Predictive Energy Management Methods for Smart Grids

A Dissertation

Presented to

the Faculty of the Department of Electrical & Computer Engineering

University of Houston

In Partial Fulfillment

of the Requirements for the Degree

Doctor of Philosophy

in Electrical & Computer Engineering

by

Ali Hooshmand

December 2012

Predictive Energy Management Methods for Smart Grids

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Acknowledgements

This dissertation is the result of a great deal of work on the part of numerous individuals who made my years at the University of Houston a rewarding experience. The best and worst moments of my doctoral dissertation journey have been shared with many people. It has been a great privilege to spend several years in the Department of Electrical & Computer Engineering, and its members will always remain dear to me.

I wish to take this opportunity to express my appreciation for my dissertation supervisors, Prof. Heidar Malki and Dr. Javad Mohammadpour, for giving me the opportunity and freedom to pursue my research under their supervision. They have been instrumental during my studies in the University of Houston and have provided support during my stay here. I wish to thank them for their constant encouragement and patience. Their profound knowledge and scientific curiosity have set high standards and are a constant source of inspiration. Interacting with them as their student and advisee, I benefited tremendously from their numerous qualities of a mentor and collaborator. Their clarity of thought and keen insight have greatly influenced my research. Their flexibility in scheduling, gentle encouragement and relaxed demeanor made for a good working relationship and the impetus for me to finish this research. Their advice, both scholarly and non-academic, and most of all their friendship, leave me greatly indebted.

I also wish to thank the other members of my dissertation committee, Prof. Leang Shieh, Dr. Zhu Han, and Dr. Yuhua Chen, for having agreed to take the time out of their busy schedules to read my manuscript and to provide me with their comments and suggestions. I have been fortunate to associate with many remarkable people during the time spent at the University of Houston. My gratitude goes to numerous friends and colleagues at the University of Houston for providing such a creative, intellectually stimulating and fun environment. There are numerous friends who contribute to the excellent working environment and creative atmosphere. In fact, there are too many to list in the acknowledgments, but I am nevertheless truly grateful. I will always remember their support, friendship, and love. Last, and most importantly, I am forever indebted to my parents, Reza Hooshmand and Sorour Hadian. Their invaluable and relentless support, encouragement, and love are without doubt the most important reasons for my success. I could not have achieved this without their unlimited sacrifice. They bore me, raised me, supported me, taught me, and loved me. To them I dedicate this dissertation.

To my parents

Reza Hooshmand & Sorour Hadian

with all my love

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Abstract

In this dissertation, we propose energy management methods for power systems in the context of smart grids. In this regard, we consider new management problems for various configurations of smart grids, microgrids, as well as the power system generation. For different scenarios, we consider grid connection and distributed generations such as photovoltaic cells, wind turbine, and microgas turbines as energy sources. In addition, the effects and advantages of storage devices in smart grids operation are investigated by including them as one of the system components.

For microgrids operation, we consider a microgrid both in islanded mode and grid-tied mode of operation. In these modes, we develop and solve new optimization problems which aim to minimize the cost of energy within a microgrid to supply the load and maximize the lifetime of battery units simultaneously. Next, we extend the concept and consider a network of microgrids which are able to collaborate with each other. By proposing a cooperative optimization problem for microgrids network, we will show that the total cost of energy would be minimized.

On the generation side, we investigate the economic dispatch problem for power systems which include renewable sources among energy providers. In this case, we will illustrate that conventional approaches for considering renewable energy sources in the dispatching problem will not be functional anymore. In addition, we will develop a new method which can be an appropriate alternative for conventional approach. Finally, we will investigate the advantages of storage devices in the aforementioned economic dispatch problem.

Model predictive control (MPC) policies, in both deterministic and stochastic

forms, are employed to solve the underlying optimization problems. Several solution methods such as stochastic dynamic programming, linear programming, etc., will be employed to solve the MPC optimization problems. Numerous testbeds and experimental data including IEEE 14-bus system and California ISO data will be utilized to demonstrate the efficiency and optimality of the proposed energy management methods.

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Chapter 1

Introduction

1.1 Electrical power systems

An electrical power system is an interconnected assemblage of elements and networks in order to generate, transfer, and consume the electrical energy. Power system components are divided into three general categories: generators, transmission and distribution network, and consumers:

- **Generators**: A generator, which is the main component of each power plant, converts different types of energy into electrical power. Most of the generators burn fossil fuels such as natural gas, oil, and coal to produce electricity, and some of them utilize nuclear energy, but the usage of renewable sources such as wind, solar, geothermal, bio, and hydroelectric has been increasing in recent years as well.

- **Transmission & distribution network**: Transmission system carries electrical energy from suppliers in generation side to electrical substations in demand side. Using the transmission network, electricity is transferred at high voltage (110 kV and higher) in order to decrease the power loss during the transmission of the power. Overhead power lines are usually utilized as transmission networks. Underground power lines are used just in the city or sensitive areas because they have higher cost and operational restrictions.

  At the final step, the distribution network receives electrical power in substations from transmission lines. After reducing the level of voltage (less than

50 kV) by substations, distribution system delivers electricity to consumers in demand side. Figure 1.1 illustrates the power system in its traditional configuration. Transmission and distribution networks are shown by blue and green color, respectively.

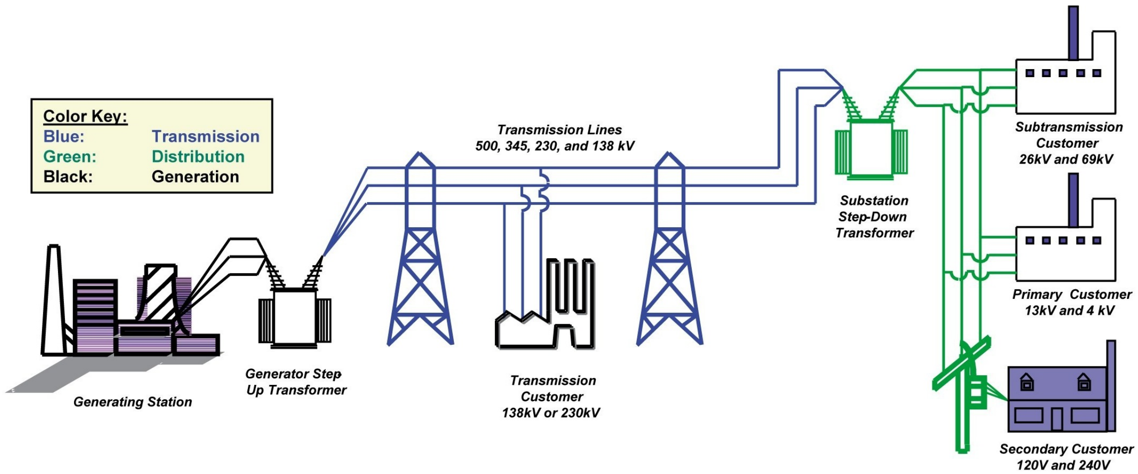

Figure 1.1: Traditional configuration of power system

- **Consumers**: The last component of power systems is consumers. Consumers or loads receive electrical power from distribution network as end users. The size of loads varies from small household appliances to huge industrial machinery.

1.2 Smart grids vs. traditional power systems

The topology of the conventional power system is unidirectional as shown in Figure 1.2. In this hierarchical configuration, a failure in any component is transferred to other components in the chain and may result in poor power quality such as power cuts or even blackouts. In this system, just 33% of fuel energy is converted into electricity and 8% of generated power is lost in transmission lines over long distances from power plants to consumers [1]. In addition, 20% of power plants' capacity is kept to balance peak demand which only happens 5% of the time.

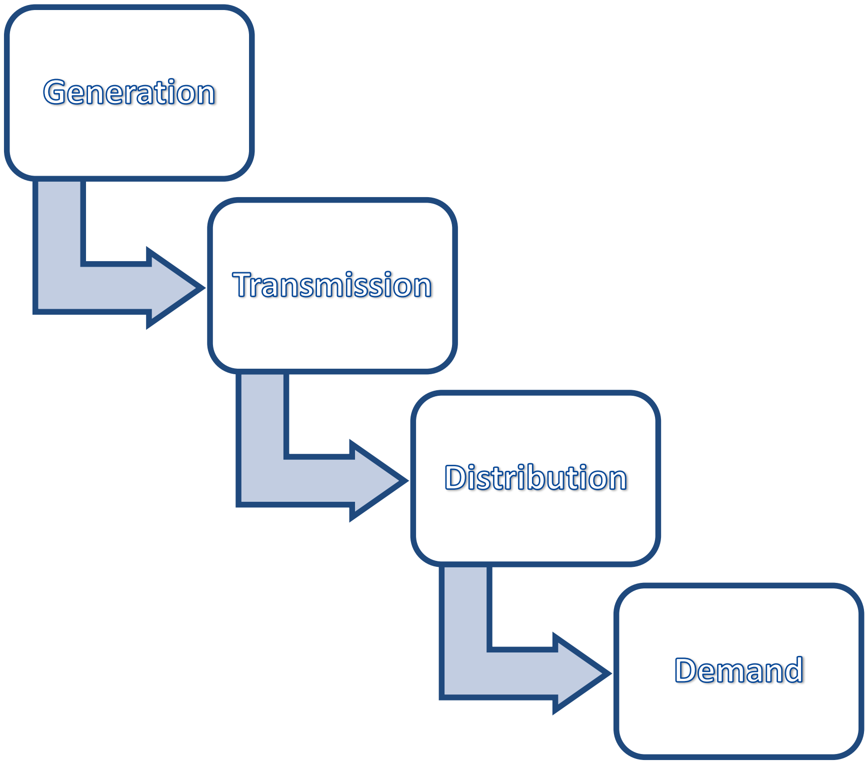

Figure 1.2: Unidirectional power flow from generation side to demand side

Furthermore, continuous increase in the electricity consumption around the world places considerable stress on aging power system. It is projected that electricity usage in the United States will increase from 3873 TWh in 2008 to 5021 TWh in 2035 [2]. Summer peak demand in the U.S. is expected to increase by 40% from 2008 to 2030 as well [3]. Environmental pollution and global warming due to the use of fossil fuels for electricity generation and depletion of fossil fuel reserves have already raised serious concerns about sustainable operation of power systems in the future.

To address those issues, in recent years, power systems around the world are populated by a variety of non-conventional/renewable energy sources and energy storage devices such as solar photovoltaic (PV) systems, wind turbines, fuel cells, combined heat and power (CHP) systems, microturbines, batteries, etc. Continuous decline in the manufacturing cost combined with the incentives offered by governments and utility companies have contributed to widespread utilization of these technologies. Only in 2010, the U.S. installed 887 MW of grid-connected PV which is a 104% growth from 2009 [4]. These installations include large scale PV power plants and wind farms directly connected to the transmission system, and distributed generations (DGs) and storage devices connected to low and medium voltage distribution networks with capacities less than 50 MW [5]. Up to the year 2007, more than 12 million DG units were already installed across the U.S. with a total capacity over 200 GW. In 2003, these units generated approximately 250000 GWh [6]. By spreading the distributed generations in different levels, power system makes its future generation, or the so-called smart grid [7]. Hence, in smart grid context, the unidirectional form of power system will change to a bidirectional form in which all participants in the system will be able to interact with each other and manage their generation and consumption. Moreover, distributed generation and storage provide following technical, economic and environmental benefits over centralized power generation [5]:

- Due to the non-conventional/renewable nature of most DGs, their implementation can decelerate depletion of fossil fuels in the world.
- Exploitation of DGs is expected to considerably increase the generation of eco-friendly clean power with much lesser environmental impact.

- Physical proximity of generation and load can considerably enhance electric efficiency of the system due to minimal losses in transmission lines. Also, DG provides a better scope for co-generation and utilization of waste heat for other applications which in turn increases overall efficiency of the system.

- DGs and storage devices provide the flexibility of supplying the load while disconnecting from the grid (islanded operation) in case of any blackouts or in remote areas where the electricity grid is not accessible. This in turn increases power quality and reliability of electricity for end-users.

