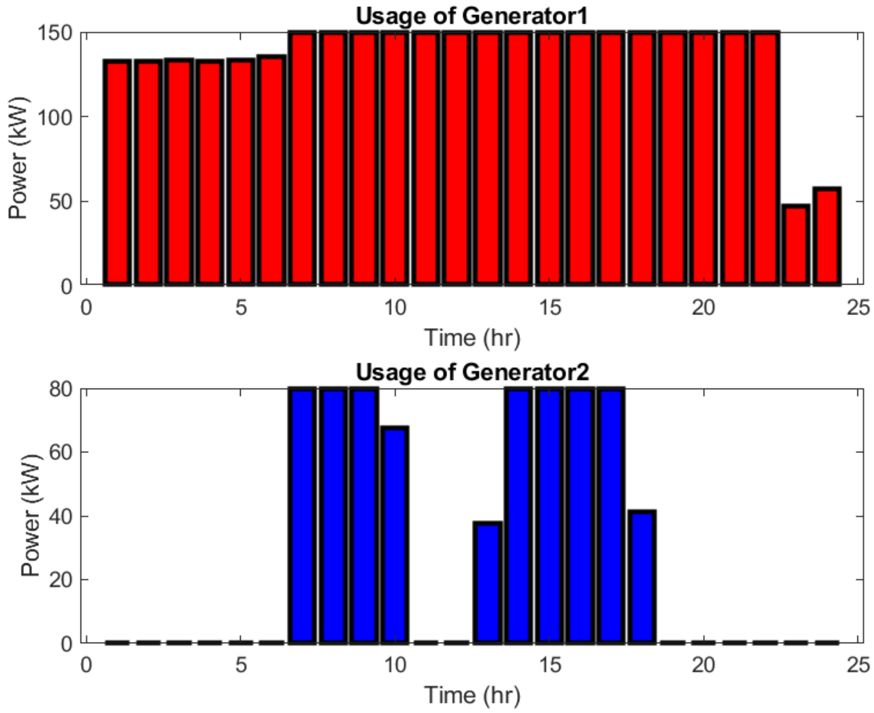

Figure 5.8. Generator decisions for the Expected Value.

The unit commitment of the generator is still dominant on the side of using “Generator 1”. However, not only the utilization of “Generator 1” but also the number of hours that work with the full capacity of "Generator 2" are quite considerable. Still, it is obviously the usage of electric generators is high.

We observe the state of storage units as discharging during peak loads, charging in the opposite conditions. The fact MPC gives the result of the upcoming 24 hours and applies the first one then finds a new set by throwing the rest. After for example a week later, with changing all conditions, decisions may vary completely according to the day. Related to the main grid, while buying decisions are preferred within the subject of peak hours, selling decisions are favored during the minimum demand.

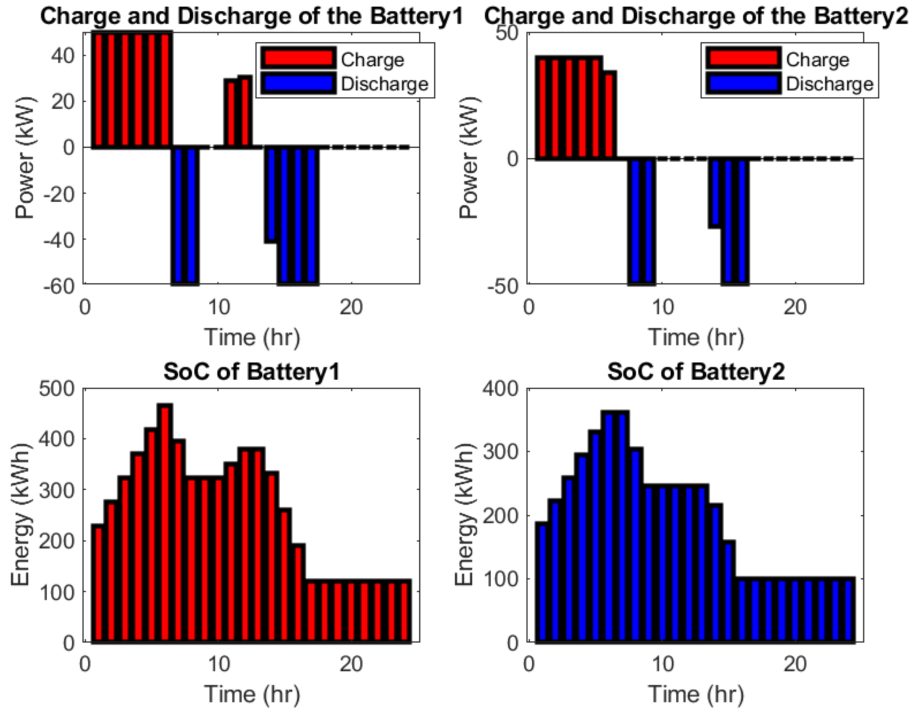

Figure 5.9. Change of SoC based on charge and discharge decisions according to Expected Value method.

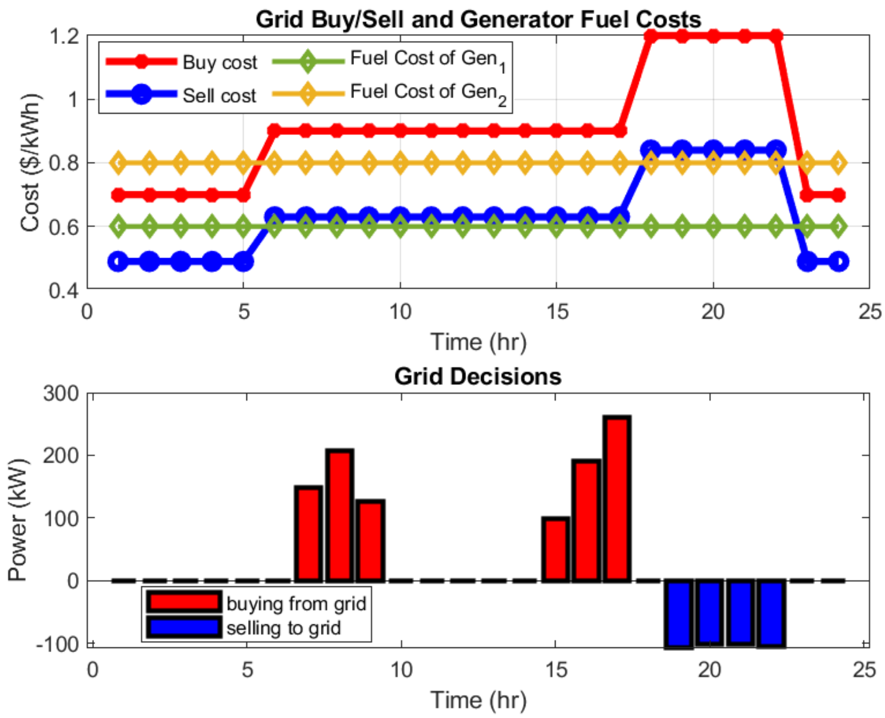

Figure 5.10. Amount of power bought/sold between grid and consumer according to Expected Value method.

In Figure 5.11, we give all the optimization outcomes of the expected value method. The range of the plot is quite narrow than the Worst-Case. In both, generator 1 is always on during the horizon, and the notable action is while making a decision of selling increasing, buying is decreasing in the grid side.

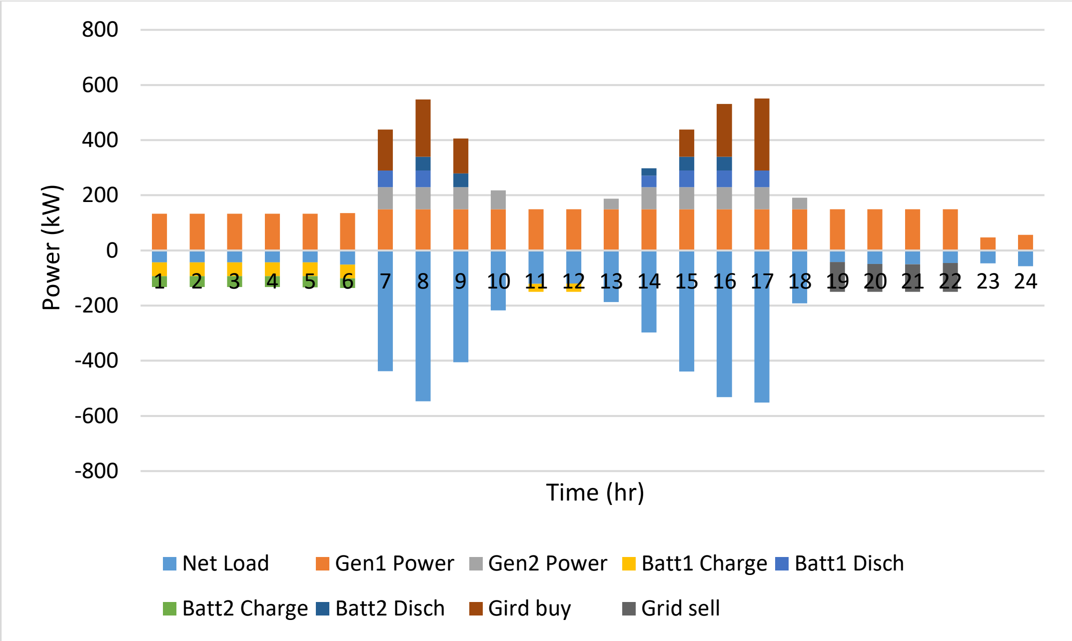

Figure 5.11. Microgrid decisions through the horizon according to Expected Value method.

The solution and formulation of the Worst-case and Expected value methods are based on a deterministic solution; however, both methods take into account the distribution of data to obtain the decision set. For these reasons, we investigate both of them under the stochastic chapter. Next, we continue to the different method, which is easy to implement, and computationally not an expensive method.

5.1.2. Chance-Constrained Method

As the net load is a random variable, we add a probabilistic constraint. We formulate the expression for the probabilistic constrain as equation .This equation allows to a violation in defined limits to increase the feasible regions (Farina et al., 2016). The solution of the proposed MILP problem by the integration of a Chance-Constrained Method is possible by taking the power balance equation based on equation (28) (see Chapter 4.2) with a minor change and without changing the objective function (see Chapter 4.1, equation (29)). The implementation of Chance-Constraint to our problem is as equation (30):

$$\Pr\left\{P^{GR-buy}(k) - P^{GR-sell}(k) + \sum_{i=1}^{N^G} P_i^G(k) + \sum_{j=1}^{N^B} P_j^{BD}(k) - P_j^{BC}(k) \geq P^{NL}(\mathrm{k})\right\} \geq 1 - \alpha, \forall i, \forall j, \forall k \tag{30}$$

where α is related to the design parameter which defines the risk of the performance and can take a value between 0 and 1;therefore, $1 - \alpha$ defines the confidence level in the management problem.

Until this point, we always tried to satisfy energy demand completely. The Chance Constrained defends that we can meet the electrical demand with a high degree of probability. In general, this probability is chosen as 90 or 95% (Birge, 2011). We get as 95%, which means there is a chance to 5% for fail and chance to 95% for the meet demand. The implementation of Chance-Constraint by taking α as 0.05 to equation (30) ensures the meet of demand mostly. The objective function is not different from the deterministic approach. We are still paying the expenditure of the microgrid system, but the difference is input. Herein, it is valuable to express, how we detect the demand. In Chapter 5, we always deal with the net load. By taking Inverse Cumulative Density Function (ICDF) of historical data of net load for every hour we detect the point that gives probability is equal to $1 - \alpha$. The value is recorded now is the demand that you should cover along delta T.

In a similar manner to the previous methods, we show our presented approach for the Chance-Constraint at 12 pm. in Figure 5.12. We apply ICDF for the entire horizon to detect the probabilistic net load vector.

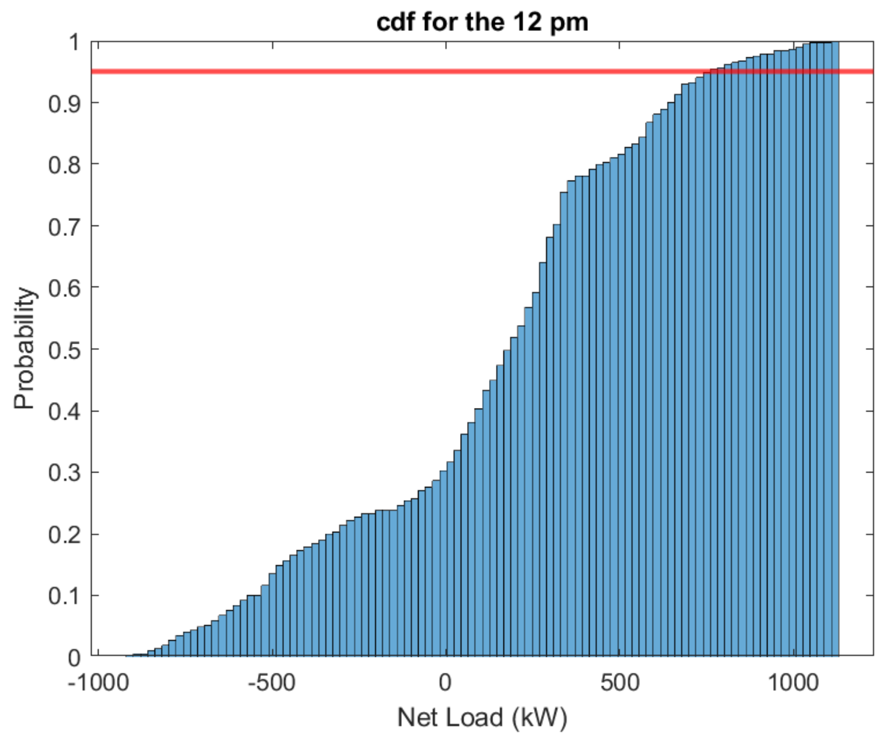

Figure 5.12. Representation of the net load Cumulative Distribution Function for the 12 pm to specify net load and corresponded probabilities by taking α as 0.05.

In the end, we just find the Nx1 demand vector P^{NL} for the 24-hours horizon. With this conversion, we appoint current electrical demand and give in Figure 5.13.

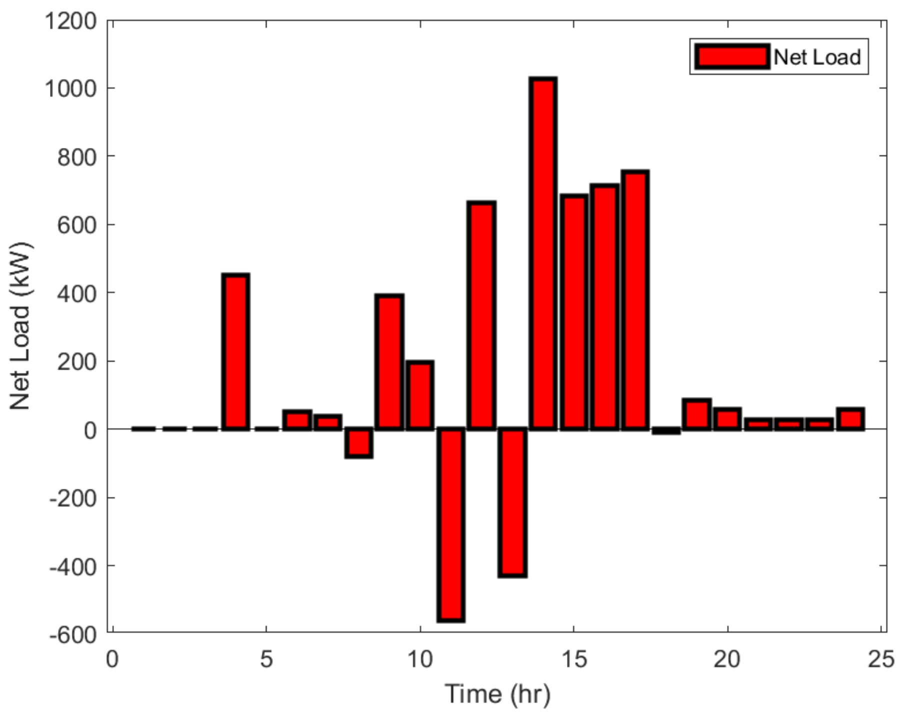

Figure 5.13. The Net Load for Every Hour based on Chance-Constrained.

In this case, we observe a couple of time generation expectation is more than consumption. In several intervals, we record zero net loads. On the other hand, the magnitude of peak hours in kW is between Worst-Case and Expected Value.

To compare system decisions of Chance-Constrained with Worst-Case and Expected Value, we give the MPC results of the current method in Figure 5.14, Figure 5.15, Figure 5.16 and Figure 5.17, respectively.

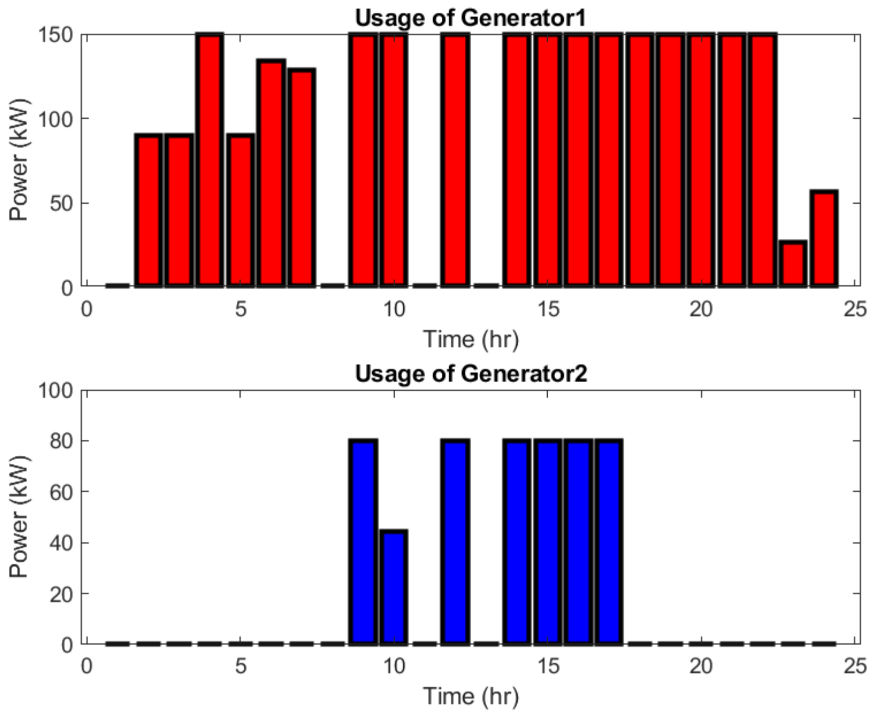

Figure 5.14. Generator decisions for the Chance-Constrained.

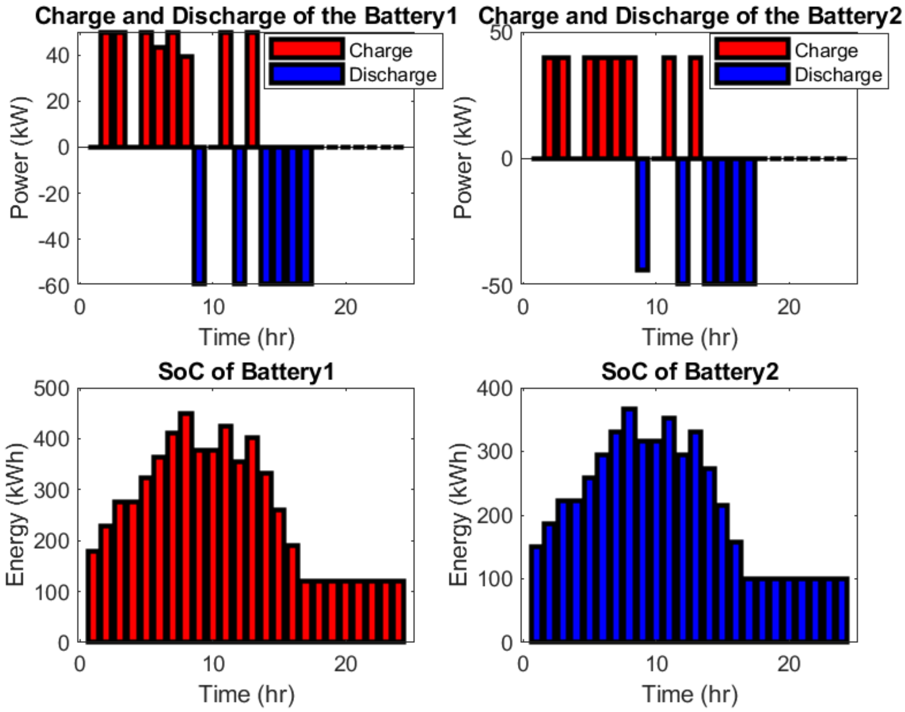

Figure 5.15. Change of SoC based on charge and discharge decisions according to Chance-Constrained.

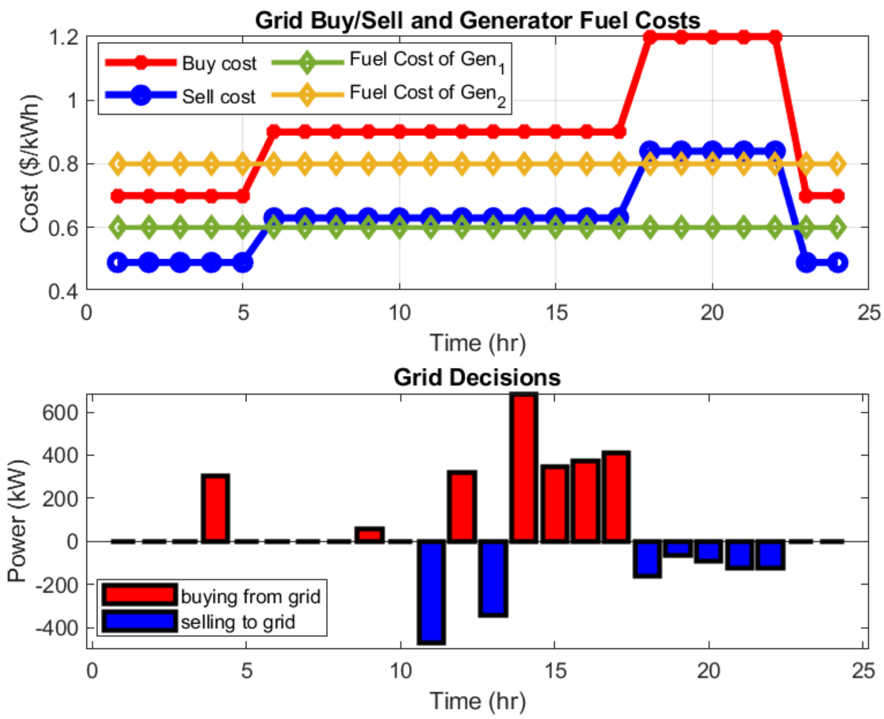

Figure 5.16. Amount of power bought/sold between grid and consumer according to Chance-Constrained.

Although we encounter a higher level of demand in the Chance-Constrained Method, the movement on the side of profit is more than the previous approach.

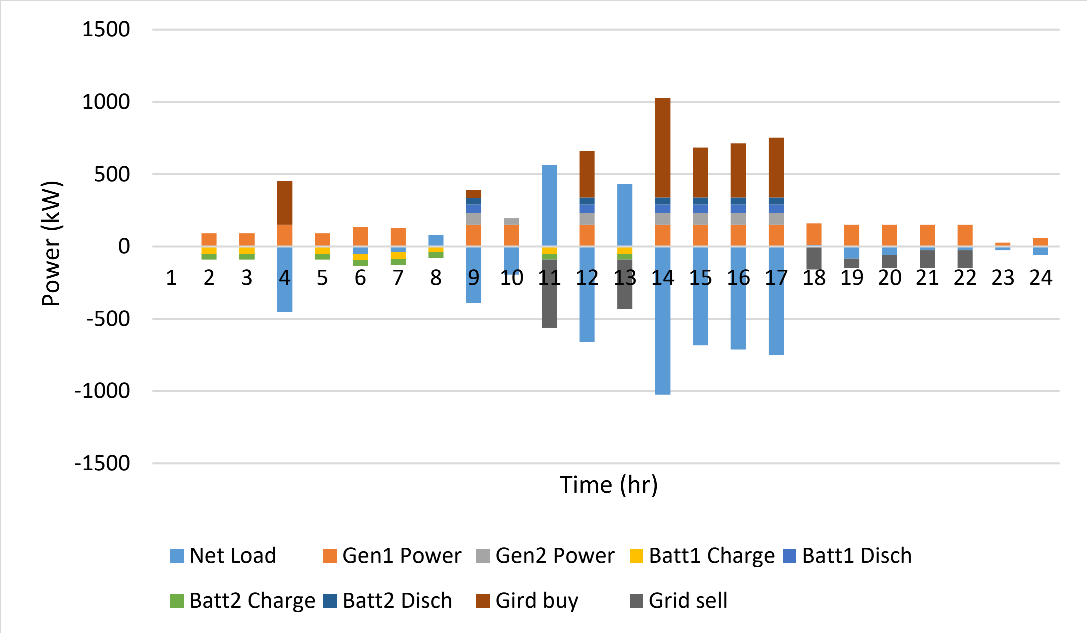

Figure 5.17. Amount of power bought/sold between grid and consumer according to Chance Constrained.

5.1.3. Two-Stage (Recourse) Method

In this case, we have to make a set of decisions without the complete knowledge of some random events (net load demand) such decisions are called “first-stage decisions” or “here and now decisions”. Then, because of the realization of those random vectors, complete information is obtained for the net load. After that, the second stage or corrective actions are taken for microgrid energy management and it called as “second stage decisions” or “wait and see decisions”.

Random vector ξ has a finitely supported distribution ξ, in other words it takes $\xi = \xi_1, \dots, \xi_h$ (called scenarios) with respective probabilities $p_1, \dots, p_h$.

For a realization of the random demand vector ξ, we can find the optimal solution with linear programming problem:

$$\min\ ((f^T x) + (q^T y)) \tag{31}$$

While x representing first stage decisions, y represents the second stage. In this thesis, only net load gives the uncertainty to the problem, and we prefer to limit the second stage with only grid decisions. At the first stage, it has to be taken a set of decisions x on random net load ξ, at the second stage, after realization of demand becomes known; necessary grid actions y can be taken. In this case, we update the formulation of the MILP with adding some probability terms to the objective function and solving many power balance equations as many as the proposed number of scenarios for the second stage part. Only grid decisions include probability terms. Of course, we write the objective function with respect to their probabilities. We can write the second-stage part of the objective function as in equation (32).

$$\sum_{h} p_h \left(\left(P_h^{GR-buy}(k) C^{GR-buy}(k) \right) - \left(P_h^{GR-sell}(k) C^{GR-sell}(k) \right) \right) \tag{32}$$

where h is the number of scenarios that we will solve.

More specifically, we can formulate the objective function instead of equation (29), we arrange the second-stage decisions of objective function as equation (32) and integrate into the objective as we completed in equation (33).

Grid decisions are the only option to bring into balance for every load demand. On the contrary to D-MPC, two-stage method solves power balance equations as many as the number of scenarios. Power balance equation of our problem as in equation (34).

$$\begin{aligned} \min \sum_{k=t+1}^{t+24} \Bigg(\sum_{i=1}^{2} \Big(& P_i^G(k)(C_i^{G-PC} + C_i^{G-LC}) + C_i^{G-SU} \alpha_i(k) + C_i^{G-SD} \beta_i(k) \\ & + C_i^{G-I} z_i(k) \Big) + \sum_{j=1}^{2} \left(P_j^{BC}(k) C_j^{B-LC} + P_j^{BD}(k) C_j^{B-LC} \right) \\ & + \sum_{h} p_h \Big(\left(P_h^{GR-buy}(k) C^{GR-buy}(k) \right) \\ & - \left(P_h^{GR-sell}(k) C^{GR-sell}(k) \right) \Big) \Bigg) \end{aligned} \tag{33}$$

s.t.

$$\begin{aligned} P_h^{GR-buy}(k) - P_h^{GR-sell}(k) + \sum_{i=1}^{2} P_i^G(k) + \sum_{j=1}^{2} P_j^{BD}(k) - P_j^{BC}(k) - P_h^{NL}(\mathrm{k}) \\ = 0 \,, \forall i, \forall j, \forall k, \forall h \end{aligned} \tag{34}$$

In fact, the stochasticity is related to both load demand and PV output power as we mentioned before. To solve this, the distributions of data are generated based on historical data. If we know the distributions, it is possible to create finitely many possible paths we call scenarios. Instead of checking both PV and load distribution, we prefer to work with net load and represent the possible future with as few as scenarios. We prefer to study with histograms based on yearly historical net load. Since we started to talk about scenarios, the formulation is refreshed for the two-stage method. The probability part is related to only grid decisions because we preferred to compensate for uncertain load with the electrical grid only. In this situation all the battery storage and electrical generator decisions are made before the realization of net load in the first-stage, then we take the grid decisions as buy or sell based on the amount of net load in the second-stage.

To solve this problem, we divide the histogram of each hourly net load distribution into 5 parts for every hour. We demonstrate this explanation and procedure in Figure 5.18 for the 12 pm.