The development and evolution of the smart grids will result in the plug-and-play integration of intelligent structures called microgrids (MG) that will be linked with each other through particular channels for power, information, and control signals exchange [8, 9, 10]. An MG can be a residential place like a house or a commercial area such as a huge shopping center or even a bigger place. Figure 1.3 shows the aforedescribed topology. Typically, a microgrid includes one or multiple sources of on-site distributed generations (DGs), an energy storage unit, a variety of electric loads (such as AC units and lighting system in a building), and a utility connection to import/export power from the grid if necessary. From the operation point of view, microgrids can be operated in two modes. They might work in islanded-mode which are disconnected from the grid and operated as independent entities; or, they might be operated in the form of a microgrid which interacts with the grid as a single aggregated system. This mode is called grid-tied or interconnected mode. Globally, according to [11] total capacity of microgrids currently operating or in the development phase is more than 1.8 GW which resulted in total revenue of approximately $200 million in 2011. The market is expected to grow to 3 billion dollars in 2016. Figure 1.4 shows

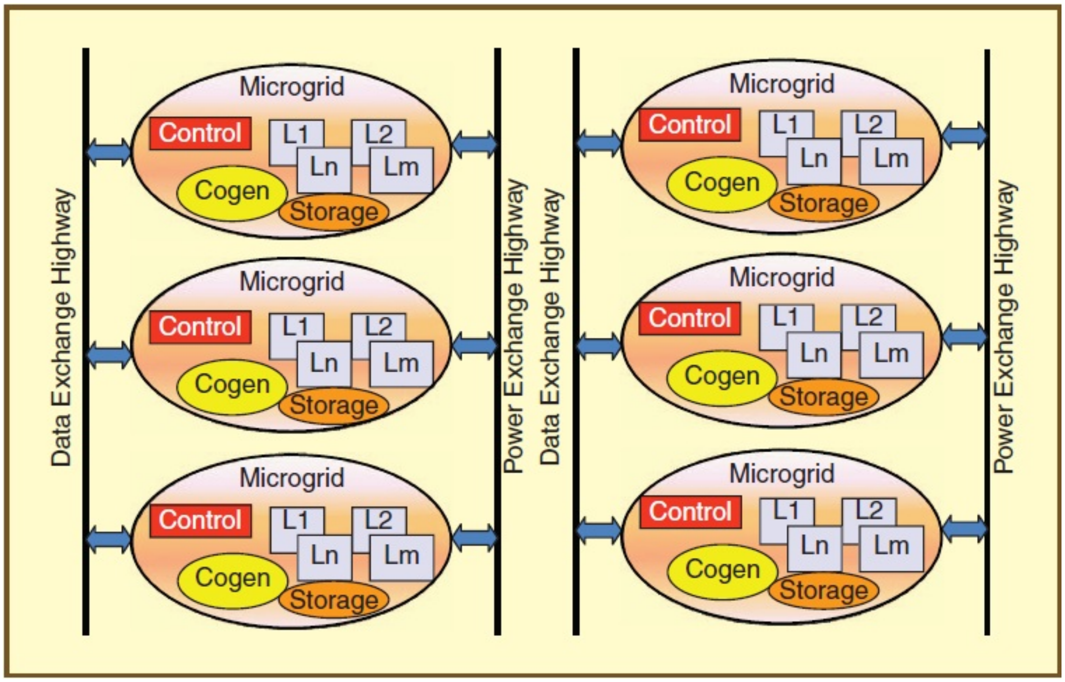

Figure 1.3: Smart grid topology [1]

the general structure of a grid-tied microgrid with both power and data flow among different components of the system. Batteries are the most favorable option for energy storage and also the most expensive components in microgrids. From the market point of view, having the capability of storing electricity is beneficial to both utilities and electricity consumers. Utility companies can centrally manage distributed storages in a network to provide frequency regulation and ancillary services for power systems. Distributed storage can also be used for transmission and distribution investment deferral and congestion management which allows a two- to four-year capital deferral of new equipment such as transformers, as well as new lines in rural and urban areas where load growth is low and capital expenditures are very large [12]. In regions with non-flat electricity rates (e.g., time of use rates), energy customers can store cheap electricity from the grid during off-peak hours in the battery and use it during peak

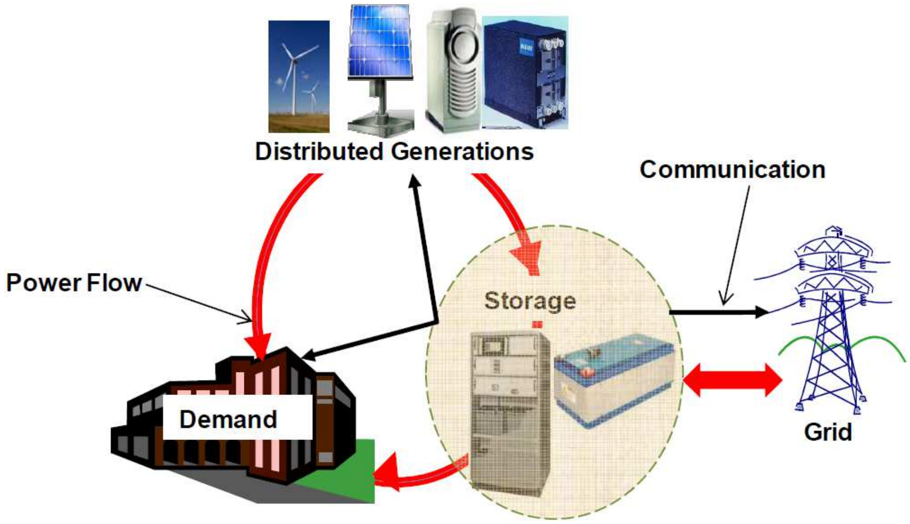

Figure 1.4: Microgrid

hours to reduce their electricity bill. Storage units can also provide peak-shaving capability which reduces the demand charge for energy consumers. In areas with feed-in-tariffs lower than electricity retail price, storing excess distributed generation in a local storage unit instead of selling it back to the grid results in more cost savings. It is predicted that within the next five years, the electricity storage market only in commercial building applications can reach $1 billion globally [13].

Electric loads can vary significantly based on the time of the day, season and load type (residential, commercial, industrial, etc.). Renewable distributed generation outputs also change continuously depending on the irradiation level, wind speed and other meteorological parameters. The pattern of change in DG power outputs can be totally independent of the changes in the load. Forecasting tools have been widely developed and used to estimate the future generation and demand profiles.

Forecasted data can be used to schedule generation from local dispatchable sources

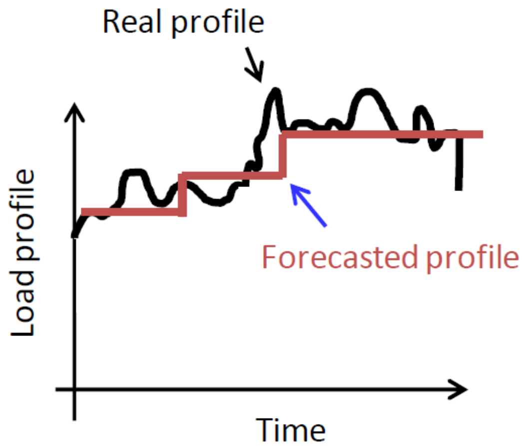

Figure 1.5: Forecasted and real load profiles

(if any) or importing a certain level of power from the grid to a microgrid on a long time-frame basis (e.g., hourly) to supply the shortage in renewable generation. However, forecasting errors and fast variations (e.g., minute by minute) in the load and DG power outputs always introduce uncertainty to smart grids' operation. The difference between a forecasted load profile and a real load profile is depicted in Figure 1.5.

Unpredictable variations in the load profile and intermittent nature of most DGs such as wind and PV results in a significant uncertainty in the operation of smart grid and microgrids. This makes the conventional unit commitment and economic dispatch strategies more erroneous and unreliable since they are open-loop control policies, and hence, there will be no real-time control over any deviation from forecasted load and renewable generation profiles. Therefore, a real-time power management framework as a supervisory control is an absolute necessary procedure in smart grids similar to the various regulatory actions in conventional power systems. In this regard, many research studies have been conducted in recent years in power system and control engineering academic societies. Some of these studies and methods will be discussed in the next section. The real-time management system should be able to not only satisfy the operational constraints and supply-demand conditions but also to guarantee the optimality in performance of the system. To this purpose, we have selected model predictive control (MPC) technique to design the framework of a real-time management system. MPC is a powerful control method that uses a model to project the behavior of the system. Based on this model, it can predict the future response of the system to various control actions and forecasted profiles to obtain the optimal decision. For problems such as energy management of power systems and smart grids which highly depends on the forecasted value of demand and renewable energy productions, this method is very effective. In addition, due to its closed-loop nature, MPC can correct errors in load and renewable energy generations prediction and improve system stability and robustness [14, 15].

1.3 Recent Works

In recent years, different types of management systems have been proposed and published to control and solve the various problems of smart grids and microgrids. Authors in [16] solve the economic dispatch problem for microgrids. In this paper, they try to handle the uncertainty problem of distributed generation by defining reserve requirement constraints in the dispatch problem. In addition, they consider additional reserve for microgrids to guarantee the stability in islanded mode of operation. In [17], a method is proposed to co-optimize the consumption of different types of energy within a microgrid such as electricity, gas, and heating systems. In this regard the correlation between different energy infrastructures is taken into account as operational constraints. An optimal power flow problem is designed to solve the economic scheduling of the combined heat and power microgrid system. In order to reliable operation of microgrids in power systems, a management system has been developed in [18] which is called intelligent distributed autonomous power systems (IDAPS). This system enables the microgrids to operate in both normal and emergency situations such as power systems outages and natural disasters. In [19] a hierarchical model for smart grids is considered. Based on this model, a distributed control scheme is proposed which not only solves the economic dispatch problem but also guarantees the frequency regulation for the smart grids.

Due to deregulated characteristic of power systems, economic operation of smart grids and microgrids also affects the electricity markets subjects such as energy market design, locational marginal pricing, financial transmission rights, ancillary services markets, etc. Authors in [20] and [21] propose a pricing methodology for microgrids to participate in day-ahead and spot local markets. In this way, microgrids will be able to maximize their revenue by energy trading capability in local energy markets. A control solution for microgrids is introduced in [22] which works based on game theory methods. The scheduling problem is solved through defining a game between loads and generators in smart grids. This algorithms aims to eliminate the role of central management system and consequently increase the system reliability. In [23], a dynamic structure for wholesale energy markets is designed in which the intermittent nature of renewable sources is taken into account. Moreover, a methodology is described in this framework for real-time pricing of electricity. The pricing algorithm employs a state based game approach and includes locational marginal price and its congestion component. The stability of market equilibrium in the presence of load and renewable generation fluctuations is also proved.

Authors in [24] have designed a day-ahead electricity market structure for smart grids. To this end, they introduced new concepts such as microgrids' reputation score and trustworthy model for microgrid market. The obtained market system handles microgrids electricity transactions to improve their economic operation. In [25], microgrid is identified as a power system which can implement an electricity market within itself. The management system in this configuration is interpreted as an independent system operator (ISO). It receive different bids for selling and purchasing energy, and conducts day-ahead and real-time market to calculate the market clearing price and manage the microgrid in real time. Authors in [26] investigated the advantage of using storage devices in electricity market. They have shown that the flexibility of storage devices to charge and discharge can be an effective tool for load aggregators. Aggregators would be able to obtain a more efficient energy cost by compensating their day-ahead load forecasting errors in real-time market through charging or discharging the storage devices.

The operation of large wind farms and large solar farms also results in new challenges in dispatching problem. In [27] and [28], authors have considered the integration of wind farms in economic scheduling problem at generation side of power systems. They proved that it is more efficient to consider the wind generation as a dispatchable source of energy. In this way, system operator can utilize the high ramp rate characteristic of wind power and solve the short-term dispatch problem more economical.

1.4 Organization of the Thesis

This dissertation is divided into 7 chapters. In chapter 2, we will provide a general overview of Model Predictive Control concept. We will explain how this control technique calculates the most efficient current control inputs by optimizing an objective index defined on a finite time horizon.

In chapter 3, we will develop a centralized controller for managing a microgrid in islanded mode to minimize the cost of operation. Because of uncertainties in forecasting load and renewable generation profiles, a stochastic model for the microgrid will be obtained. Hence, to design the energy management system, a stochastic version of MPC is proposed that utilizes dynamic programming and empirical mean tools to find the optimal solution.

Chapter 4 proposes a multi-objective energy management method for grid-tied microgrids which include local generation sources, grid connection, energy storage units and various loads. Minimization of energy cost and maximization of battery's lifetime in an interconnected microgrid are considered as two main objectives which are optimized simultaneously.

Chapter 5 presents a power flow management method for a network of cooperating microgrids within the context of a smart grid by formulating the problem in the model predictive control framework. In order to reliably and economically provide the required power to the costumers, the proposed method enables the network of microgrids to share the power generated from their renewable energy sources and minimize the power needed from the micro gas turbines.