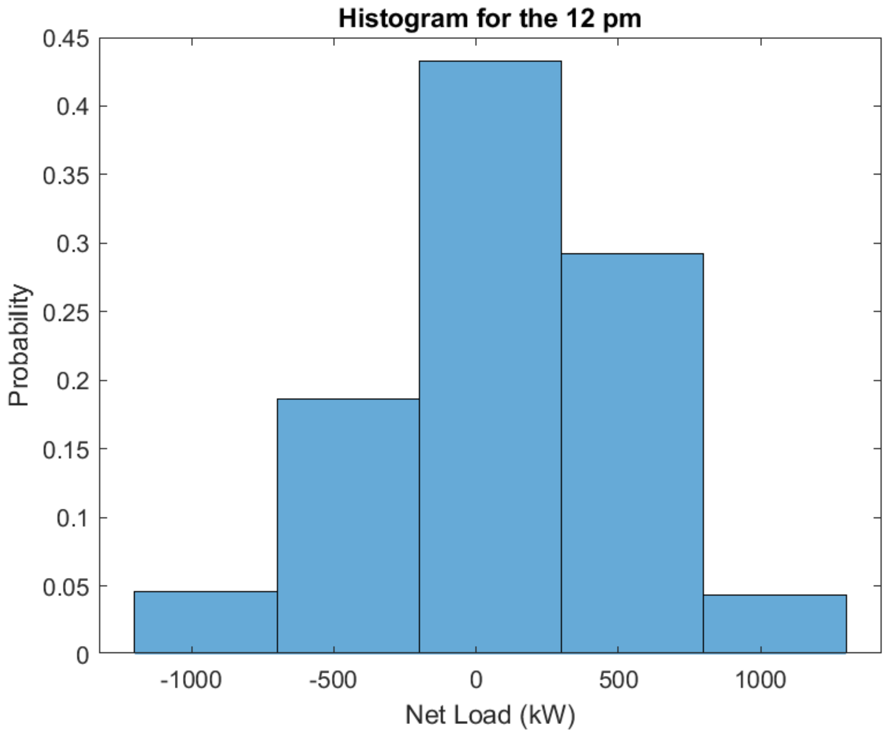

Figure 5.18. Histogram of the net load time series for the 12 pm.

Even the single hour division brings five possible scenarios, this procedure is valid every single hours. In this case, the number of possible scenarios is equal to $5^{24} = 5.96x10^{16}$. Of course, to check all these paths is computationally expensive and takes a long solution time. Therefore, we apply the scenario reduction method to detect a reasonable number of scenarios. Figure 5.19 demonstrates the scenario tree for the following 24 hours by including all the possible paths.

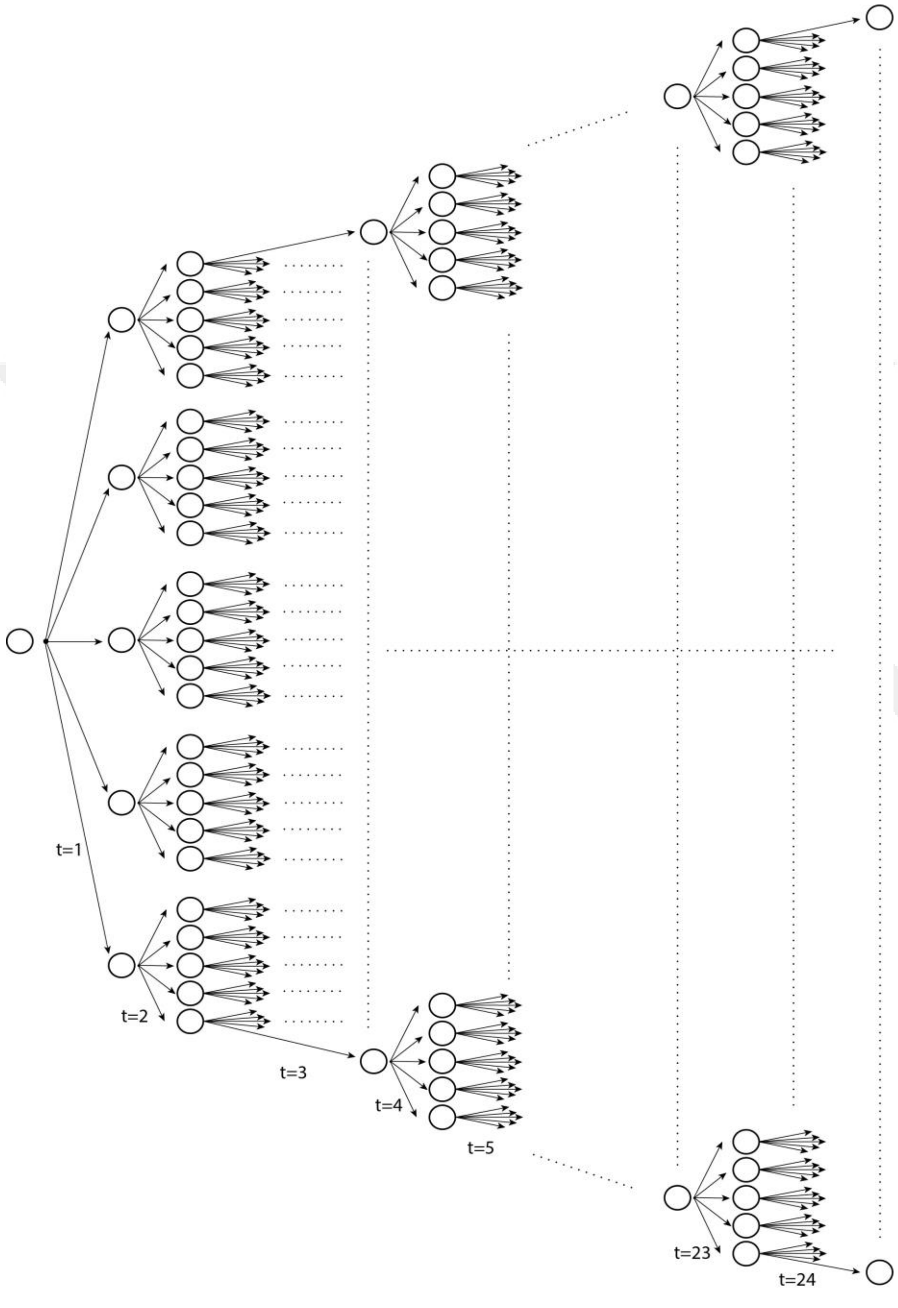

Figure 5.19. Representation of scenario tree for the horizon before scenario reduction applied.

The recourse model works with a scenario set and corresponding probabilities; thus, we define the road of scenario generation and their probabilities and illustrate these steps in Figure 5.20.

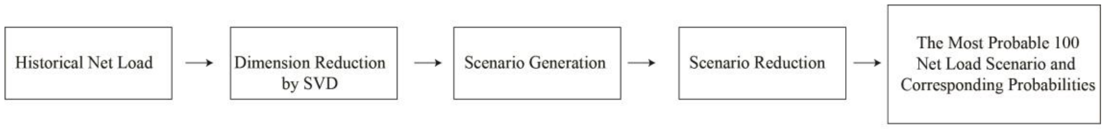

Figure 5.20. The general arrangement details of scenario generation for the proposed two-stage (recourse) method under the stochastic approach.

We present all the details of the dimension reduction, scenario generation, and finally reduction below.

Scenario Generation and Reduction:

There are many ways to reduce the number of scenarios. Reducing of dimension is one of the valid methods. Historical raw data includes precious and hidden information, so we can extract the necessary information by investigating the raw data. In machine learning, this hidden information is discovered by the help of eigenvalues and eigenvectors. Generally, by using Principal Component Analysis (PCA) and Singular Value Decomposition (SVD), we can understand the prominent parts that have the largest information of the data. The important point is reducing dimensionality and complexity without losing accuracy and generality. If we can explain the data with fewer components, we may reach better knowledge without loss of information and study with less effort for both analyzing and plotting (Alpaydin, 2004). The much more details of the PCA can be found in this press. While SVD helps to create fewer components that explain still the general, PCA eliminates non-crucial components. The basic idea is using SVD to specify expandable components in the original SVD matrix to find PCA. We accomplish the reduction of the dimension by using SVD is highly relevant to PCA in many approaches. While PCA works with only a square matrix, SVD is the solution to this as A can be an arbitrary (mxn) matrix. This proves that SVD is a more robust and overall method for altering of basis and decreasing dimensions (Cynthia, 2019). Also, SVD provides a computationally efficient way of actually locating PCs and provides further insight into what a PCA really does, and it offers valuable means of representing the effects of a PCA, both graphical and algebraic (Jolliffe, 2002).

A yearly-recorded net load 24x365 is considered as x, but we apply SVD on X, which is equal to the difference between x and an hourly average of x to center the data and study with zero-center. There are 24 features represented by rows and 365 observations represented by columns, and we are trying to explain X with fewer “r” features. Before implementing and deciding anything, we analyze importance of eigenvalues to perceive possibility of reduce dimension in the demand data.

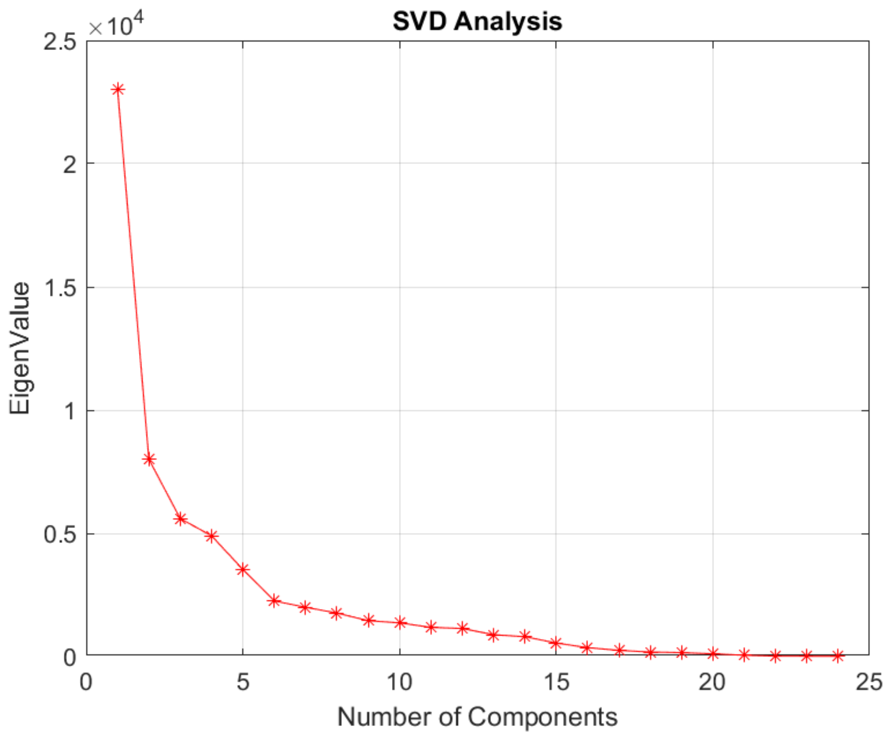

Figure 5.21. SVD analysis for understanding the importance of components based on eigenvalues.

As we can from Figure 5.21, after some points number of components do not help to explain data. However, we present further analysis and specifying procedures to decide what the efficient reduced size is; thus, we continue to the SVD. X matrix can be decomposed into factors by using SVD as in equation (35).

$$X = U\Sigma V^{-1} \tag{35}$$

U and V are orthogonal matrices with orthonormal eigenvectors and Σ is a diagonal matrix (Orumie & Onyinyechi, 2019). The square root of diagonal elements gives the singular values. We created the T transformation matrix by reducing the number of basis from 24 to r by using the orthonormal P matrix.

$$Z = T'X \tag{36}$$

In equation (36), the new Z matrix has r rows and m columns as much simpler and still the descriptive for the data set. We determine to r by measuring SMAPE. r is selected while comparing the mean of SMAPE between X and TZ multiplication for different values which shows various descriptor levels for the whole data set.

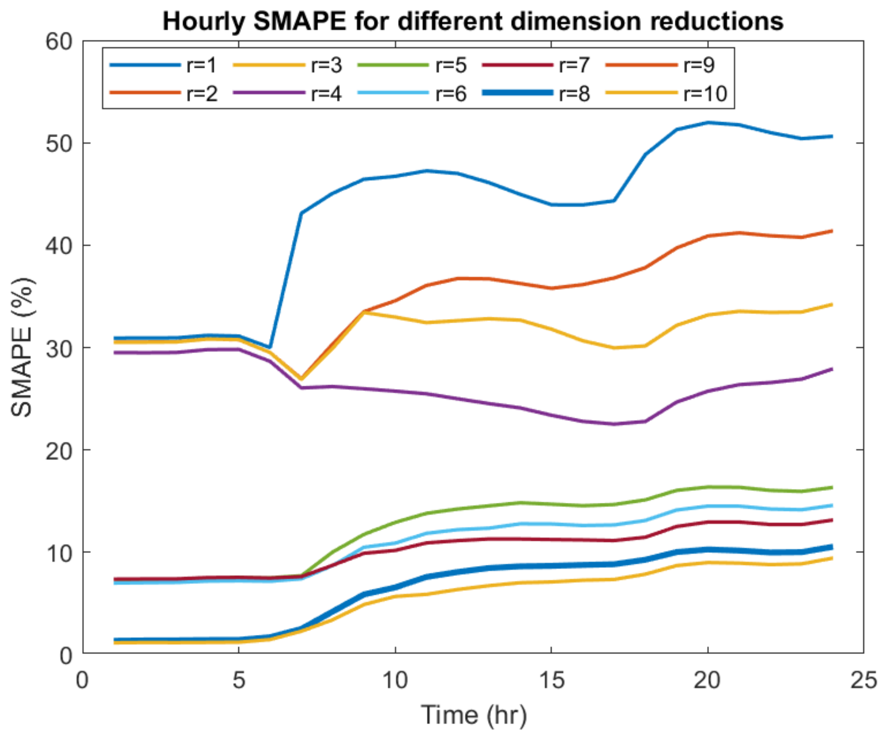

Figure 5.22. Hourly SMAPE (percentage) for different number of reduced singular value of the net load.

We catch the noticeable positive progress without increase complexity needlessly at a level 8. There are three different levels in Figure 5.22, when the number of singular value is equal to four (purple line); this situation causes a high-level error, with 5, 6, and 7 singular value represents the model close performance. The investigation of 8 singular value (thicker blue line) presents observable and desired progress with under 10% SMAPE. Figure 5.23 illustrates that eight features capture the movements and character highly successfully of the data set. We prefer to present this comparison plot for a weekly range of any randomly chosen to see readably. It is possible to go further captures by increasing the number of singular value, but we should aware of increasing complexity cause some damages in the application.