In chapter 6 we investigate the effects of renewable generations in operation of power systems. In this regard, we develop a model predictive control (MPC) based method for dynamic economic power scheduling in power grids. The proposed method is first applied to the power systems with relatively low penetration of renewable generation sources. The proposed MPC-based optimization method is then extended to the case, where a high penetration of renewable sources is expected. In the latter case, instead of considering power generated from renewable sources as a negative load, the system operator (SO) takes these sources into account as dispatchable in solving the dispatching problem. Various constraints pertinent to power systems including transmission congestion and generators capacity are also considered in the optimization process. Consequently, we will show that the use of storage devices will be an effective way to reduce the cost of generation in the future generation of power systems.

Chapter 7 summarizes the tasks completed in this dissertation and explains our findings on energy management problems and the significant impact that they can have on the operation of future smart grids. In addition, it introduces future work that can be pursued and explored based on current research.

Chapter 2

Model Predictive Control

Model Predictive Control (MPC) is an advanced control strategy which has been utilized in industries such as chemical processes and petroleum refineries since 1980s. In order to perform the control task, MPC employs a dynamic model of the system under control. Based on this model, MPC predicts behavior of the system over a finite prediction horizon based on the latest measurements collected from the plant. Based on these measurements, MPC solves an optimization problem at each sampling time and calculates a control input sequence, from which only the first element is implemented. At the next time instant, the procedure is repeated. The following example explains the concept of MPC application in real life.

2.1 Example 1

In a company, the manager of a research team decides to complete a project in a business day with the help of team members [29]. We assume the business day begins at 9 o'clock and consists of 8 hours which means a finite time period. The completion of project depends on different parameters, such as the level of attempt of members, the quality of teamwork, requesting some helps from other departments. These parameters are controllable or decision variables. On the other hand, there are some restrictions such as the level of knowledge of members about the project, how many members are expert in applying different tools for solving the problem, etc.. In order to accomplish the project with the best performance, the manager has to take into account all control variables and different limitations.

After having a meeting with the people in the team, the manager assigns the task for each member for each hour of the day based on project decision parameters and restrictions. According to this assignment, the project will be finished at the end of the day.

After one hour working on the project, the manager asks every one to send him a feedback about their achievements. He compares these achievements with their assigned expectations. For various unpredicted reasons including the Internt disconnection, phone calls, etc., the feedback is not the same as expectations. Hence, the project cannot be completed on time. Based on updated information about members performance at the end of the first hour, the manager plans another assignment for each member at 10 o'clock for the rest of the day. Again at 11 o'clock, the manager assesses the team members' results and plans another tasks for them. The process of updating, planning, and working procedure is repeated until the goal of the project is achieved by the end of the day.

2.2 MPC Components

Based on example 1 (EX1), we are now able to identify the elements of MPC. This section describes different components of MPC.

2.2.1 Modeling

To accomplish the controlling task, MPC needs to project the future response of the system to different control actions. To this purpose, a model of the system is used to show the relations between system outputs, inputs, and other variables. This model can be a linear or nonlinear, deterministic or stochastic one. In EX1, to plan the assignment of team members, the manager needs a model which shows the dependencies of project progress as system output to decision parameters such as members attempts, teamwork level, etc..

It should be noted that MPC uses the model only for calculating the future outputs which are under control. Therefore, the model does not need to be a complete model of the system from different perspectives. It only requires to be accurate enough to illustrates the relation between interested outputs and inputs. for instance, in EX1, the manager only needs to consider the knowledge of members which is directly related to the project, not their general knowledge. Hence, in various practical situations, although the real system is completely nonlinear, but it would be sufficient to consider an appropriate linear model of that system.

2.2.2 Optimality Criterion (Objective Function)

In order to perform a task such as completing the project in EX1, there might be some different ways or input sequences that achieve the goal. For example, the manager can either hire 10 people to finish the project in 4 hours and pay more money, or hire 5 people to finish it in 8 hours and pay less. Therefore, the optimality criterion in accomplishing a task should be determined in advance. In MPC policy, this optimality criterion is called objective or cost function. By optimizing the cost function, MPC not only selects the control inputs to perform a task like finishing a project, but also guarantees that selected inputs are optimal with respect to predetermined objective function such as minimum payment or minimum time.

2.2.3 Optimization Horizon & Receding Horizon Policy

Optimization horizon is the time window that MPC is able to look into future for predicting the system response. Longer the optimization horizon, MPC can have longer range of prediction and make a better or more efficient decision. On the other hand, considering a very big horizon increases the complexity of the problem. Assume that the project in EX1 was supposed to be completed in a week. If the manger considers the whole hours of the week as optimization horizon, it will be very difficult to plan the assignment of members for each hour of the week.

To address this issue, MPC utilizes the receding horizon strategy. Based on receding horizon strategy, MPC optimizes the behavior of the system over the optimization horizon; but at the next sampling time when information and measurements are updated, it again calculates the optimal control inputs for the next upcoming optimization horizon period. In EX1, if the project requires one week to accomplish, the manager can still consider one business day or 8 hours as his optimization horizon, but at the beginning of every hour he will update his information and plan for the next 8 business hours. This procedure continues until the end of the project lifetime.

2.2.4 Constraints

One of the most important points about MPC is its ability to handling different kinds of constraints in the problem. By handling, we mean MPC can satisfy problem constraints while it optimizes the system performance. The constraints can be either static or dynamic. Static constraints are constant over the time. In EX1, the availability of tools for using in the project is a static constraint. Dynamic constraints are dependent on the period of time they are considered and usually described in the form of an inequality or equality differential equation. In the example, the progress of each hour working is limited and also depends on the results on previous hour. This constraint is defined as a dynamic constraint in the problem.

2.3 MPC Formulation

Based on basic ideas and concept of MPC, the standard formulation of MPC is presented in this section [30].

In this dissertation, the systems under control by MPC are modeled in discrete time. Therefore, the typical system can be described here in terms of a general difference equation as

$$x(t+1) = f(x(t), u(t)), \tag{2.1}$$

where $x(t) \in R^p$ is the state variable and $u(t) \in R^q$ is the system input at time t, $t \in \{0, \infty\}$. The function $f : R^p \times R^q \to R^p$ is a continues function and its initial value is zero. General form of constraints are also as follows:

$$\begin{aligned} x(t) &\in \mathcal{X}, \\ u(t) &\in \mathcal{U}, \end{aligned} \tag{2.2}$$

which means both state variables and system inputs are restricted by $\mathcal{X}$ and $\mathcal{U}$ sets respectively.

The primary task for MPC is to navigate the state variable to a set point. This navigation should be accomplished in an optimal way. Optimality is calculated by measuring the performance of the system which is described by a cost or objective function. Hence, optimal control of the system means controlling the system to the set point while the cost function is optimized by MPC as well. It should be noted that set point is not necessary constant in time. Time varying set point is called reference trajectory and the problem which includes a reference trajectory is called a tracking problem.

The cost function is optimized over the finite interval of optimization horizon, $k \in [0, T]$ where $T > 0$. The future behavior of the system is calculated in terms of forecasted state variables, $\hat{x}(k)$, as

$$\hat{x}(k+1) = f(\hat{x}(k), \rho(k)). \tag{2.3}$$

Initial value of predicted state variable is equal to measured value of system state at current time, t. It means

$$\hat{x}(0) = x(t), \tag{2.4}$$

and $\rho(k)$ is control input at $k \in [0, T]$. The forecasted state at k, $\hat{x}(k)$, is prediction of the system state $x(t+k)$ and the control input $\rho(k)$ corresponds to the system input at time $t+k$, $u(t+k)$. After each time solving the optimization problem, a set of T elements, Ω, is obtained which shows the value of $\rho(k)$ for each moment of optimization horizon. It should be noted that both predicted state variables and control inputs belong to $\mathcal{X}$ and $\mathcal{U}$ sets respectively.

The cost function, $C : R^p \times \Omega \to R$ is expressed in general form as

$$C(\hat{x}, \rho) := \sum_{k=0}^{T} c(\hat{x}(k), \rho(k)), \tag{2.5}$$

with initial condition $\hat{x}(0) = x(t)$. The function $c : R^p \times R^q \to R_+$ is a continues nonnegative function and its initial value is equal to zero.

By using the measured state variable as initial condition for predicted states, MPC solve the optimization problem to find the optimal solution, $\rho^\star$, such that

$$C(\hat{x}(0), \rho^\star) \leq C(\hat{x}(0), \rho) \qquad \forall\ \rho \in \mathcal{U}. \tag{2.6}$$

The optimal solution, $\rho^\star$, is a sequence of T elements as

$$\rho^\star := \{\rho^\star(0), \rho^\star(1), ..., \rho^\star(T-1)\}, \tag{2.7}$$

from which only the first element is implemented as the control command or system input at time t as

$$u(t) = \rho^\star(0). \tag{2.8}$$

By applying $u(t)$ to the system, state variable vector at the next time step, $x(t+1)$, is obtained. This measured output is considered as initial condition for optimization problem in the next iteration based on receding horizon policy. It should be added that since $u(t)$ is calculated based on measured output, $x(t)$, it can be stated using a function with respect to $x(t)$ as

$$u(t) = \varphi(x(t)). \tag{2.9}$$

Hence the integration of system and MPC makes a closed loop control system as

$$x(t+1) = f(x(t), \varphi(x(t))). \tag{2.10}$$

There are various analytical and numerical methods to solve the MPC optimization problem such as dynamic programming, linear programming, dynamic matrix control, etc.. In addition, the solution methods can be either deterministic or stochastic. In the following chapters, based on the nature of the system and formulation of the problem, these methods will be utilized to solve the optimization problem.

2.4 MPC Advantages

The advantages of employing MPC are itemized as follows:

- MPC is functional and applicable for controlling various types of systems such as time domain or frequency domain systems; continuous or discrete time systems; linear, quadratic, or nonlinear systems.

- Generally, control methods for solving optimization problems with linear and nonlinear systems and constraints are open loop. But, based on receding horizon strategy, MPC performs a closed loop control algorithm which increase the system robustness.

- MPC is able to include different types of constraints in terms of control inputs and state variables. Also, this method is one of the few algorithms which can handle both static and dynamic constraints.

- MPC guarantees the stability of closed loop system for linear and nonlinear systems with input and state variable constraints [31].

- MPC's capability in tracking task is good since it employs predicted reference trajectory for a finite horizon in calculating the optimal decision.

- MPC is an adaptive method for dealing with changes in the system and constraints parameters since optimization problem is solved repeatedly in MPC strategy. In MPC, fixed information and coefficients are only required for a finite horizon and can be changed in next iteration, while optimal control methods which include infinite horizon have to know all future parameters on the problem in the beginning time.

- MPC has been widely used in industries such as chemical processes and oil refineries due to its properties such as finite horizon control, control input and state variable constraints, closed loop behavior, etc., accord with the requirements of real physical systems.

Chapter 3

A Stochastic Control Method For Microgrid Management in Islanded Mode

Using the plug-and-play feature of a microgrid, it can operate in two modes: grid-connected mode or islanded mode, *i.e.,* separated from the grid [32], [33]. In this chapter, we mainly focus on the islanded mode operation.

To efficiently accomplish the management task of microgrids, there will be a need to a microgrid central controller (MGCC) to control the operations and perform optimizations so as to minimize the power generation cost. In other words, an MGCC tries to optimize the future behavior of the grid to meet the predicted demand based on forecasted renewable generations. Therefore, due to the nature of this problem, one of the effective tools to achieve the optimized operation is model predictive control (MPC) [34]. There are several ways to solve a model predictive control (MPC) problem. In the problem under study in this chapter, the stochastic terms appear due to the uncertainties in the prediction of demand or renewable energy generations. Therefore, dynamic programming (DP) method [35] is selected to solve the MPC problem. The advantage of using DP is that by extending it into a stochastic dynamic programming (SDP), this method can be employed to deal with stochastic terms [36]. This method is essentially an extension of Bellman's equations. Solving SDP using stochastic version of Bellman's equations is not, however, easy if there exist state or control input constraints.

Contribution of this chapter is as follows [37]: we first consider a 3-node graph associated with a microgrid with different generation and storage options. The microgrid is in islanded mode and disconnected from the grid. To solve the microgrid power management problem taking into account the stochastic disturbance inputs and various constraints imposed by the distribution lines and battery level of charge, we propose a solution method to the stochastic MPC problem motivated by [30] using the empirical mean and dynamic programming tools.

3.1 System Modeling & Problem Formulation

The islanded microgrid we consider in this chapter is assumed to be a graph consisting of three nodes as illustrated in Figure 3.1. The first node represents the renewable energy generation sources such as a wind turbine and a battery unit. The power generated in this node is

$$P_1(t) = P^{wind}(t) + w^{wind}(t) + P^{batt}(t), \tag{3.1}$$

where $P_1(t)$ is the total power generated in node 1 at time instant t, $P^{wind}(t)$ is the power generated by the wind turbine (or a wind farm in general) at time instant t, and $w^{wind}(t)$ is a disturbance term representing the uncertainty in the wind profile prediction. The latter is assumed to have a gaussian distribution. In addition, $P^{batt}(t)$ is the power generated by the battery unit. The change in battery state of charge (SOC) can be described by a linear difference equation as [38]

$$SOC(t+1) = SOC(t) - P^{batt}(t). \tag{3.2}$$

It is noted that $P^{batt}(t)$ can be either positive or negative, where a negative value

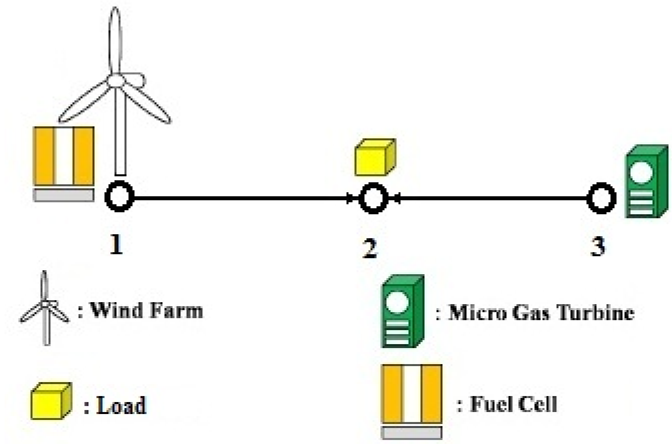

Figure 3.1: The microgrid's graph

implies that the battery is being charged. Due to a limit on the battery level of charge, we have the following constraint for SOC

$$0 \leq SOC(t) \leq SOC^{max}. \tag{3.3}$$

Node 2 in Figure 3.1 represents the load connected through the transmission line to Node 1. The total generated power $P_1(t)$ should not exceed the line capacity. This constraint can be mathematically represented by

$$0 \leq P_1(t) \leq L_{12}^{max}, \tag{3.4}$$

where L_{12}^{max} is the maximum power allowed to be transferred through the line between nodes 1 and 2. In addition, the demand profile is forecasted in advance but there will be some perturbation around the predicted profile. This can be described by a disturbance term in the load equation, and we assume a normal distribution for this term. We choose the demand model as

$$D(t) = d(t) + w^d(t), \tag{3.5}$$

where D, d, and w^d represent the actual load profile, the load profile prediction, and demand prediction disturbance, respectively. Finally, the third node includes a micro gas turbine, whose amount of generation $P^{gas}(t)$ is commanded by MGCC. The generated power $P^{gas}(t)$ is transferred to the demand node via the line between nodes 2 and 3. Hence, the constraint imposed by the line capacity is

$$0 \leq P^{gas}(t) \leq L_{32}^{max}, \tag{3.6}$$

where L_{32}^{max} is the maximum power allowed to be transferred through the line between the nodes 3 and 2. The graph shown in Figure 3.1 is a directed graph with two edges from nodes 1 and 3 to the node 2. The direction of edges shows the direction of power flowing from supply to demand in the MG. Obviously, the ultimate goal is for the MGCC to set the generation source power such that the supply could meet the demand. The latter statement can be mathematically described by

$$P_1(t) + P^{gas}(t) = D(t). \tag{3.7}$$

This should be achieved so that the cost of generation be minimized and the battery SOC is kept as high as possible by scheduling the micro gas turbine generated power.

To take these design objectives into account, we define the following cost function

$$\begin{aligned} J &= \frac{1}{2}(SOC^{max} - SOC(T))^T P (SOC^{max} - SOC(T)) \\ &+ \sum_{t=0}^{T-1}[\frac{1}{2}(SOC^{max} - SOC(t))^T Q (SOC^{max} - SOC(t)) \\ &+ \frac{1}{2}(P^{gas}(t))^T R P^{gas}(t)]. \end{aligned} \tag{3.8}$$

The above optimization problem is a finite horizon problem with T being the horizon length. P, Q, and R are weighting matrices. As described before, we will formulate our grid management problem in an MPC form. First, we convert the above cost function to a standard MPC quadratic cost function form by changing the variable $SOC(t)$ as

$$z(t) = SOC^{max} - SOC(t). \tag{3.9}$$

So, (6.12) is now rewritten as

$$z(t+1) = z(t) + P^{batt}(t), \tag{3.10}$$

and (3.3) is written as

$$0 \leq z(t) \leq SOC^{max}. \tag{3.11}$$

Consequently, the cost function in (3.8) becomes

$$\begin{aligned} J &= \frac{1}{2}z(T)^T P z(T) \\ &+ \sum_{t=0}^{T-1}[\frac{1}{2}z(t)^T Q z(t) + \frac{1}{2}(P^{gas}(t))^T R P^{gas}(t)]. \end{aligned} \tag{3.12}$$

Therefore, for the microgrid management, the goal is to solve the following MPC problem

$$\min_{P_{gas}} J := \frac{1}{2}z(T)^T P z(T) + \sum_{t=0}^{T-1}[\frac{1}{2}z(t)^T Q z(t) + \frac{1}{2}(P^{gas}(t))^T R P^{gas}(t)]$$

$$\begin{aligned} &\text{subject to:} \\ &P_1(t) = P^{wind}(t) + w^{wind}(t) + P^{batt}(t), \\ &0 \le P_1(t) \le L_{12}^{max}, \\ &D(t) = d(t) + w^d(t), \\ &0 \le P^{gas}(t) \le L_{32}^{max}, \\ &z(t+1) = z(t) + P^{batt}(t), \\ &0 \le z(t) \le SOC^{max}. \end{aligned} \tag{3.13}$$

In the next section, we will describe a solution method to the above stochastic model predictive control problem by taking advantage of dynamic programming.

3.2 Stochastic Control Method

In this section, an algorithm is proposed to solve the stochastic model predictive control problem described in the previous section considering the input and state constraints. To this end, we first combine the constraints in (3.13) to reduce the number of constraints and put them in a compact form. Using (3.1), (3.5), (3.7), (3.10), and (3.11), the following constraint is obtained

$$\begin{aligned} z(t+1) = z(t) + d(t) + w^d(t) - P^{wind}(t) \\ - w^{wind}(t) - P^{gas}(t). \end{aligned} \tag{3.14}$$

In addition, by combining (3.1), (3.4), (3.6), and (3.7), we determine that

$$max\{D(t) - L_{12}^{max}, 0\} \leq P^{gas}(t) \leq L_{32}^{max}. \tag{3.15}$$

Therefore, the optimization problem to be solved is now in the following form

$$\begin{gathered}
\min_{P_{gas}} J := \frac{1}{2} z(T)^T P z(T) + \sum_{t=0}^{T-1} [\frac{1}{2} z(t)^T Q z(t) + \frac{1}{2} (P^{gas}(t))^T R P^{gas}(t)] \\
\text{subject to:} \\
0 \leq z(t) \leq SOC^{max}, \\
z(t+1) = z(t) + d(t) + w^d(t) - P^{wind}(t) - w^{wind}(t) - P^{gas}(t), \\
max\{D(t) - L_{12}^{max}, 0\} \leq P^{gas}(t) \leq L_{32}^{max}.
\end{gathered} \tag{3.16}$$

The presence of the stochastic disturbance inputs in the problem under study brings a challenge in solving the MPC problem. Second challenge is due to the existence of input and state constraints resulting in the minimization of the cost function expected value over a finite horizon to become difficult to solve. In these situations, where an analytical solution does not exist, Monte Carlo methods have received attention in controls theory [39, 40, 41]. For this section, we propose an algorithm to solve the described MPC problem using *empirical mean* and *dynamic programming* tools to handle the constraints and expectation value computation.

3.2.1 Empirical Mean

The expectation of a cost function, i.e., $\mathbb{E}J$, can be appropriately approximated using its so-called empirical mean $\hat{\mathbb{E}}J$. By choosing n independent, identically distributed samples from w, empirical mean can be computed as

$$\hat{\mathbb{E}}J = \tfrac{1}{n}\textstyle\sum_{i=1}^{n} J(w_i). \tag{3.17}$$

Such an approximation is valid only if the error defined by $|\mathbb{E}J - \hat{\mathbb{E}}J|$ can be somehow evaluated. Due to the stochastic nature of the empirical mean function, this error can be measured in a probabilistic way. For example, we can guarantee with a probability of α that the estimation (3.17) has the accuracy γ if $|\mathbb{E}J - \hat{\mathbb{E}}J| < \gamma$. This lower bound on the probability, i.e., α, can be computed through Chebyshev inequality as [42]

$$Prob(|\mathbb{E}J - \hat{\mathbb{E}}J| < \gamma) \geq 1 - \frac{\sigma(J)}{n\gamma^2} = \alpha, \tag{3.18}$$

where σ represents the variance. It is trivial to show that as $n \to \infty$, the empirical mean converges to the expected value.

3.2.2 Stochastic Model Predictive Control Algorithm

The well-known dynamic programming method can be employed to solve the optimization problem corresponding to the MPC problem backwards from $t = T$ to $t = 0$ at each horizon. For the stochastic systems, we have to compute the cost function expected value which is an easy task only for the first stage corresponding to $t = T$. However, this calculation is not straightforward for other stages since the expected value of the cost function is not a quadratic function anymore. Hence, by having a sufficient number of samples, empirical mean can be utilized as an appropriate alternative to estimate the expected value. We describe below the steps of the proposed solution method for the stochastic MPC problem using the concept of empirical mean along with the dynamic programming method:

Step 1: Compute n using the Chebyshev inequality (3.18).

Step 2: To solve the DP problem using empirical mean, generate a sufficient number of disturbance samples and consequently state samples. To this end, n samples of disturbance are arbitrarily extracted at the first stage, i.e., $t = 0$. Having the initial conditions corresponding to state ($z(0)$) and control input ($P^{gas}(0) = 0$) along with the wind and load profiles, we can determine n possible $z(1)$, namely $z^i(1), i = 1, 2, ..., n$, through (3.14). For each $z^i(1)$, there will be n possible disturbance samples. So, we will have n^2 possible $z(2)$, namely $z^i(2), i = 1, 2, ..., n^2$. Continuing this process, n^{T-1} possible $z(T-1)$ in the final stage will be obtained. We call $z(0)$ the root node, $z^i(j)$ for $i = 1, ..., n^j, j = 1, ..., T-2$ intermediate nodes, and $z^i(T-1), i = 1, ..., n^{T-1}$ leaf nodes. Using the notation described, a *tree* is constructed for stochastic dynamic programming stages based on disturbance samples.

Step 3: Solve the MPC problem starting from the last stage using the dynamic programming policy. To this purpose, compute the cost function for each leaf node as

$$
\begin{aligned}
J(P^{gas}(T-1)) &= \frac{1}{2} z(T)^T P z(T) \\
&+ \frac{1}{2} z(T-1)^T Q z(T-1) \\
&+ \frac{1}{2} (P^{gas}(T-1))^T R P^{gas}(T-1),
\end{aligned}
$$

where $z(T)$ can be found in terms of $P^{gas}(T-1)$ using (3.14).

Step 4: Calculate the empirical mean over cost functions corresponding to each n leaf nodes connected to the same intermediate node.

Step 5: Minimize the empirical mean value of cost functions obtained in Step 4 over P^{gas}. The achieved optimal value will be the terminal cost for the next step.

Step 6: For each intermediate nodes $t = T-2, ..., 1$, compute the cost function value using the terminal cost of Step 5, find the empirical mean over the obtained cost functions corresponding to the same node in their previous stage, minimize the achieved empirical value, and consider this minimum value as the terminal condition for previous stage.

Step 7: At $t = 0$, consider the calculated minimum value of the cost function as the minimum value of (3.12) at this iteration. If the difference between this value and the minimum value obtained in the previous iteration is lower than γ, the stochastic MPC problem has been solved and this value is chosen as the optimal solution. Otherwise, based on the new value of P^{gas}, we update $z(t)$ for each node of tree and go back to Step 3.