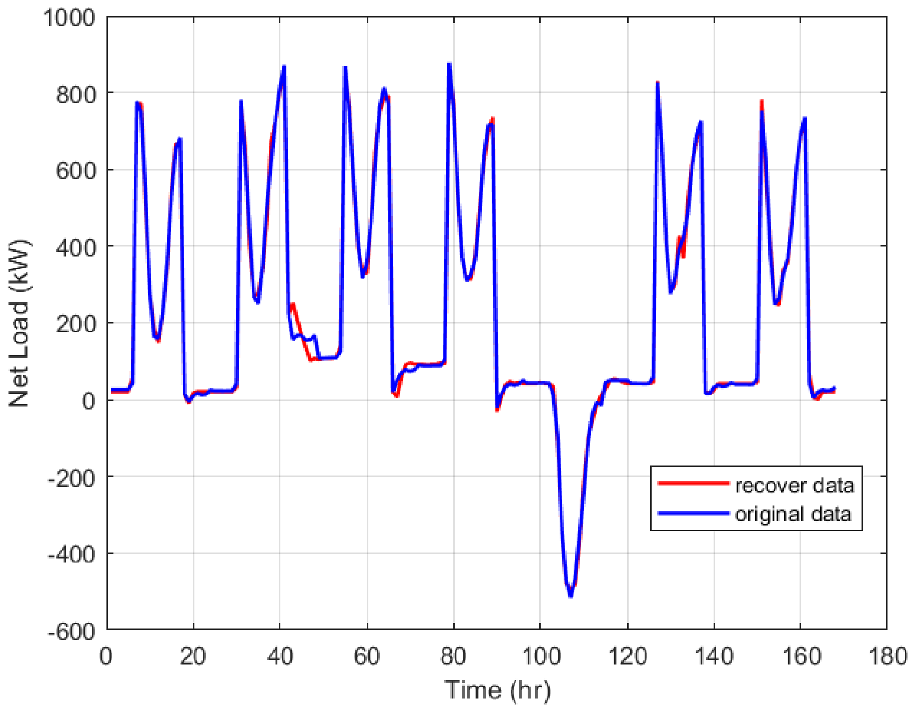

Figure 5.23. Comparison of original net load and the recovered data after the reduction of the dimension.

Results of Scenario Generation by Dimension Reduction:

Instead of proceeding with 5^{24} huge of the number of scenarios, with the dimension reduction approach, now we can study with 8 components. Even with this, the new Z matrix still covers the more than 80% of the knowledge and character of data. Therefore, the total scenario is equal to $5^8 = 390625$. However, it is still quite a large number for integration to the S-MPC problem. We give the representation of the scenario tree in Figure 5.24 to show how the number of scenarios exponentially increases even for 8 components and why we need to still reduce the number of scenarios.

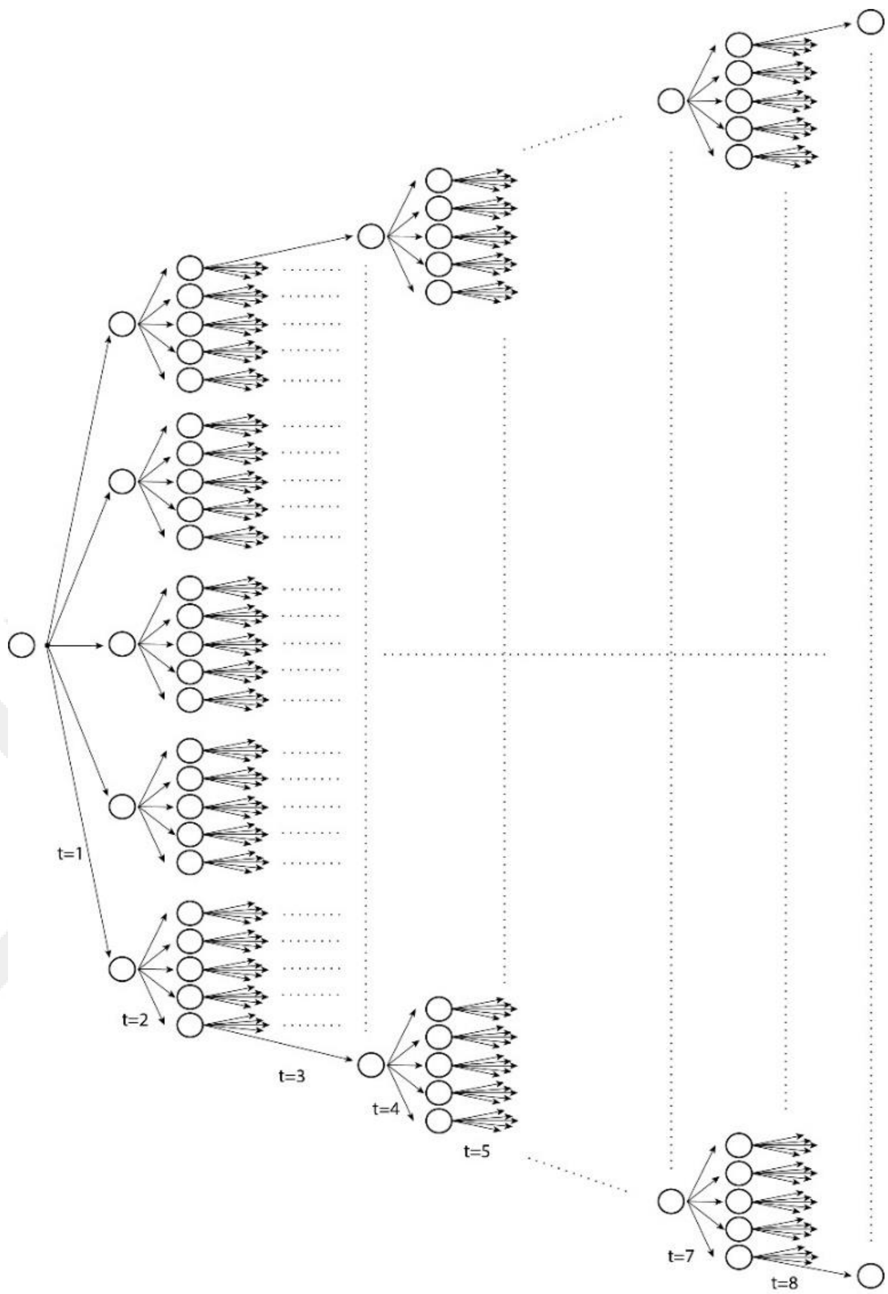

Figure 5.24. Representation of scenario tree after the dimension reduction.

The final step related to scenarios is to generate all possible ($5^8 = 390625$) ones and eliminate low probabilities. Instead of analyzing each one, we decide to choose the 100 scenarios, which have the highest probabilities. We prefer to limit our scenario numbers since the computer is not capable of solving a large number of scenarios within a reasonable time in the optimization problem. Figure 5.25 represents the chosen scenarios that have the highest probabilities and Figure 5.26 indicates the corresponding probability values to these loads. After the selection of the scenario set, we arrange the probabilities of the selected group so that their summation equals to 1.

As we mentioned before, the first stage decisions relate to electrical generators and battery storage units. This means no matter which scenario or demand occurs, these decisions will not change. Figure 5.27 and Figure 5.28 shows these generator and battery decisions and change of SoC along the horizon. Almost all scenarios have a common point that the demand is relatively low and plateau between 20.00 pm and 5.00 am. In light of this information, it was an expected fact the minimum usage level for both generators corresponds to this interval of time. Here, although startup, shutdown, and lifetime costs are lower for the second generator, the first generator which has a lower fuel cost for the unit energy is in demand. We conclude the unit fuel cost is quite effective in the decision mechanism of this optimization.

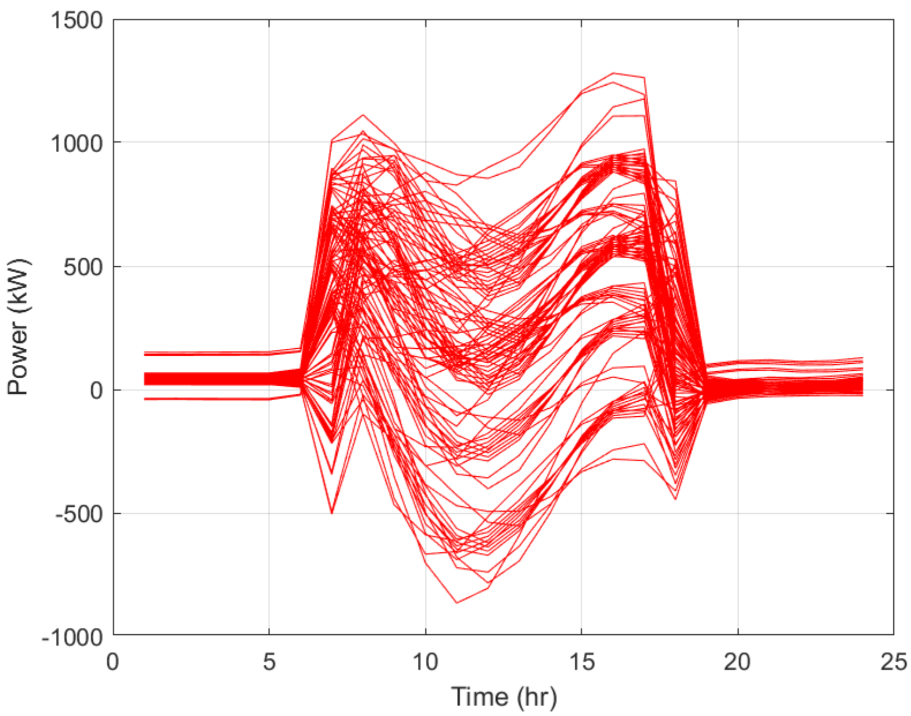

Figure 5.25. 100 sample of net load scenarios, which is the most probable ones.

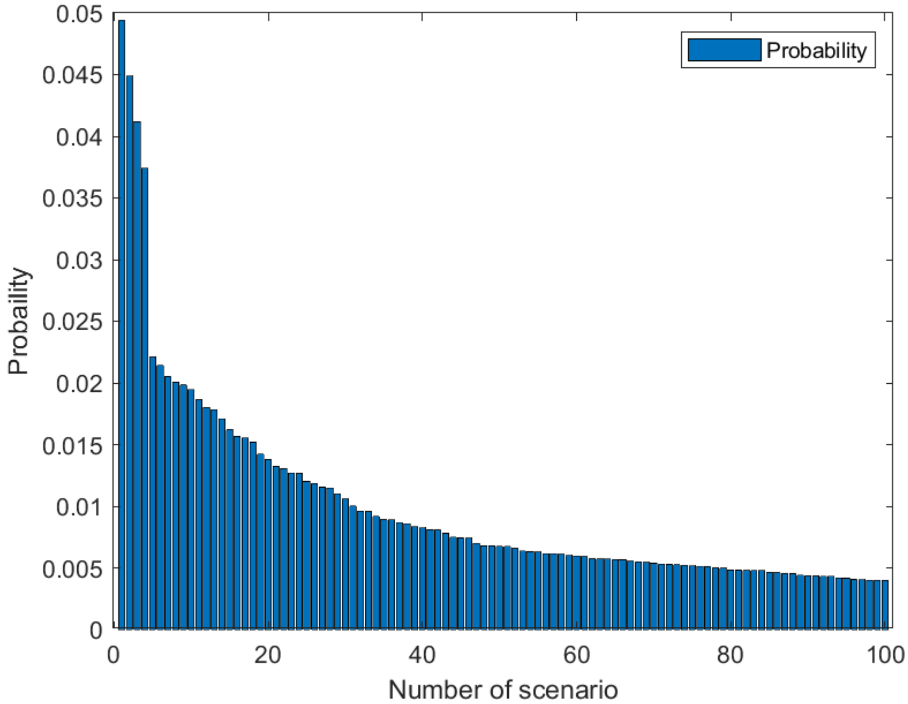

Figure 5.26. Probability of each scenario.

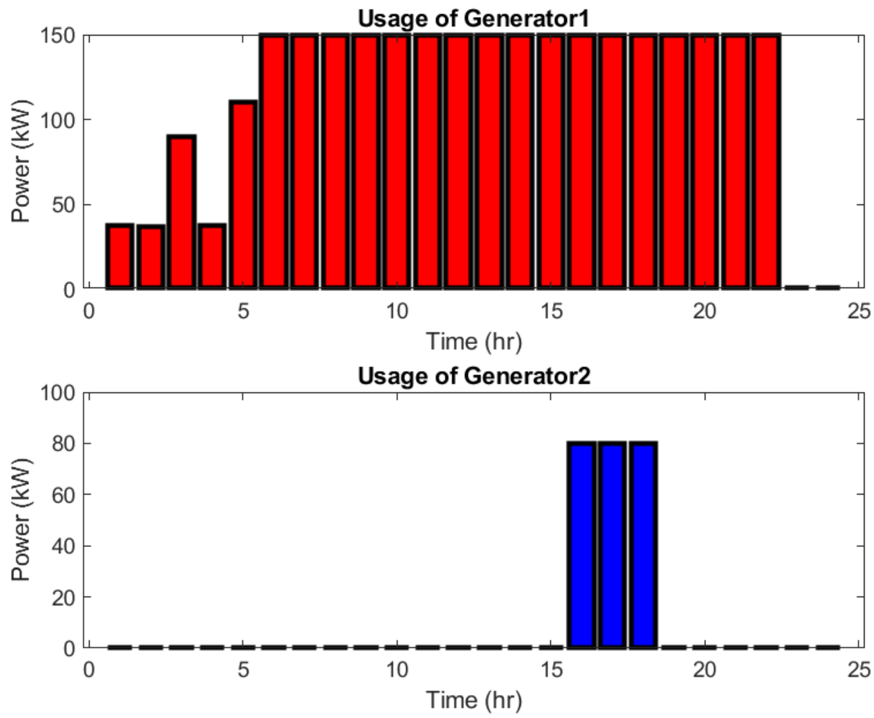

Figure 5.27. Two-stage decisions for the generators.