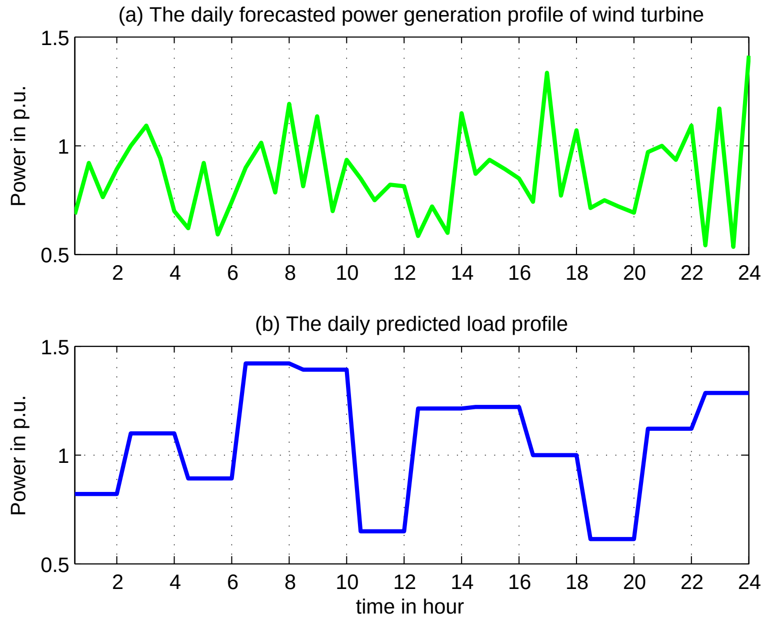

Figure 3.2: (a) The daily forecasted power generation profile of wind turbine; (b) the daily predicted load profile

3.3 Simulation

In this section, we demonstrate the viability of the proposed microgrid management method described in the previous section using an illustrative example, where we first generate artificial data for MG graph and the corresponding cost function. It should be noted all the values reported in this section are converted to per unit (p.u.). For simulation purposes, the daily power generation profile of the wind turbine in node 1 is generated using a random distribution. This profile is shown in Figure 3.2(a). The uncertainty in the wind power forecast is also modeled by

$$w^{wind}(t) \sim \mathcal{N}(0, 0.05). \tag{3.19}$$

In addition, maximum capacity of battery SOC^{max} is assumed to be 0.5, and maximum capacity of the distribution lines, i.e., L_{12}^{max} and L_{32}^{max}, is considered to be 1.3 p.u.

In node 2, we assume a load, whose daily load profile is also generated randomly for the simulation purposes. This profile is shown in Figure 3.2(b). In addition, the uncertainty in load prediction is described by

$$w^d(t) \sim \mathcal{N}(0, 0.03). \tag{3.20}$$

The penalty coefficients in cost function are assumed to be

$$P = 12, Q = 10, R = 12. \tag{3.21}$$

The first step in the algorithm described in the previous section is to find an acceptable number of samples n through Chebyshev inequality. Choosing $\gamma = 0.1$, we obtain $n = 7$. By having a sufficient number of samples, we can implement the stochastic MPC algorithm described before. Due to the computational limitations in MATLAB, we set $T = 4$. The final calculated state, i.e., $z(4)$, will be considered as the initial state for the next set of data. In addition, IBM ILOG CPLEX Optimization Studio 12.2 [43] is used for performing minimizations required in steps 5 to 7. Since the defined cost function is convex, CPLEX determines an optimal solution. A *mex* function is coded and employed to link CPLEX and MATLAB. Next, we describe the performed analysis and simulation results.

Figure 3.3 illustrates the demand profile of load in node 2, as well as the total power generated in microgrid by wind turbine and battery in node 1 and micro gas turbine in node 3. As observed, the generated power, i.e., supply, follows the demand

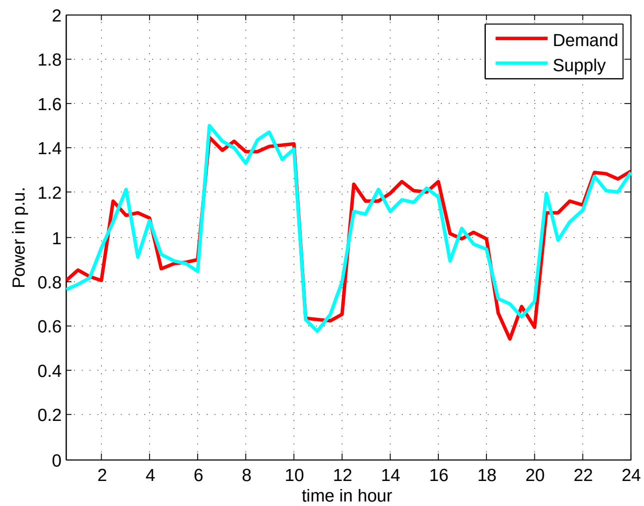

Figure 3.3: Noisy load profile and optimized microgrid's total generated power (from wind turbine, battery and micro gas turbine)

curve closely, and hence, the primary design objective is satisfied.

Shown in Figure 3.4(a) is the total power generated in node 1 of the microgrid that is supplied by the wind turbine and battery. This power is transferred to the demand side through the line between nodes 1 and 2. As observed, the power is always below the maximum line capacity, i.e., $L_{12}^{max} = 1.3\ p.u.$ This implies that the line capacity constraint has also been met. We have shown in Figure 3.4(b) the power generated in node 3 supplied by the micro gas turbine. Examining this figure implies that the MPC algorithm has tried to keep this generation as low as possible as it was one of the objectives in the defined cost function. Furthermore, the power generated in this node is transferred to the demand node through the line between nodes 3 and 2. As expected, the transferred power is always below the maximum line capacity, i.e., $L_{32}^{max} = 1.3\ p.u.$ Hence, the line capacity constraint between the nodes 2 and 3 is met as well. Finally, shown in Figure 3.4(c) is the battery state of charge SOC. As indicated before, one of the design objectives was to keep the SOC as close as

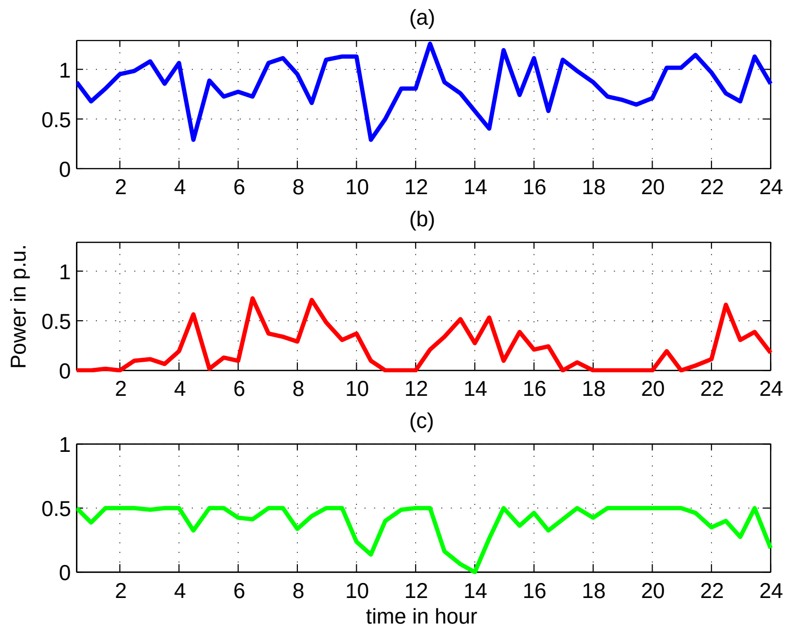

Figure 3.4: (a) power generated by wind turbine and battery; (b) power generated by micro gas turbine; (c) battery state of charge

possible to its maximum value (which is 0.5 $p.u.$ for the example discussed here). As illustrated in Figure 3.4(c), this goal is met as well.

Chapter 4

Multi-Objective Energy Management Method for Grid-tied Microgrids

The first objective for management system of microgrids is real-time dispatching of energy generations in a way that minimizes the operational cost while it guarantees the balance between supply and demand at the presence of unpredictable variations of distributed generations (DGs).

In order to relax the issue of sudden unforecasted unbalances between supply and demand, energy storage devices are normally utilized. Among various types of storage devices, battery is the most favorable option and also one of the most expensive components of microgrid. In grid-tied microgrids, any shortage in the supply-side (power outputs from DGs and the scheduled power from the grid) should be met whether by the battery or by purchasing extra power from the grid or a combination of both. At the first glance, it might be preferred to use battery first. But irregular discharge pattern of a battery might shorten its lifetime and incur a replacement cost for battery. Authors in [44] described three parameters mainly affecting a battery lifetime: 1) depth of discharge (DoD), 2) discharge power, and 3) temperature. It is shown how discharge power in different DoDs can determine the battery life period. Based on this idea, in microgrids operation, it is beneficial to utilize battery's power in a way that maximizes its lifetime. Therefore, maximizing the battery's life span should be considered as another important objective in addition to minimizing the micorgrid's operational cost.

To solve this problem, a novel multi-objective management system for real-time controlling of microgrids using MPC strategy is proposed in this chapter. Simulation results show the effectiveness of the proposed method in adjusting the battery lifetime and minimizing the cost of energy.

4.1 Problem Statement

The microgrid considered in this chapter is a directed graph which includes four nodes as follows:

- Node 1: Demand ($D(t)$)
- Node 2: Imported power from the grid ($P_G(t)$)
- Node 3: Battery unit
- Node 4: Total generated power by renewable sources such as PV and wind turbine ($P_{renew}(t)$)

As illustrated in Figure 4.1, $P_G(t)$ can be sent directly to demand node, $P_G^D(t)$, and/or stored in battery, $P_G^B(t)$. Hence, the following equality holds at each time, t,

$$P_G(t) = P_G^D(t) + P_G^B(t). \tag{4.1}$$

Since $P_{renew}(t)$ is uncontrollable with almost free marginal cost, it is beneficial to consume it directly by load, $P_{renew}^D(t)$, and/or store it in battery unit, $P_{renew}^B(t)$, as much as possible. $P^B(t)$ is battery discharge power which supplies the load. Considering the microgrid's graph and its elements, an optimization problem is defined in order to optimally dispatch different energy sources within the microgrid. Similar to other optimization problems, the proposed mathematical formulation has two main parts:

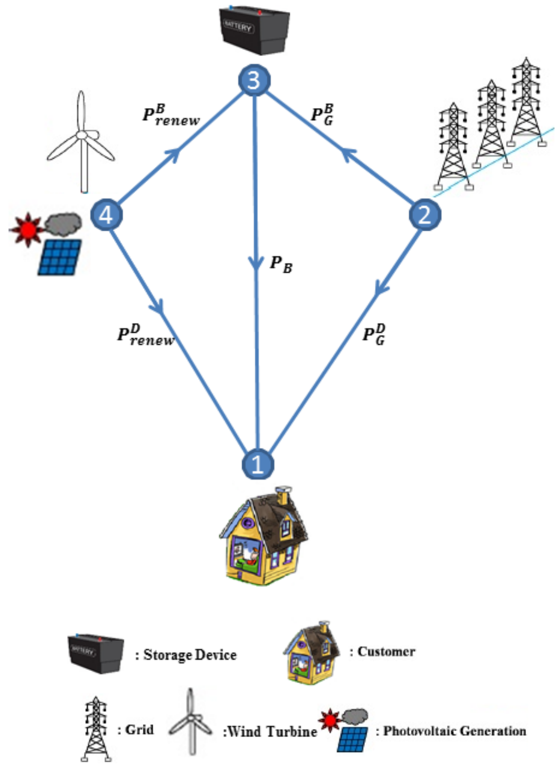

Figure 4.1: Schematic of a typical microgrid

Objective function which should be optimized, and static and dynamic constraints of microgrid which should be satisfied.

4.1.1 Objective Function

As mentioned above, there are two objectives for the proposed microgrid scheme that should be optimized: 1) minimizing the cost of energy, and 2) maximizing the battery lifetime.

4.1.1.1 Energy Cost Minimization

In every power dispatching problem, primary objective is to schedule the generators output to reliably supply the power requested by end users. This scheduling should be implemented in a cost-efficient way. In Figure 4.1, cost of energy for the microgrid is equal to the cost of importing power from the grid. Hence, first objective function J_1 is the grid power cost over the optimization window. We assume the marginal cost of grid power for any level of generation is constant. Therefore, J_1 is modeled by a linear equation as

$$J_1 := \sum_{t=0}^{T} C_G(t) P_G(t), \tag{4.2}$$

where T is optimization horizon, $P_G(t)$ is imported power from grid at time t, and $C_G(t)$ is grid power marginal price at time t based on time-of-use rates.

4.1.1.2 Battery Lifetime Maximization

To formulate the objective of battery lifetime maximization and integrating it with energy cost minimization, the maximization problem is translated into a minimization one. To this purpose, we need to estimate battery lifetime using its cumulative discharges and its DoD [44]. For a battery cell which has been operated for a certain period of time, τ, and experienced k discharge events, the estimated lifetime, BL, can be calculated as

$$BL = \frac{L_R D_R C_R}{\sum_{i=1}^{k} d_{eff}(i)} \tau, \tag{4.3}$$

where C_R is rated amp-hour capacity at rated discharge current, D_R is DoD for which rated cycle life was determined, and L_R is cycle life at rated DoD and rated discharge current. $d_{eff}(i)$ is the effective discharge (ampere-hours) for a particular discharge event i and is calculated as

$$d_{eff}(i) = \left(\frac{DoD(i)}{D_R}\right)^{x_1} e^{x_2\left(\frac{DoD(i)}{D_R} - 1\right)} \frac{C_R}{C_A(i)} d_{act}(i), \tag{4.4}$$

where $DoD(i)$, $C_A(i)$, and $d_{act}(i)$ are DoD, actual capacity of a battery, and measured discharge ampere-hours for i^{th} discharge event respectively. Coefficients x_1 and x_2 are calculated by applying a curve fitting procedure to cycle life versus DoD data that are available from the battery data sheet. To perform curve fitting task, particle swarm optimization (PSO) technique is employed [45]. PSO is a curve fitting tool compatible with nonlinear battery characteristics.

Having the estimated lifetime, we can evaluate the number of battery replacements, NBR, during the total life of the project, Y_{proj}. According to number of required replacements, equivalent uniform annual cost (EUAC) is calculated as

$$EUAC = RBC[(CC + RC\sum_{n=1}^{NBR}\tfrac{1}{(1+i_{act})^{n\times Y_{rep}}})CRF(i_{act}, Y_{rep}) + OMC(1+f)^n], \tag{4.5}$$

where RBC is rated battery capacity (kW), CC is capital capacity ($\$/kW$), RC is replacement cost ($\$/kW$), and Y_{rep} is replacement year. i_{act} is actual interest rate (%) and is obtained as

$$i_{act} = \frac{i_{nom} - f}{1+f}, \tag{4.6}$$

where i_{nom} is nominal interest rate (%) and f is inflation rate (%). Finally, CRF is capital recovery factor and is calculated as

$$CRF(i_{act}, Y_{rep}) = \frac{i_{act}(1+i_{act})^{Y_{proj}}}{(1+i_{act})^{Y_{proj}} - 1}. \tag{4.7}$$

Once the EUAC is determined, the battery usage price, BUP, can be calculated by dividing EUAC by the expected annual kWh usage of the battery as [46]

$$BUP = \frac{EUAC}{8760 \times RBC}. \tag{4.8}$$

If the battery is charged by renewable generation, price of power extracted from the battery, C_B is equal to BUP because marginal cost of power from renewable sources is almost free. In the case of charging the battery by other generator assets such as a diesel generator or grid, C_B can be written as

$$C_B = BUP + C_{charge}, \tag{4.9}$$

where C_{charge} is the cost of charging the battery ($\$/kWh$). In summary, the cost of discharging battery power (second objective, J_2) can be modeled as

$$J_2 := \sum_{t=0}^{T} C_B P_B(t), \tag{4.10}$$

where $P_B(t)$ is battery discharge power obtained from measured discharge ampere-hours at time t.

By transferring battery lifetime maximization problem into a battery power cost minimization problem, we are able to embed the objectives (4.2) and (4.10) into a single optimization problem in which the objective function, J, can be written as

$$J := \sum_{t=0}^{T} C_G(t)P_G(t) + C_B P_B(t). \tag{4.11}$$

4.1.2 Constraints

The operational and physical constraints of problem are listed as follows:

1) Supply-Demand balance which is an equality constraint and the primary task of management system. This constraint is formulated as

$$P_G^D(t) + P_B(t) + P_{renew}^D(t) = D(t), \tag{4.12}$$

which means the summation of generated power by grid, battery, and renewable source should be equal to demand at each time.

2) Battery state of charge (SoC) difference equation is given by

$$soc(t+1) = soc(t) - \alpha P_B(t) + \alpha P_G^B(t) + \alpha P_{renew}^B(t), \tag{4.13}$$

in which $soc(t)$ is battery SoC in ampere-hour (Ah) at time t, and α is a coefficient which changes kW unit into Ah.

3) Upper and lower bound for battery SoC which by considering the SoC difference equation (4.13) will be a dynamic inequality constraint as

$$soc^{min} \leq soc(t) \leq soc^{max}, \tag{4.14}$$

4) All decision variables ($P_G^D(t)$, $P_G^B(t)$, $P_{renew}^D(t)$, $P_{renew}^B(t)$, and $P_B(t)$) are physical variables. Therefore, they are always greater than or equal to zero, and can be

expressed as

$$P_G^D(t) \geq 0, P_G^B(t) \geq 0, P_B(t) \geq 0,$$
$$P_{renew}^D(t) \geq 0, P_{renew}^B(t) \geq 0. \tag{4.15}$$

5) Renewable inequality constraint which states that the summation of $P_{renew}^D(t)$ and $P_{renew}^B(t)$ should be less than or equal to available renewable generation at each time. Thus,

$$P_{renew}^D(t) + P_{renew}^B(t) \leq P_{renew}(t), \tag{4.16}$$

in which $P_{renew}(t)$ is the available renewable power at time t based on forecasted profile of renewable generations.

6) Peak shaving inequality constraint which provides the management system with the ability of performing peak shaving task. By satisfying this constraint, management system guarantees that the total imported power from the grid at each time is less than a predetermined constant value, P_{PSH}. Therefore, we state this inequality constraint as

$$P_G^D(t) + P_G^B(t) \leq P_{PSH}. \tag{4.17}$$

It should be noted that this constraint is an optional objective for management system and is not a mandatory task for normal type of operation.

For defining and solving optimization problem, it is sufficient to pick $P_G^D(t)$, $P_G^B(t)$, $P_{renew}^D(t)$, $P_{renew}^B(t)$ as decision variables since other variables can be described based on this parameters. Hence, we can summarize the optimal dispatching problem for the finite horizon T as

$$\min_{\substack{P_G^D, P_{renew}^D, \\ P_G^B, P_{renew}^B}} \quad J := \sum_{t=0}^{T} C_G(t) P_G(t) + C_B P_B(t) \tag{4.18}$$
$$\text{subject to:} \qquad (4.12) - (4.17).$$

4.2 Model Predictive Control Utilization

In this section, the proposed real-time management problem is embedded into the framework of MPC. In order to build the MPC model, we need to have some information about the system. In the management problem under study, for making the model of operation for microgrid, some current and future information such as forecasted load and renewable generations profiles, time-of-use grid electricity rates, current battery SoC, SoC model for battery charging and discharge, battery power pricing model, etc. are required. In this way, MPC will be able to perform the real-time management task based on following steps:

Step 1: Current system information and system response to previous inputs are measured. In addition, forecasted profiles of load, renewable generations, and grid electricity rates are updated for new optimization horizon.

Step 2: Based on update information, system model, optimization objective function, and constraints are updated.

Step 3: The proposed economic dispatching problem is solved which results in a sequence of control actions (output power of each energy source in different nodes) for each time instance of optimization horizon.

Step 4: The first control action is implemented which means the output of each energy source and battery is determined for current time. The rest of the control sequence will be ignored.

Step 5: System response (new level of battery SoC, battery power price, etc.) to control commands is measured and utilized as a feedback for next iteration to improve system performance.

Steps 4 & 5 together help the management system to perform a closed-loop control algorithm. As mentioned before, closed-loop characteristic increases the reliability for dealing with errors in system modeling and forecasting the renewable generations and load profiles.

Step 6: Horizon control recedes just one time step and MPC repeats the algorithm by going back to step 1.This step lets MPC to act as an on-line manager for microgrid which optimizes its behavior in every time step.

4.3 Simulation Results & Discussion

For simulation purposes, a grid-tied microgrid is considered in this study which includes wind turbine and PV solar panels as DG resources, grid connection, a storage package, and a load. To highlight the effectiveness of proposed method, first, we illustrate the simulation results for one day operation of microgrid. To this purpose, 24-hour profiles of time-of-use grid electricity rate, load, and renewable generation have been extracted based on real data and are illustrated in Figure (4.2). As it can be seen, based on three different grid electricity tariffs during the day, three different types of region have been introduced which are named off-peak time, partial peak time, and peak time. An Intensium Flex High Energy Lithium-Ion battery package has been selected as the storage unit for simulation purpose. Table (4.1) describes

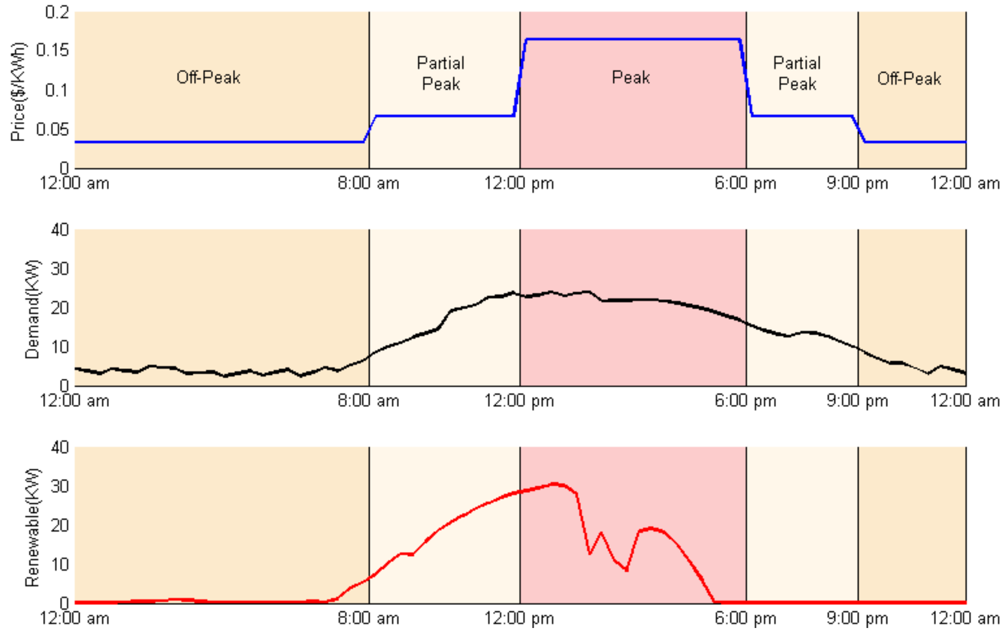

Figure 4.2: Daily Profiles of grid electricity price (blue line), demand (black line), and renewable generation (red line)

the specifications of battery package. Model predictive optimization horizon is 12 hours and receding step is 20 minutes which means optimization problem over the next 12 hours is solved and repeated every 20 minutes. In addition, it is assumed that 12-hour prediction of renewable generation is not a perfect forecast and has some uncertainty. To consider the uncertainty of forecasting, a random prediction error profile is generated and combined with renewable generation daily profile. This profile states that the error propagates up to 50% during the 12 hours of forecasting. Figure (4.3) shows the error propagation along the optimization window. Finally it should be mentioned that since we focus on cost minimization and battery lifetime maximization objectives, peak shaving constraint is excluded from the MPC problem. However, adding peak shaving task to the management system responsibilities is

Table 4.1: Characteristics of Intensium Flex High Energy Lithium-Ion battery package

Nominal voltage of each cell, V	48
Rated capacity, Ah	45
Rated lifetime at +20 °C, year	20
Rated life cycle	3000
Rated DoD	80%
NO. of cells in series, and parallel	18, and 1

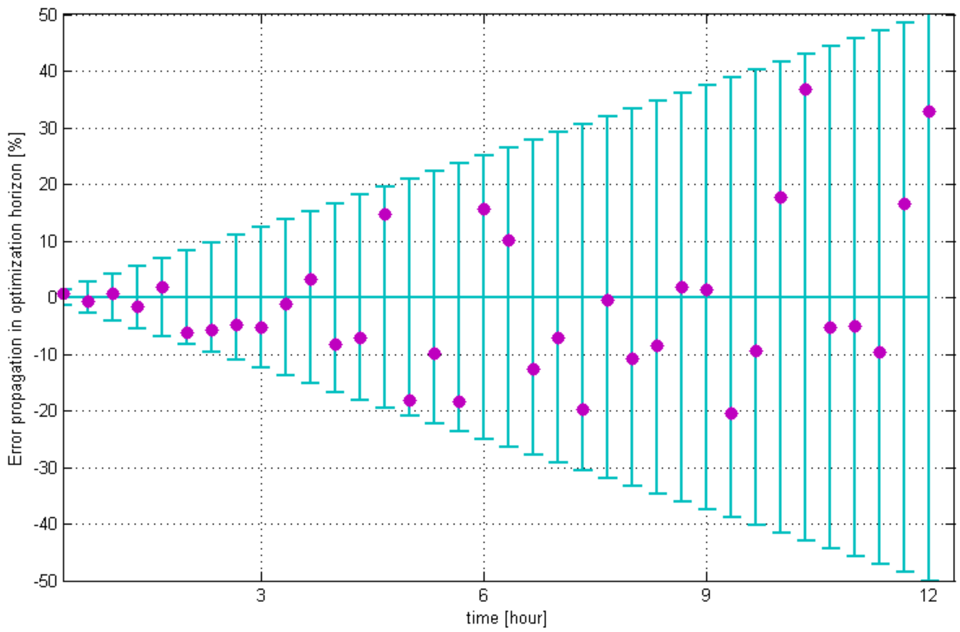

Figure 4.3: Error propagation along the forecasting horizon

straightforward and does not change the formulation. Detailed dynamic models of microgrid components are developed in MATLAB environment along with the proposed management framework. In addition, MATLAB optimization toolbox is utilized to solve the MPC problem. Figure (4.4) illustrates the first task of management system which is the balance between total generation and demand. It means that the total output of energy sources, e.g. grid connection, renewable generations, and battery equals to demand at each time instance.