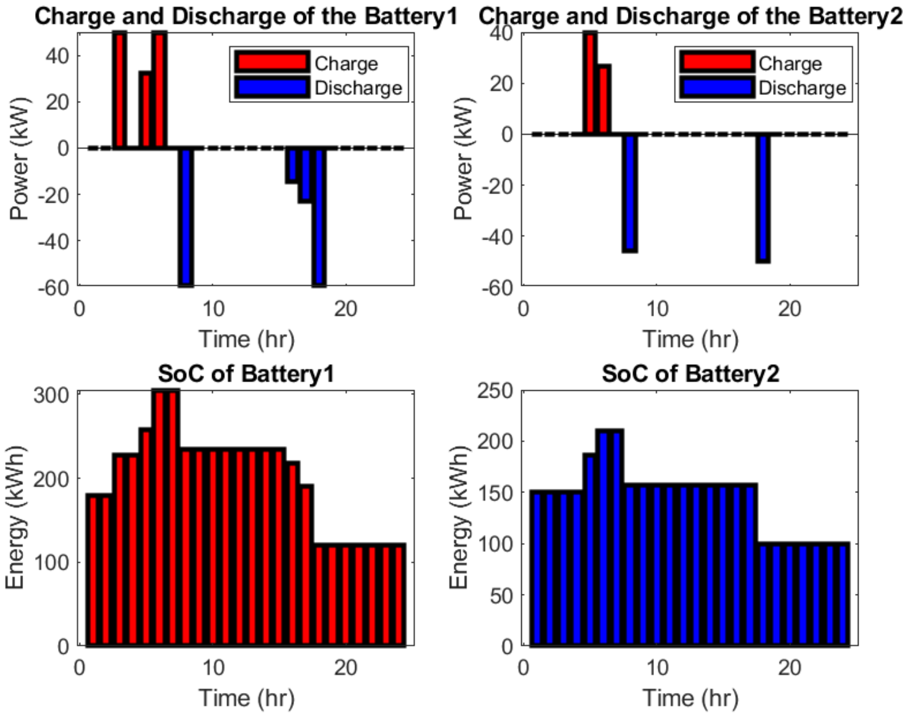

Figure 5.28. Change of SoC based on charge and discharge decisions.

In parallel to the actions of controllable generators, charging acts are in the early morning, and on the other hand, the discharging processes occur in both high demand and relatively high grid cost.

Figure 5.30 presents all decisions except the decisions of the main electric grid. After the first level decisions completed according to the expected 100 scenarios of the net power demand, the plus or minus part of the amount of energy needed will be net off with the main grid. In order to exemplify this, we demonstrate the decision set of grid buy/sell in Figure 5.29, with respect to the most probable scenario. The trend of the bar and line have similar ups and downs.

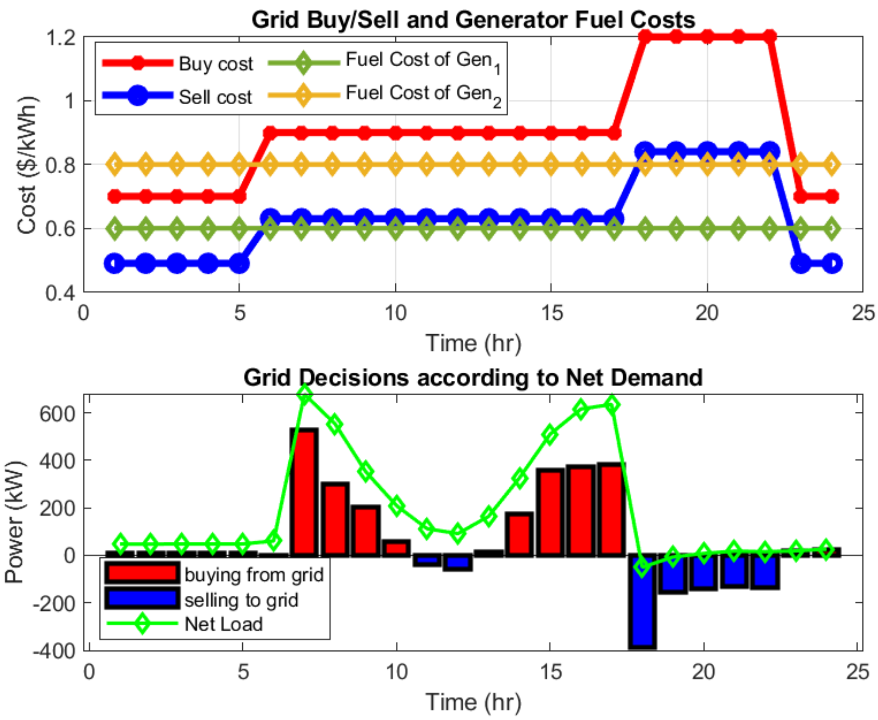

Figure 5.29. Amount of power bought/sold between grid and consumer for the most probable scenario.

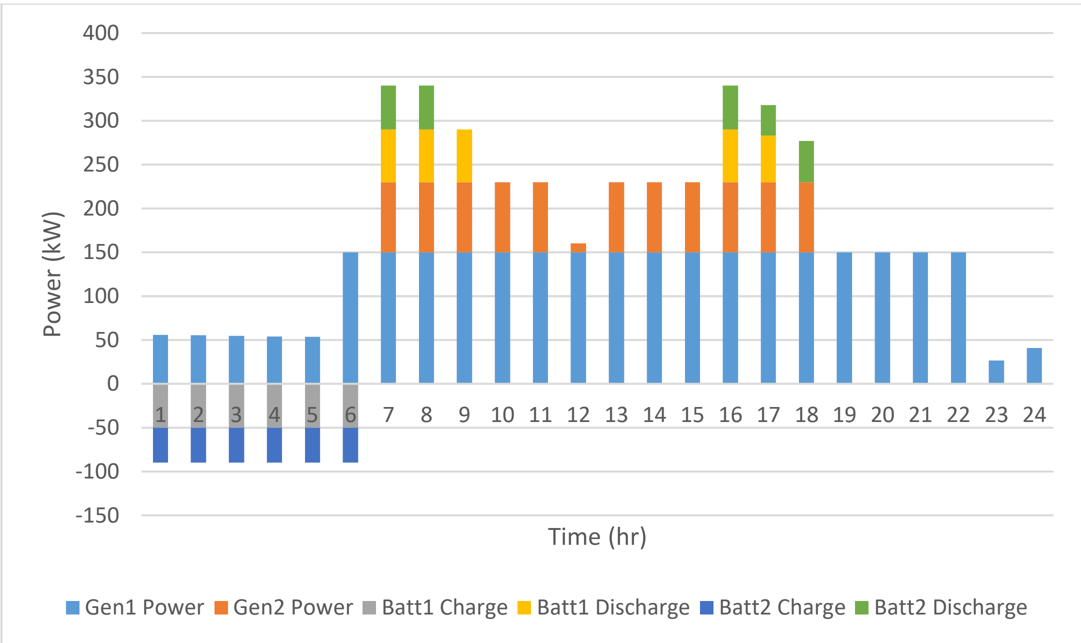

Figure 5.30. First stage decisions of energy management problem of microgrid.

We give expected daily operational costs of each method in Table 5.1.

Table 5.1. Comparison of control strategies for all S-MPC approaches.

Control Strategy	Total Operational Cost
Worst-Case	16138
Expected Value	3391.4
Chance-Constrained	3376.8
Two-Stage	3572

The Table 5.1 indicates that while the worst-case method gives the unnecessarily high cost, the expected value and chance-constrained are really close to each other. On the other hand, the two-stage solution shows a relatively higher cost than chance-constrained and expected value solutions do for the same day. If we solve the same day by using perfect knowledge that refers to the realized net load for the same day, the cost is equal to 6271. The results point out that we cannot give certain comments based on the solution of a single day. For this reason, we will take the comprehensive results for all year in Chapter 6.

5.2. S-MPC based on both Distributions and Forecasts

In this study, the third and the last approach for the MPC is hybrid solution. The basic idea is accurate forecasts help to minimize the cost; however, we should take into consideration the uncertainty of these deterministic forecasts. While chapter 4 presenting these point estimations by looking recent past, chapter 5 gives the stochastic attitude on yearly-based data. Here, we propose a hybrid approach that helps the usage of deterministic forecasts in a stochastic manner.

5.2.1. Worst-Case and Expected Value Method

In this method, we implement the same procedure with Chapter 5.2.1. However, we change the input matrix by adding the net load forecasts into the yearly forecasting error instead of yearly-recorded net load data, with the aim of employing more information related to the next day that we run the MPC. Worst-case method cause to extreme overestimation of electrical demand, because it specifies the net demand by taking into consideration the highest load for the entire period. Figure 5.31 illustrates the all decisions for the entire period of the next day. We also show the obtained load demand by this process.

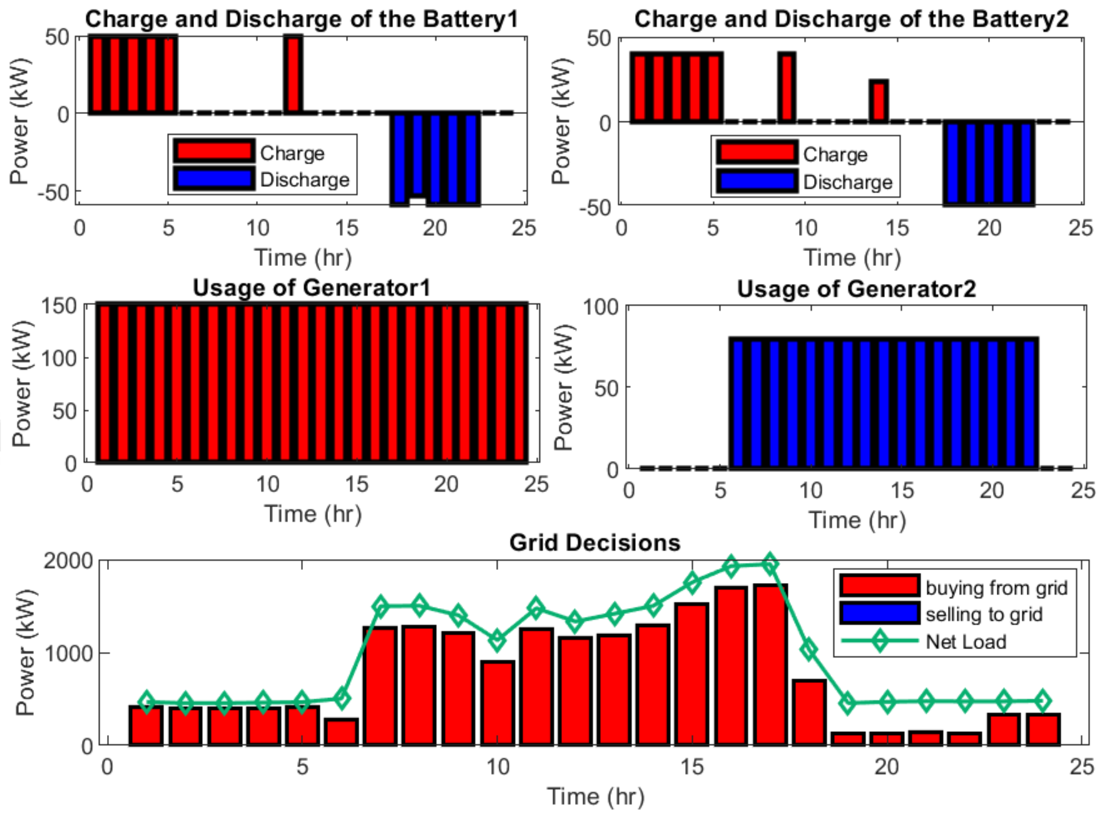

Figure 5.31. Battery, generator, and main grid decisions of H-MPC in Worst-Case method.

Load demand that is the input of MPC highly influences the decisions of controllable components. Whereas worst-case takes the highest power, each generator is usually active during the considered period and both battery units deploy to store during low energy prices and discharge in the reverse conditions. On the other hand, the main grid is always able to cover the missing power since there are some boundary constraints related to other components than the grid.

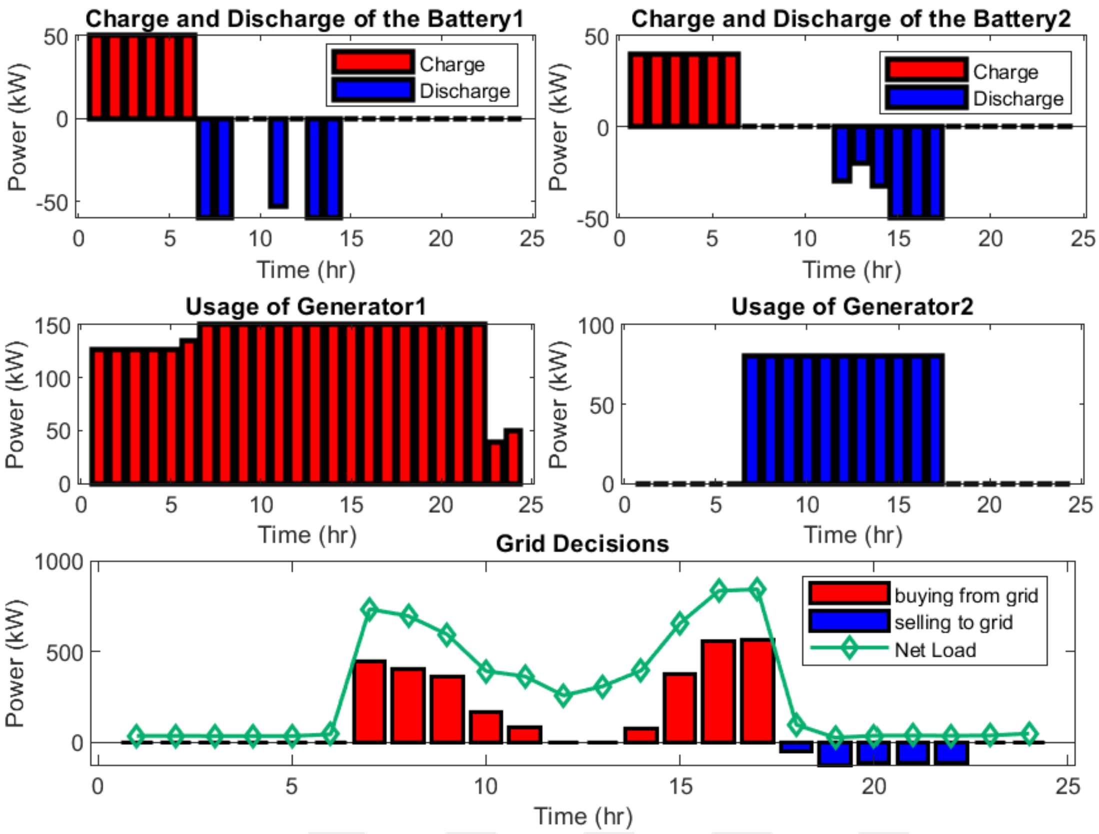

Figure 5.32. Battery, generator, and main grid decisions of H-MPC in Expected Value method.

Although the worst-case solution brings overestimated demand and corresponded unrealistic decision set, it underlines the being aggressive is not a solution to help to meet the demand and minimize the operational cost at the same time. In a similar manner with Chapter 5.2.1, we implement the expected value method to be more realistic to the same demand matrix. The obtained MPC results are in Figure 5.32. Still, we use electric generators densely; however, in this case, the net load is around the average during midday. Even it seems possible to sell to the grid during higher electricity costs to earn more money.