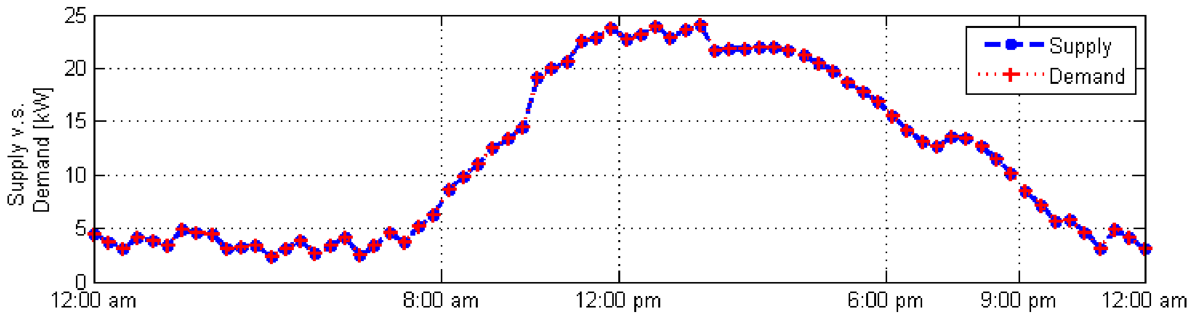

Figure 4.4: Balance between supply and demand

In order to evaluate the performance of proposed energy management system, we compare the results of this method with the outcomes of static algorithm proposed in [45]. Authors in [45] have tried to optimize the operational cost and battery lifetime as well; but they optimize microgrid performance at each time instance independently and without considering the future conditions and information. Figure (4.5) illustrates the operational cost for one day operation of microgrid based on two management strategy, the proposed MPC management method and static algorithm in [45]. As it shows, initially the operational cost for MPC method is higher but this cumulative cost will stay below the operational cost curve of the static method after $6:00pm$. The total operational cost for static method is \$8.27 while the total operational cost for MPC method is \$6.48. It means utilizing the proposed management method will create the opportunity for 21.6% more saving in one-day operational cost.

Now, we investigate the reasons which help the proposed management method to reduce the operational cost. To this end, we track the flow of power from microgrid energy sources. Figure 4.6 shows the extracted power from the grid for sending directly to load, P_G^D, for both MPC and static methods versus load. It shows that the static method extracts much more power from the grid in peak time in which the

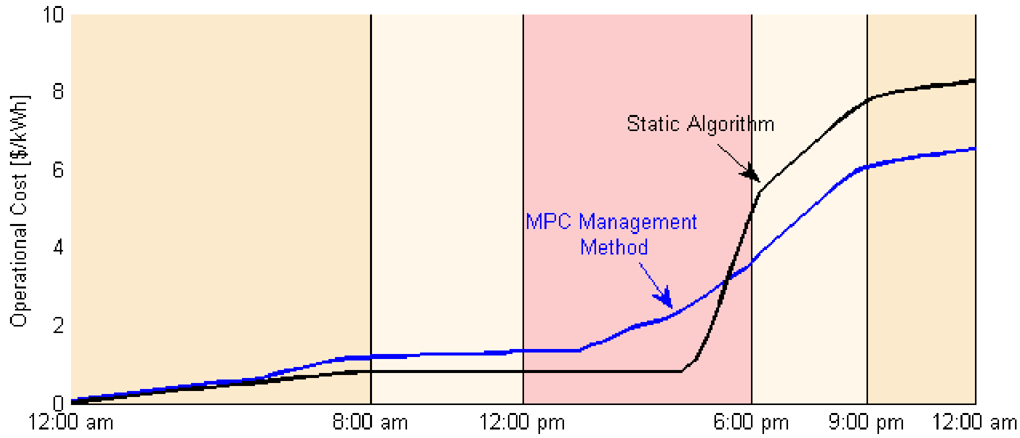

Figure 4.5: Operational cost based on MPC management and static management strategies

grid electricity price is in its maximum rate period. Figure 4.7.b illustrates the power that charges the battery based on static algorithm. By looking at figure 4.7.a we find that the battery is charged only when there is some exceeded renewable power. In this way, static method could charge the battery up to 70% of its full capacity, figure 4.7.c. Since the static method does not utilize any future information, the stored power will be discharged as soon as there will be any mismatch power for balancing the demand.

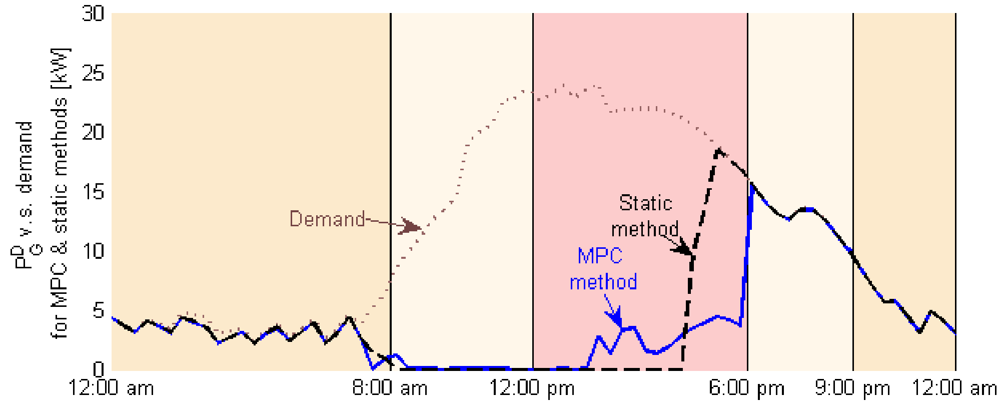

Figure 4.6: Extracted power from the grid for sending directly to load for both MPC and static methods versus load

On the other hand, figure 4.8.a shows the battery charging power based on MPC management method. Since, this method can forecast the availability of renewable generation, it predicts that in peak time there is not enough renewable power to compensate the load. Hence, there will be need to import some power from the grid. To minimize importing expensive grid power in peak time, MPC stores some grid power but in off-peak period in which grid power is cheaper. This power has been shown by dashed line in figure 4.8.a. MPC stores this power up to a level that allows fully utilization of exceeded free-of-charge renewable power. Figure 4.8.b depicts that MPC employs the full capacity of battery (100%SoC) and discharges all permitted battery power (80%DoD) in peak period in order to obtain the minimum operational cost.

For investigating the performance of the proposed management method in extending the battery lifetime, we need to operate the system for a longer time period. To

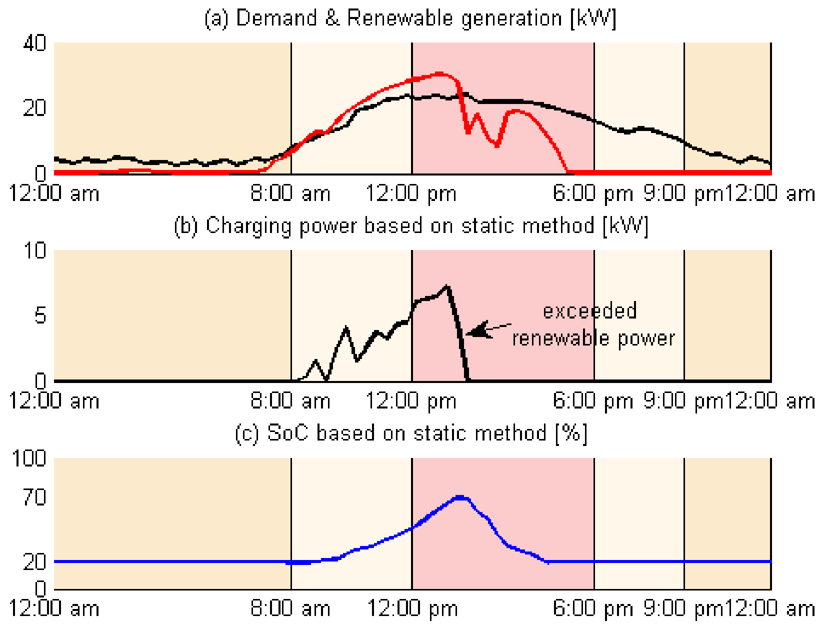

Figure 4.7: (a) Demand & renewable generation, (b) Battery charging power, and (c) Battery SoC related to static method

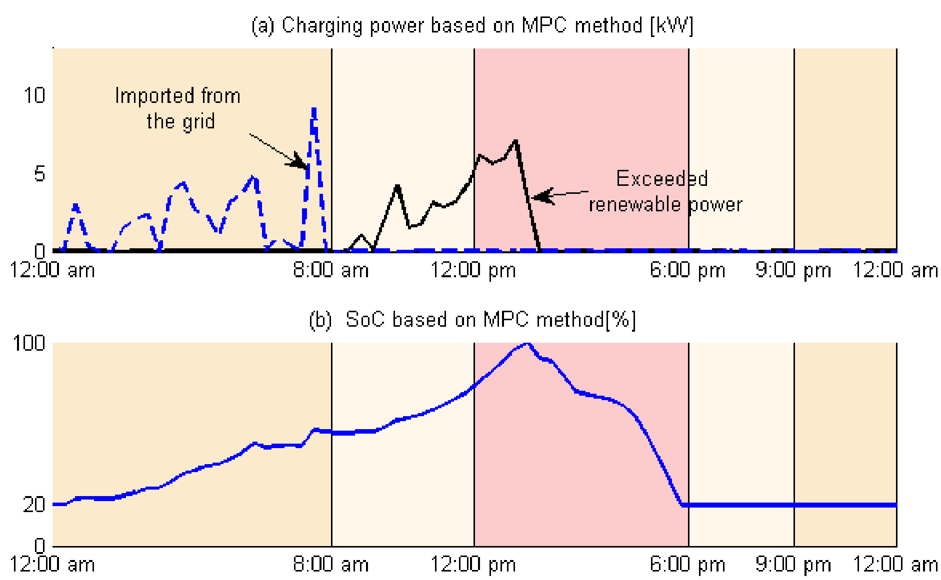

Figure 4.8: (a) Battery charging power based on MPC method, (b) Battery SoC based on MPC method

this purpose, the microgrid is operated for 30 days using the monthly profiles of time-of-use grid electricity rate, load, and renewable generation. In addition, in order to demonstrate the advantage of considering battery lifetime maximization objective in MPC management algorithm, we run the MPC once with battery lifetime extension objective, and once without it.