5.2.2. Chance-Constrained Method

We already have formulated the chance-constrain method. With the change of input set, we know the decisions related to microgrid management. Therefore, we apply the same approaches in Chapter 5.2.2. We give the obtained current power set points in Figure 5.33.

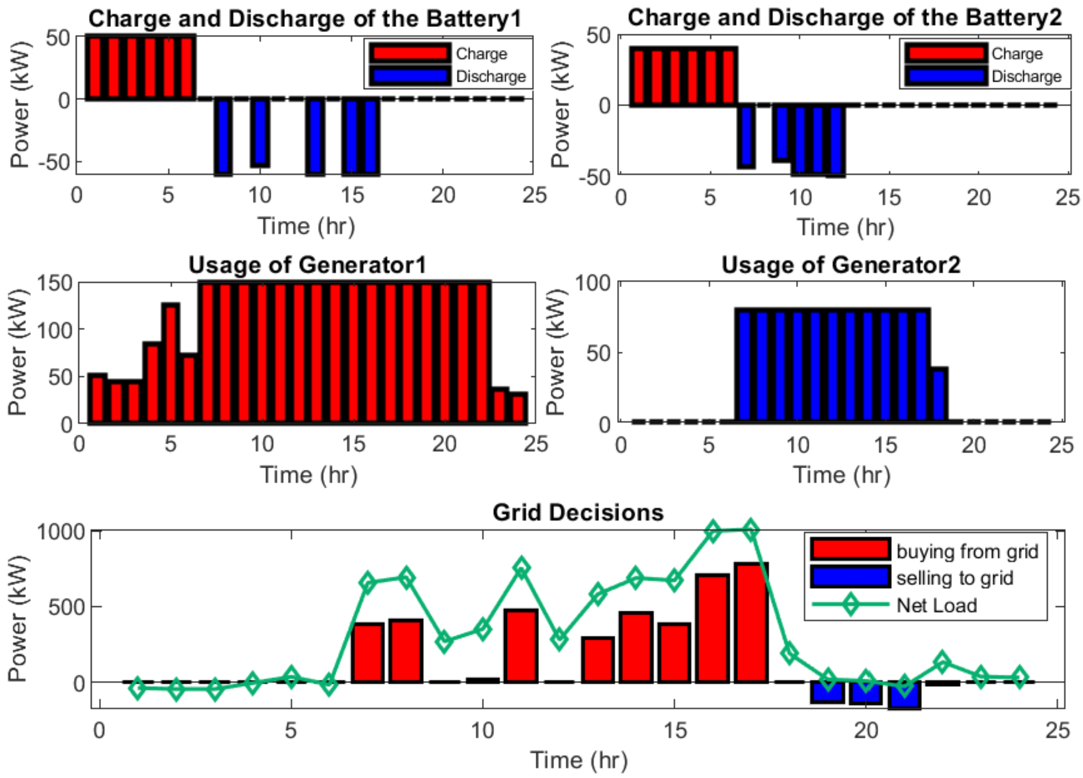

Figure 5.33. Battery, generator, and main grid decisions of H-MPC in Chance-Constrained method.

5.2.3. Two-Stage (Recourse) Method

In H-MPC solves the microgrid problem with the same attitude in Chapter 5.1.3. Naturally, the objective function and power balance equation are the same with equation (33) and (34). However, the net load scenarios and corresponding probabilities that are provided by the histograms change and we solve the problem with the new scenario set with respect to all microgrid constraints. We propose two approaches related to the constitution of new scenario sets under the scope of integrating point estimations with the histogram of the time series. The first approach is relatively simpler and this solution defends making some corrections on the previous results that we already have. This approach defends making some corrections on scenarios that we generate in Chapter 5.1.3 by using net load forecasting.

On the other hand, the second approach supports using knowledge about the histogram of forecast error. We believe the hourly average forecasting errors helps to arrange point estimations in a realistic way. We illustrate the flow of both approaches in Figure 5.34.

To use previously generated demand scenarios, we should shift each value in the set as much as the difference (Δ) between point estimations that use as input in D-MPC in Chapter 4 and the hourly mean of the net load scenario set.

$$\Delta = F_{NL} - \mu_{\bar{S}} \tag{37}$$

F_{NL} is forecasted net load, $\mu_{\bar{S}}$ is an average of every hour for the day. This Δ represents the diversion of the mean from forecasting and we can estimate as written in equation (37). When we add the Δ into constituted scenario set, we can obtain the combination of the historical data and 24-hour forecasts of the net load. This hybrid frame is valuable since it keeps the hourly net load out of big diversions and takes consideration into to very recent past. We can mathematically express the scenario set of Hybrid Approach-I as in equation (38).

$$H_{L_1} = \widetilde{S_L} + \Delta \tag{38}$$

where, $\widetilde{S_L}$ is the scenario set of the net load, which is the obtained in the previous Chapter 5.1.3.

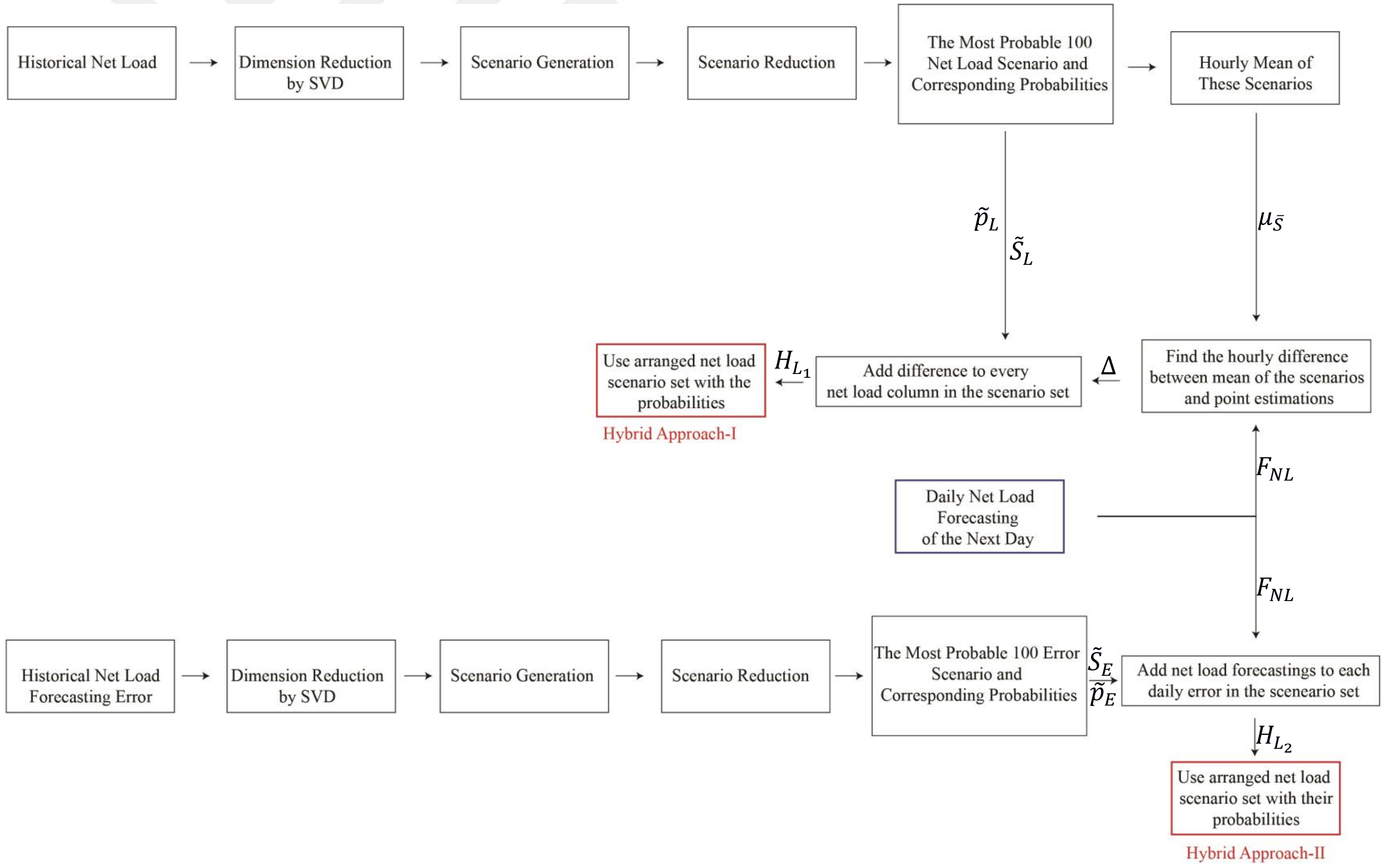

Figure 5.34. The general arrangement details of scenario generation for the proposed two-stage (recourse) method under the hybrid approach.

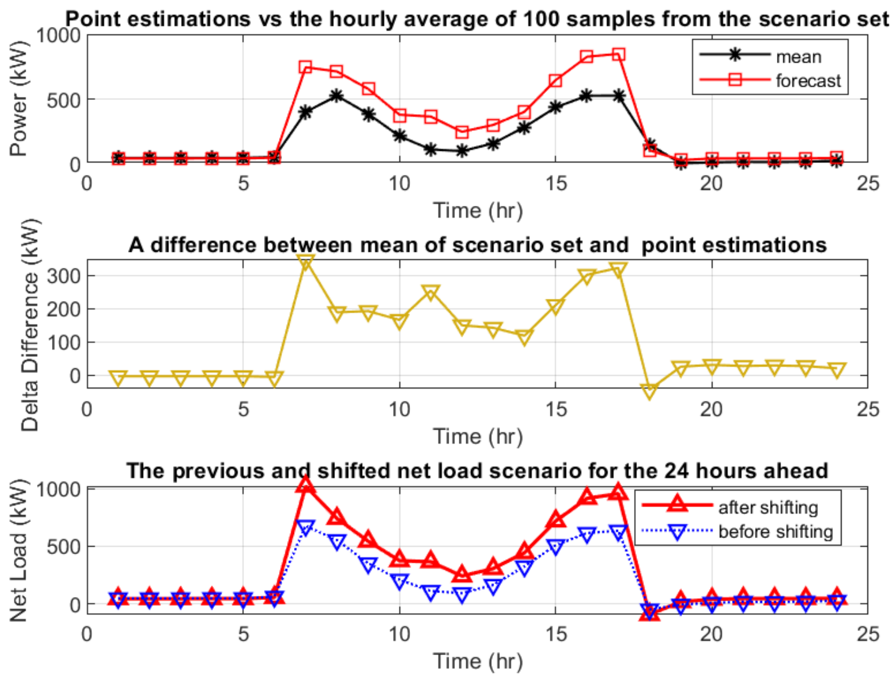

Figure 5.35. Representation of Hybrid Approach-I on a sample.

Figure 5.35 visualize this hybrid process in 3 parts, starts by selecting a scenario from the generated set in the first graph, then draw the difference between forecasted net load and average of the scenario set. Finally, we achieve the last version of one of the net load scenarios when we add this difference to the previously selected scenario.

In the first hybrid approach, of course we apply the same procedure to the every scenario in the set. The last version of the reorganized scenario set is as in Figure 5.36. It should be noted that we preserved the obtained corresponding probabilities from the previous chapter without making any change.

The second approach comprises the combination of forecasting error for the 24 hour with point estimations that comes from forecasting studies. We believe that if we know the hourly forecasting error than we can present a realistic scenario set of the net load by combining point estimations and these errors.

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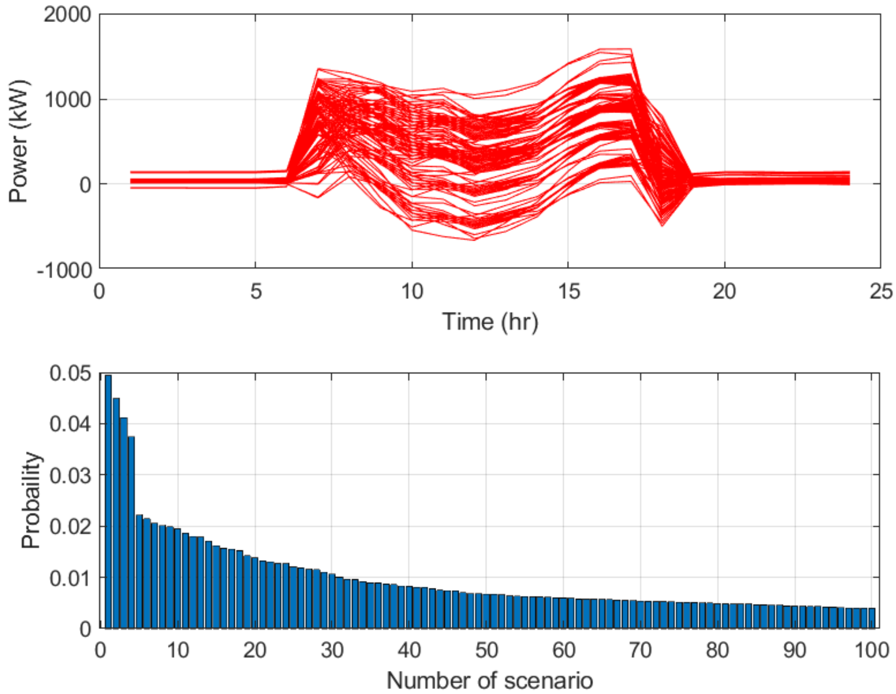


Figure 5.36. 100 most probable net load scenarios that are found at the end of the Hybrid Approach-I, and their corresponding probabilities.

As we show in Figure 5.34, to do this, we generate a new 100 scenarios based on the forecasting errors, then we add the 24 hours ahead point estimations into this scenario set. Thus, now we obtain generated a new scenario set by the help of (39).

$$H_{L_2} = \widetilde{S_E} + F_{NL} \tag{39}$$

where, $\widetilde{S_E}$ is the scenario set of the forecasting error and H_{L_2} is the net load set of the second hybrid approach. To find $\widetilde{S_E}$, we apply the SVD method to a matrix of forecasting errors to generate error-based scenarios. This time X matrix is equal to the difference between 24x365 historical forecasting errors and the hourly average of these errors. The rest of the process until to finding reduced single component is quite same, by using equation (35) and (36) we find the new component number for the forecasting error By checking SMAPE results of each tried number of singular values, we decide to take "r" is equal to 9. The reason is the considerable progress in the ability to express the model mostly is observed on 4, 6, and 9 components, but the daily average of the SMAPE falls under the 10% after 9 value, as we illustrate in Figure 5.37 with the thicker line.

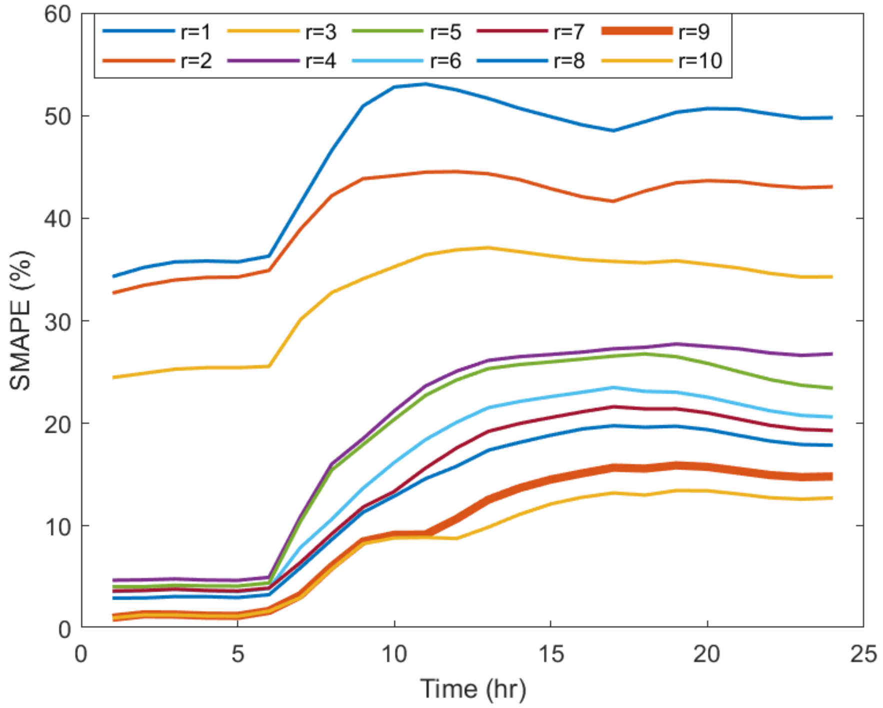


Figure 5.37. Hourly SMAPE (percentage) for different number of reduced singular value of the forecasting error.

We can still increase the number of components, but this increase brings complexity and unreasonable solution times unnecessarily. Figure 5.38 shows the general capacity to express the data set of forecasting error by using 9 singular values. Error data is noisier according to the net load; thus, the performance of the error model may have difficulty to catch the sharp-edge of the error. To analyze this situation, we take randomly a month to show the general performance and illustrate in Figure 5.38.

The scenario generating approach is based on the idea of employing a histogram. Within the very similar to Chapter 5.1.3, we divide the histogram of historical forecasting errors into 5 parts for every hour; in this case, we may generate $5^9 = 1953125$ different scenarios. To pursue the two-stage method within a reasonable time, we apply the scenario reduction method by choosing the 100 scenarios with the highest probability.

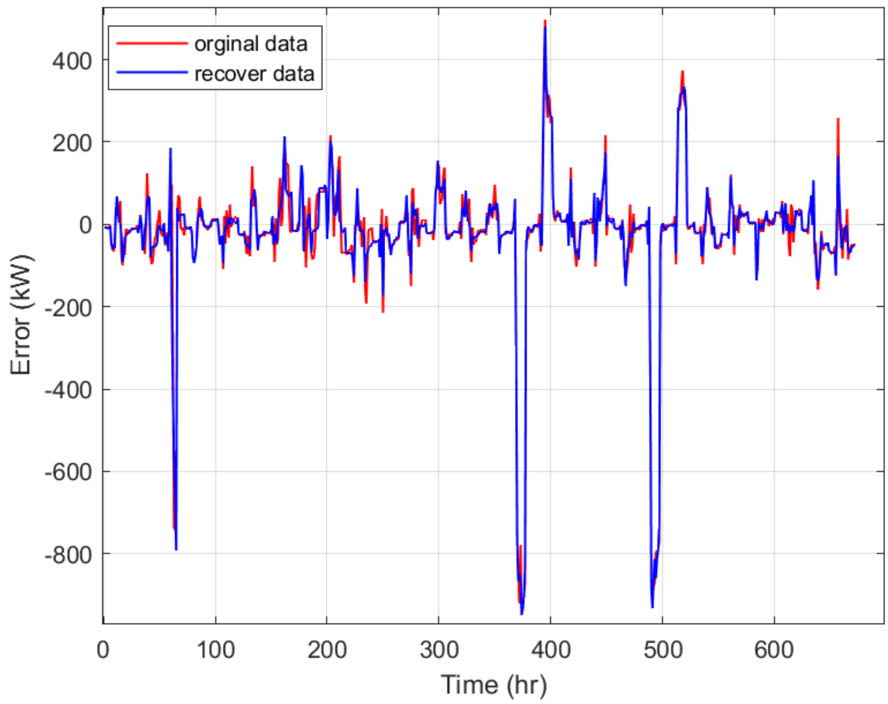


Figure 5.38. Comparison of original forecasting error and the recovered data after the reduction of the dimension.

Now, we obtain 100 different scenarios for the daily (24 hours) forecasting error, the next step can be extracted by considering Figure 5.34. Equation (39) creates the second scenario set of net load. We can solve the recourse problem under the scope of the second hybrid approach by using the generated scenario set and the related probability set that comes from the previous step. In order to represent how this idea works, we prefer to visualize for three samples out of the set as in Figure 5.39. The first graph presents the three scenarios from the forecasting error set, second shows the 24 hours ahead forecast of the net load. The last one illustrates the constituted scenarios by adding the point estimations to every scenario vector in the first graph. Figure 5.40 expresses all possible scenarios and related probabilities. According to the figure, our approach involves a very wide range; however, it is also clear that the most of the scenarios concentrate around the average, which is acceptable behavior.

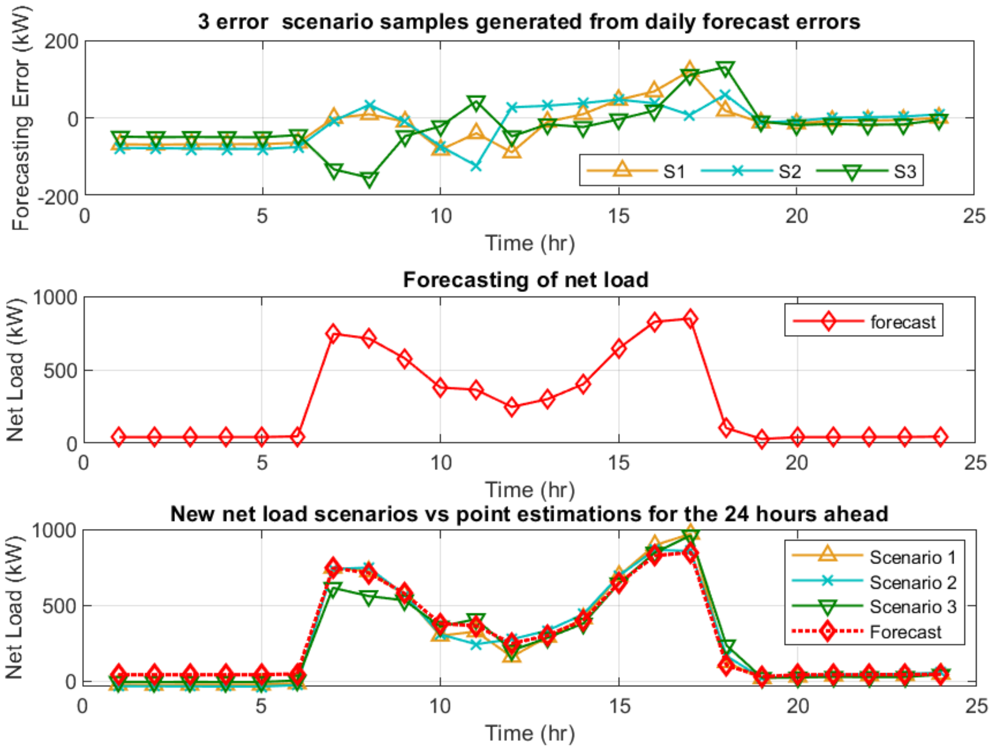


Figure 5.39. Representation of Hybrid Approach-II on 3 samples.

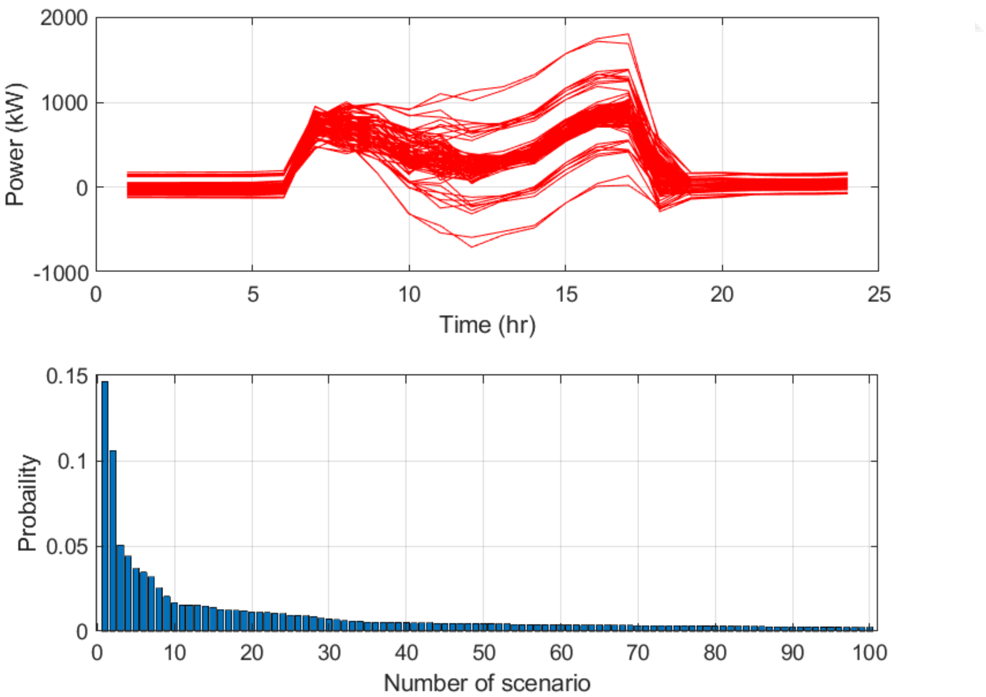
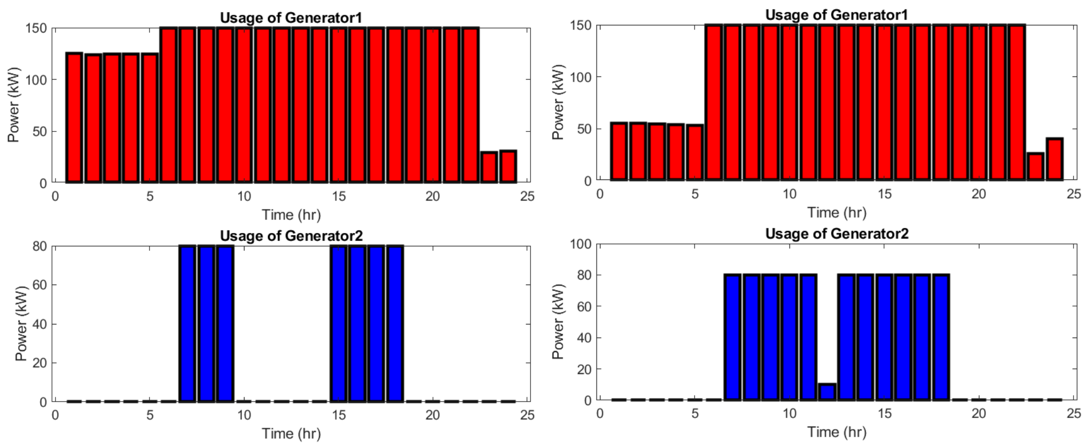


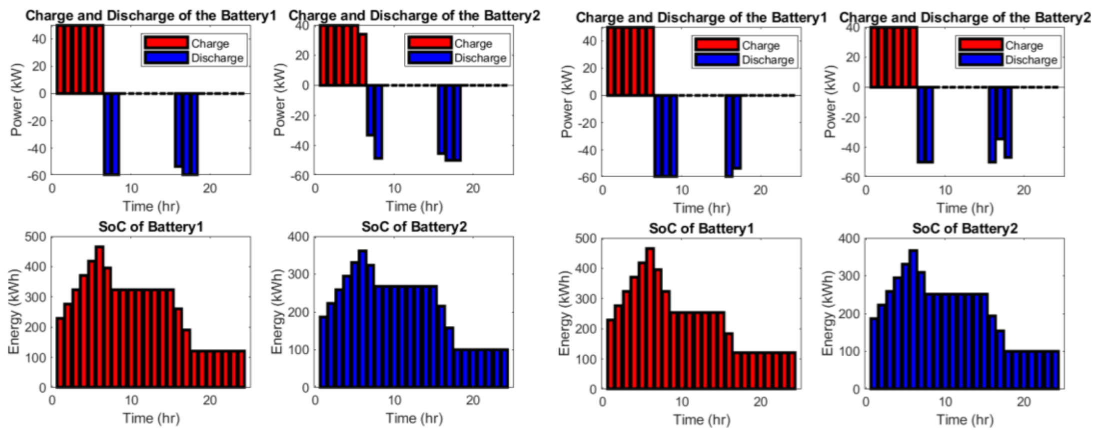
Figure 5.40. 100 most probable net load scenarios that are found at the end of the Hybrid Approach-II, and their corresponding probabilities.



a) Hybrid Approach-I b) Hybrid Approach-II

Figure 5.41. Generator decisions.

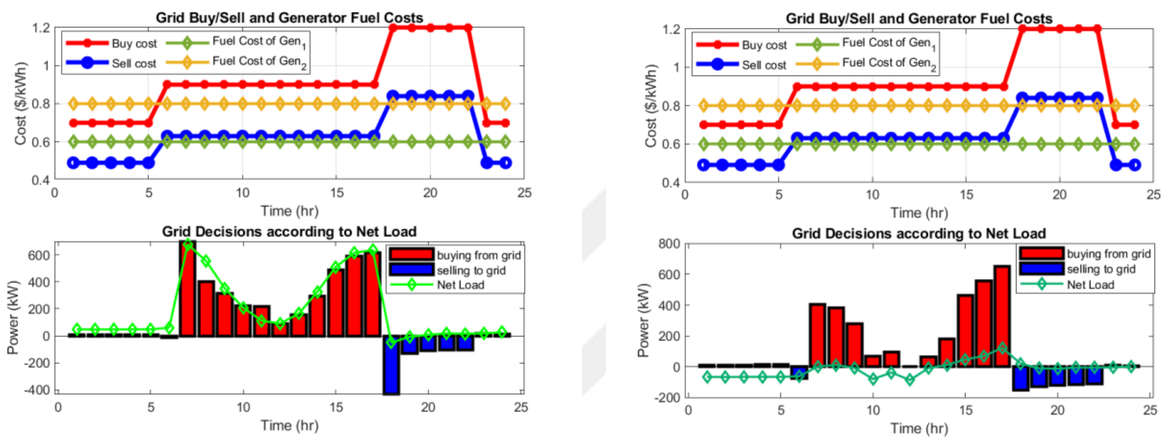
In Figure 5.41, we show the two model results of the Hybrid Approach of making decisions about using electricity generators. Their decisions are different but tend to the same attitude. For example, both solutions give priority to the Generator-1 and just use Generator-2 during the high electricity cost and high demand needs. Similarly, the storage units, batteries, also make the very close decisions to each other, Figure 5.42 illustrates the charge and discharge decisions and SoC situation, the a and b plots have the same SoC at the end.



a) Hybrid Approach-I b) Hybrid Approach-II

Figure 5.42. Change of SoC based on charge and discharge decisions.

In our two-stage implementation, as we indicated before we limited the second stage decisions with only the main electricity grid. That is why the first stage decisions, generator, and battery take similar decisions regardless of our scenario generation approaches. However, the grid buy/sell decisions are in a different manner. Grid decisions are mostly related to the probabilities, it decides by taking into consideration according to the probabilities of the scenario set. The two hybrid approaches have various type of scenario distributions and related probabilities, both Figure 5.36 and Figure 5.40 support us in this thought. Moreover, Figure 5.43 also illustrates this differentiation. Contrary to the generator and battery components, grid decisions are highly different from each other; we insert the most probable net load scenario into Figure 5.43. Both the net load through the 24 hours and its probability highly differ. The daily operational cost also shows the difference between these two approaches mostly because of proposed grid movements.



a) Hybrid Approach-I b) Hybrid Approach-II

Figure 5.43. Amount of power bought/sold between grid and consumer for the most probable scenario.

The total cost of electrical power at the end of the daily operation for the microgrid is \$5659.8 if we apply the first approach. On the other side, the second hybrid approach ends up with \$5149.3. First, both costs are more than the two-stage in the S-MPC implementation in Chapter 5.2.3. The stochastic approach considers historical data and the presented solution is far from the specificity. Naturally, the net load that is very special to the date, it should be more associating with the previous day, season, place, etc. For these reasons, we propose the hybrid model that is a combination of historical knowledge and point forecasts. We prefer to employ historical knowledge and point estimations together since we are aware of these forecasts are not certain; instead, we accept and use them as probabilistic forecasts.

Table 5.2. Comparison of Control Strategies for all H-MPC when the Horizon is 24.

Control Strategy	Total Operational Cost ($)
Worst-Case	20143
Expected Value	5224.6
Chance-Constrained	5830.6
Two-Stage	5659.8
Two-Stage	5149.3

We list the expected daily operational cost of each method in Table 5.2 based on a specified day. Still, to make a proper comment, we should take the overall performance of the year. However, we can make a naive comparison with the results of Table 5.1. As a reminder, the theoretical benchmark was 6271, and it can be seen clearly the expected costs of H-MPC solutions are much closer to the perfect solution than the S-MPC solution. However, we will make a clearer and comprehensive comparison in Chapter 6 for both S-MPC and H-MPC methods.

CHAPTER 6

COMPARISON OF D-MPC, S-MPC AND H-MPC METHODS

After we introduce all the methods that is used and applied them for a specific day, we realized that it is difficult to specify general comment about which method is outperformed to others, we run each MPC through the yearly (360 days) manner. For this reason, to compare the performance of our methods with the realized net load, we implement the following procedure by using the defining equations.

First, we find the expected cost according to the set of decisions throughout the year. Based on equation (25) in Chapter 4.1, we calculate the expected cost of every day and we reach this cost by using equation (40). Here, $\mathrm{d}, \mathrm{i},$ and j represent the simulation day, number of generator and battery storage units, respectively, and we have 360 days to calculate. Equation (40) is valid for all in this study except the two-stage method for both S-MPC (Chapter 5.2.3) and H-MPC (Chapter 5.3.3).

$$\mathrm{C^E(d,k)} = \sum_{k=1}^{24} \left(\mathrm{M_i^G(d,k)} + \mathrm{M_j^B(d,k)} + \mathrm{M^{GR}}(d,k)\right), \forall i, \forall j, \forall k, \forall d \tag{40}$$

where $k \in \{1, 2, \dots, 24\},\ i \in \{1,2\},\ j \in \{1,2\},\ d \in \{1,2 \dots, 360\}$.

For the two-stage methods that we indicated in Chapter 5.2.3 and 5.3.3, we organize the cost equations as (41) because of the probabilities.

$$\mathrm{C^E(d,k)} = \sum_{k=1}^{24} \left(\mathrm{M_i^G(d,k)} + \mathrm{M_j^B(d,k)} + \mathrm{M^{GR}}(d,k) + \sum_{\mathrm{h}} \mathrm{p_h M_h^{GR}}(d,k)\right), \forall i, \forall j, \forall k, \forall d \tag{41}$$

According to the expected net load, we run algorithms for a year to argue more generally.

After all work, we calculate the cost, which includes the additional grid decisions that we compensate for the deficit/surplus power between demand and supply side by the main grid buy/sell decisions. This total cost is much more realistic because we know the actual demand exactly anymore and we can pay the deviation of reality by taking additional grid decisions. The only thing that we should be aware of we have to meet the electricity demand to the customer, we can schedule the DERs and battery storage units in advance, but we know these decisions depend on mostly probabilistic estimations. Therefore, we rectify the imbalance by taking additional grid judgments.

To do that, we solve the optimization problem one more time for the actual net load. Thus, we can provide the optimum decisions since we know the exact demand. However, this is only to prove which method performs better. This approach supports the idea that the important point is not to find the minimum cost; instead, we should be close to the actual cost as possible. Now, we have already underlined the decision set of generators and battery units are constant, so we only counterbalance by using the main grid. We calculate the representation mentioned above by equation (42).

$$\mathrm{C^R(d,k)} = \sum_{d=1}^{360}\sum_{k=1}^{24}\left(\sum_{i=1}^{2}\mathrm{M_i^G(d,k)} + \sum_{j=1}^{2}\mathrm{M_j^B(d,k)} + \mathrm{M^{GR}}(d,k)\right), \forall i, \forall j, \forall k, \forall d \tag{42}$$

$\mathrm{C^R}$ is equal to 1330000, which means if there were no uncertainty in the problem through the year, we take the optimum decisions for each component and it corresponds to $\mathrm{C^R}$. However, the uncertainty of the real world do not let to know exactly, but we can perform better forecasts and take into consideration of probabilistic forecasting and historical information gives limited knowledge for the future. By using equation (43), we find the cost of scheduled microgrid components except for the grid, then after the realization of net load exactly, we detect the additional amount and reach the final cost for each method.

$$\mathrm{C^1(d,k)} = \sum_{k=1}^{24}\left(\sum_{i=1}^{2}\mathrm{M_i^G(d,k)} + \sum_{j=1}^{2}\mathrm{M_j^B(d,k)}\right), \forall i, \forall j, \forall k, \forall d \tag{43}$$

$$P^D(d,k) = \sum_{k=1}^{24}\left(\sum_{i=1}^{2}\mathrm{P_i^G(d,k)} + \sum_{j=1}^{2}\mathrm{P_j^{BC}(d,k)} - \mathrm{P_j^{BD}}(d,k)\right), \forall i, \forall j, \forall k, \forall d \tag{44}$$

$$\mathrm{P_{GR}^R(d,k)} = \left(\mathrm{P^{act}(d,k)} - P^D(d,k)\right), \forall k, \forall d \tag{45}$$

$$\mathrm{C^2}(d,k) = \begin{cases} C^{GR-sell}(d,k).\mathrm{P_{GR}^R(d,k)}, & \mathrm{P_{GR}^R(d,k)} < 0, \forall k, \forall d \\ C^{GR-buy}(d,k).\mathrm{P_{GR}^R(d,k)}, & \mathrm{P_{GR}^R(d,k)} \geq 0, \forall k, \forall d \end{cases} \tag{46}$$

$$C^F(d,k) = \sum_{d=1}^{360}\sum_{k=1}^{24}(C^1(d,k) + C^2(d,k)), \forall k, \forall d \tag{47}$$

We present the yearly total cost comparison between the MPC methods in Table 6.1.

Table 6.1. Yearly predicted and realized costs for each MPC method.

		Predicted	Realized	Variation (%) $(R-P)/P$
D-MPC	Perfect Prediction	1,330,000		
	Point Estimations	1,410,000	1,561,400	10.74%
S-MPC	Expected Value	1,429,100	1,387,800	-2.89%
	Chance Constraint	1,673,500	1,445,100	-13.65%
	Two-stage	1,556,000	1,362,400	-12.44%
H-MPC	Expected Value	1,410,600	1,558,800	10.51%
	Chance Constraint	1,537,700	1,561,100	1.52%
	Two-stage-I	1,495,400	1,353,700	-9.48%
	Two-stage-II	1,441,800	1,355,400	-5.99%

It is clear that the minimum and the closest yearly cost of microgrid management belongs to the two-stage method; but to be more specific, the first approach of the H-MPC two-stage method gives the best performance. As it was argued in the last part of the Chapter 4, we expect that the two-stage and H-MPC combinations will outperform and these results support our beliefs.

CHAPTER 7
CONCLUSION AND FUTURE STUDIES

7.1. Summary and Conclusion

In this thesis, we have examined the various MPC approaches to control DERs and storage units in the microgrid by taking into consideration of uncertainties. These uncertainties based on renewable energy generation of the PV system and electricity load of the consumers. We take the net load as the amount of power that we should supply. The optimal control of the microgrid is possible with accurate and precise knowledge about these stochastic inputs. Thus, the role of realistic net load in the microgrid management system is very crucial to make the right decision set to minimize the operation cost. For this reason, we apply different forecasting methods for both load and PV power. By checking the forecasting performance that minimizes the average MSE of 360 days, we consider to the MLP model, which gives better performance than regression and SARIMA. After identifying forecaster and forecasts, we start to implement them for the MPC frameworks.

We can list the contributions of this thesis as follows:

i. We use point estimations of electrical load consumption and solar power generation in D-MPC to ensure that optimal dispatch of the microgrid control by including the unit commitment solutions of the power and energy set points.

ii. We generate the scenarios from the reduced-order transformed data by using the SVD technique first time to accomplish model order reduction.

iii. We execute the S-MPC method by using the historical data set.

iv. We make the correction to the priorly generated scenario set during the S-MPC method by the integration of point estimations.

v. The novel approach for scenario generation and reduction is employing the forecast errors and hybridize them with previously obtained point estimations.

vi. Lastly, we compare and evaluate all these approaches with the solution of perfect knowledge that we used it as a theoretical benchmark.

Specifically, the methods employed for the S-MPC and H-MPC that try to control microgrid, as well as minimizing the cost are Worst-Case, Expected Value, Chance-

Constrained, and Two-Stage Methods. We consider Worst-Case as a benchmark method because we know it causes the maximum cost that is possible by choosing the highest demand and lowest generation for all hours. On the other hand, the Expected Value presents an average performance by focusing on the mean. Chance-Constraint is a highly valid method if the demand is not a critical load. For the last method, before generating scenarios we apply the SVD method to reduce the dimension. In this way, we explain the historical data less dimension instead of 24 hours. We generate many scenarios, and then select the most probable 100 scenarios, and find the decisions set that minimize the objective function. The critical difference between the two-stage methods of the stochastic and hybrid frames is the hybrid considers the forecasts with the awareness that they have probability and uncertainty. In the first approach, we focus on the already constituted scenario set in S-MPC and reorganize by shifting the values up and down it according to the difference between point forecasts and mean of the historical data at the same hour. The second approach has a slightly different structure, generate a scenario set of previous years forecast errors, and add 24 hour-ahead point forecasting to every individual scenario. We compare the mentioned methods according to the yearly based in terms of operational costs of the generators, batteries, and grid decisions to meet realized net load.

The conclusions derived from these studies illustrate that the integration of intermittent renewable energy sources such as solar PV systems to the main grid is quite an active area of research. To do this safely and cost-effectively is possible with microgrid and smart grid technologies. However, the control issue of the microgrid is another concern, we detect H-MPC perform better through the completed simulations in the MATLAB environment since the hybrid frame is less affected by the uncertainty of forecasting models with the contribution of historical net load distribution. Between the forecasting performances, we apply in the study we declare that MLP gives the minimum MSE results of a 5-fold cross-validation technique to enhance the generalization ability to get through the effect of limited data set. The best MLP network presents 6.07% and 17.05% SMAPE for the solar power output and electrical load demand, respectively. Furthermore, it is still possible to improve these forecasters by adding different features and increase the historical data for at least three years. At this point, we compensate for the uncertainty and misleading of our forecasts by implementing the scenario generation approach. Indeed, we reach only the 1.75%

variation between the realizations of perfect prediction by implementing the first two-stage method in the H-MPC. This is quite good in comparison with the D-MPC performance, which shows a 10.74% variation.

7.2. Future Work

The control of microgrid is an active research area in the literature. In recent years, machine-learning methods are implemented in these systems for making realistic forecasts. Based on completed studies in this thesis, we recommend the following developments for future work.

Since the microgrid that we describe has the only electrical part, it would be more realistic and challenging to integrate the thermal part. In this literature, CHP units are beneficial components to serve similar problems. Furthermore, the microgrid problem can be expanded with increasing the number of controllable generators, type of renewable generators and storage units, adding different types of load such as critical, reschedulable, and curtailable loads can be included.

We have studied yearly examination for the forecasting errors for solar power and electrical load. We believe it is possible to decrease these errors by implementing various machine learning methods, especially recurrent networks seems appropriate to forecast these inputs. Hence, any improvement in forecasting models brings much more realistic stochastic processes; therefore, results in operational savings in the microgrid management system.

During the implementation of the MPC approach in the problem, it should have an additional lower control loop that refers to the real system behavior. In this way, MPC gives a decision set for the following 24 hours, we implement the only the very first one, discard the rest, take the current measurements of the system, and run the MPC again by using the current situation. Thus, we can demonstrate the power of MPC in the close loop with real-time simulations.

In the MPC part, the main grid is not an only way to compensate for the surplus/deficit amount of power of the net load. With a low-level optimization loop to be added, it can take the decision that will minimize the cost among all the components in the microgrid.

Instead of using historical data set to constitute histograms, the implementation of convenient distribution may give more general results for the S-MPC application.

It is possible to integrate demand response and demand-side management programs to control microgrid precisely.

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