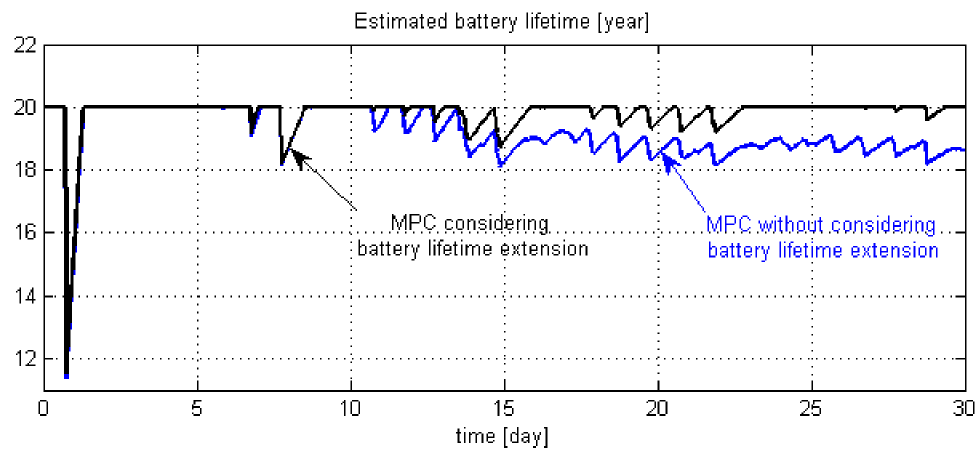

Figure 4.9: Estimated battery lifetime over one month operation of microgrid

Figure 4.9 shows estimated battery lifetime over one month operation of microgrid for both cases. It shows that if battery lifetime extension objective is not included in our management strategy, battery lifetime will be around 18 years based on the obtained one-month usage pattern of battery. On the other hand, by including the battery lifetime maximization goal in MPC objective function, the proposed management system is able to utilize the battery package for its whole rated life span which is 20 years.

Chapter 5

An Optimal Cooperation Method for Network of Microgrids

As discussed in previous chapters, a microgrid is able to manage its operation in both islanded and interconnected modes. In addition to the ability for self-managing, the microgrids in a neighborhood can collaborate through information exchange and power channels. Taking advantage of self-managing and collaborating capabilities, microgrids can compensate for the deviations from predicted demand or forecasted renewable generations through buying or selling surplus power of other microgrids' renewable energy. This will allow them to less participate in spot market for trading electricity power, and they will only buy a predetermined needed power through forward contracts for the entire day including peak hours in a much lower rate.

In this chapter, we assume that there is a network of microgrids which are not tied to the grid, but they can collaborate with each other. Each microgrid in the network has the ability to predict its own daily load curve and renewable energy generation profile. Due to the low cost of power generated from renewable sources, each microgrid first tries to supply the requested power by using the renewable sources and then, if needed, it uses its micro gas turbine that is a controllable generation source within the microgrid. Moreover, if at some point the amount of produced renewable power within the microgrid i is higher than the demand, it can find a neighbor, say microgrid j, whose renewable generation is less than its demand; in this case, microgrid i will sell the surplus power to the microgrid j. Based on this cooperation, the total cost of energy will be minimized through solving an appropriately defined optimization problem [47].

5.1 System Description

In this section, we consider a network of microgrids including n nodes as illustrated in Figure 5.1. It is assumed that each node contains a micro gas turbine, as well as a renewable source such as a PV generator or a wind turbine. The power from the gas turbine is controllable, while that from the renewable sources is uncontrollable [48]. In our formulation, we denote the total power generated by i^{th} microgrid, the power generated by i^{th} micro gas turbine, the power produced by i^{th} renewable source and the demand of i^{th} node by $G_i(t)$, $u_i(t)$, $G_i^{renew}(t)$ and $G_i^{ref}(t)$, respectively. For the node i, the generated power $G_i(t)$ at each time instant depends on its generated power at previous sampled time, its renewable generation power, its neighbors' surplus renewable power and its micro gas turbine output. The objective is to keep $G_i(t)$ as close as possible to $G_i^{ref}(t)$ for all the nodes. The daily load profile $G_i^{ref}(t)$ can be obtained in real-time using short-term electricity demand forecasting techniques [49, 50]. In addition, since the renewable source outputs are not controllable and their future profiles over a certain finite horizon time interval can be obtained in real-time using weather forecasts, it can be considered as negative load in the scheduling problem. Hence, the problem can be formulated as that of minimizing

$$||G_i(t) - G_i^{setpoint}(t)||, \tag{5.1}$$

where

$$\begin{aligned} G_i^{setpoint}(t) = \max[0, (G_i^{ref}(t) - G_i^{renew}(t))] \\ + \textstyle\sum_j a_{ij} \min[0, (G_j^{ref}(t) - G_j^{renew}(t))], \end{aligned} \tag{5.2}$$

in which a_{ij} are coefficients defining the portion of i^{th} node power that comes from the surplus power of j^{th} node. The coefficients can be determined through a forward contract. The state equation corresponding to each microgrid can be described as

$$G_i(t+1) = G_i(t) + u_i(t) + w_i(t), \qquad \text{for} \quad i = 1, 2, ..., n, \tag{5.3}$$

where $w_i(t)$ is the zero-mean white noise used to describe the uncertainties from

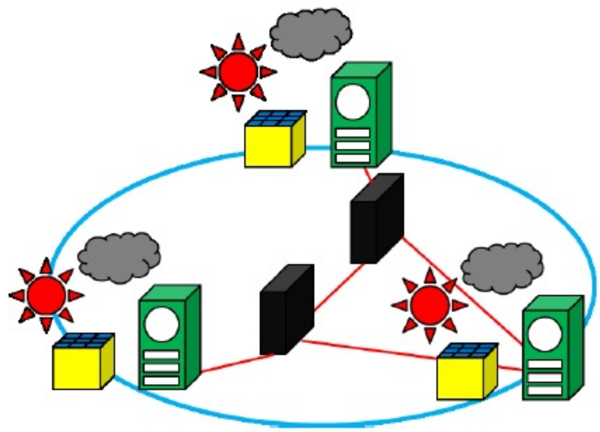

Figure 5.1: An example illustrating the cooperation between microgrids in a network [51]

either the power generated by the uncontrollable sources or the errors in demand forecast curve. The output equation for each node is the power measurement, i.e.,

$$y_i(t) = G_i(t), \tag{5.4}$$

assuming that the measurement noise is neglected. Moreover, there exists a physical constraint resulting from the limitation on the micro gas turbine generation as

$$0 \leq u_i(t) \leq u_i^{max}. \tag{5.5}$$

Putting the system difference equations described in (5.3) and (5.4) together for all the microgrids results in

$$
\begin{aligned}
G(t+1) &= AG(t) + Bu(t) + Fw(t), \\
y(t) &= CG(t),
\end{aligned} \tag{5.6}
$$

in which, for the specific network shown in Figure 5.1

$$
\begin{aligned}
G(t) &= [G_1(t), G_2(t), ..., G_n(t)]^T, \\
u(t) &= [u_1(t), u_2(t), ..., u_n(t)]^T, \\
w(t) &= [w_1(t), w_2(t), ..., w_n(t)]^T, \\
y(t) &= [y_1(t), y_2(t), ..., y_n(t)]^T,
\end{aligned} \tag{5.7}
$$

and the system matrices A, B, C and F are $n \times n$ identity matrices.

5.2 Optimal Control Method

To cope with the input constraints, as well as the proposed model characteristics, a suitable control methodology is receding horizon or model predictive control, which has become popular using state-space design methods in recent years [52, 53, 54]. To solve the MPC problem, an analytical approach [29] is employed which need some changes in mathematical modeling of the system.

5.2.1 Augmented Model

We first transform the standard state-space representation described earlier into a form appropriate for MPC design purposes, in which an integrator is also embedded [29].

$$\begin{aligned} G(t+1) - G(t) &= A(G(t) - G(t-1)) \\ &+ B(u(t) - u(t-1)) + F(w(t) - w(t-1)). \end{aligned} \tag{5.8}$$

The addition of the integrator is to ensure the reference trajectory tracking. By defining

$$\begin{aligned} \Delta G(t) &= G(t) - G(t-1), \\ \Delta u(t) &= u(t) - u(t-1), \\ \epsilon(t) &= w(t) - w(t-1), \end{aligned} \tag{5.9}$$

we obtain

$$\begin{aligned} \begin{bmatrix} \Delta G(t+1) \\ y(t+1) \end{bmatrix} &= \begin{bmatrix} A & 0 \\ CA & I \end{bmatrix} \begin{bmatrix} \Delta G(t) \\ y(t) \end{bmatrix} \\ &+ \begin{bmatrix} B \\ CB \end{bmatrix} \Delta u(t) + \begin{bmatrix} F \\ CF \end{bmatrix} \epsilon(t) \\ y(t) &= \begin{bmatrix} 0 & I \end{bmatrix} \begin{bmatrix} \Delta G(t) \\ y(t) \end{bmatrix}. \end{aligned} \tag{5.10}$$

Choosing a new state variable vector as $x(t) = [\Delta G(t)^T \;,\; y(t)^T]^T$, we have

$$\begin{aligned} x(t+1) &= Mx(t) + N\Delta u(t) + E\epsilon(t) \\ y(t) &= Hx(t). \end{aligned} \tag{5.11}$$

5.2.2 Prediction of State and Output Variables

Based on the augmented model derived in section 5.2.1 , we calculate the predicted plant output using future control inputs as the adjustable variables. Suppose that at the time instant t, the state vector $x(t)$ is available through measurement. The future control trajectory is denoted by [29]

$$\Delta u(t),\; \Delta u(t+1),\; \ldots,\; \Delta u(t+N_c-1), \tag{5.12}$$

where N_c is the control horizon which determines the number of future control actions. The future state variables and outputs are predicted for N_p steps (prediction horizon) through given information $x(t)$. The parameter N_p is also the length of the optimization window and $N_c \leq N_p$. The chain of future state variables is

$$x(t+1|t),\; x(t+2|t),\; \ldots,\; x(t+N_p|t), \tag{5.13}$$

where $x(t+N_p|t)$ represents the predicted state at the time instant $t+N_p$ using the information at current time $x(t)$, which is equal to

$$x(t+N_p|t) = M^{N_p}x(t) + \sum_{j=0}^{N_c-1} M^{N_p-1-j}N\Delta u(t+j). \tag{5.14}$$

Note that in the equations above used for prediction, since the disturbance is white noise and its expected value is zero, the term related to disturbance does not appear. The prediction of outputs can be found by the use of predicted state variables as

$$y(t+N_p|t) = HM^{N_p}x(t) + \sum_{j=0}^{N_c-1} HM^{N_p-1-j}N\Delta u(t+j). \tag{5.15}$$

By defining new vectors as

$$\begin{aligned} Y &= [y(t+1|t)^T,\ y(t+2|t)^T,\ \ldots,\ y(t+N_p|t)^T]^T, \\ \Delta U &= [\Delta u(t)^T,\ \Delta u(t+1)^T,\ \ldots,\ \Delta u(t+N_c-1)^T]^T, \end{aligned} \tag{5.16}$$

we obtain

$$Y = \Gamma x(t) + \Phi \Delta U, \tag{5.17}$$

where

$$\Gamma = \begin{bmatrix} HM \\ HM^2 \\ . \\ . \\ . \\ HM^{N_p} \end{bmatrix}, \tag{5.18}$$

and

$$\Phi = \begin{bmatrix} HN & 0 & ... & 0 \\ HMN & HN & ... & 0 \\ HM^2N & HMN & ... & 0 \\ . & & & \\ . & & & \\ . & & & \\ HM^{N_p-1}N & HM^{N_p-2}N & ... & HM^{N_p-N_c}N \end{bmatrix}. \tag{5.19}$$

Finally, it should be noted that all of the predicted variables (states and outputs) are calculated in terms of the current system state $x(t)$ and the future control actions.

5.2.3 Optimization

In this section, we define an objective function resulting in the control inputs to keep the predicted output as close as possible to a set-point signal $r(t)$. By solving the problem of minimizing this cost function, an optimal control trajectory ΔU will be obtained that minimizes the error between set-point and the predicted output. Suppose that the set-point vector is

$$R_s = \begin{bmatrix} r(t)^T & r(t+1)^T & ... & r(t+N_p-1)^T \end{bmatrix}^T. \tag{5.20}$$

Having the set-point vector R_s, the objective function J can be defined as

$$J = (R_s - Y)^T(R_s - Y) + \Delta U^T \bar{R} \Delta U, \tag{5.21}$$

where $\bar{R}$ is a tuning matrix used to shape the desired closed-loop performance. By expanding the vector Y, J can be rewritten as

$$\begin{aligned} J &= (R_s - \Gamma x(t))^T(R_s - \Gamma x(t)) - 2\Delta U^T\Phi^T(R_s - \Gamma x(t)) \\ &+ \Delta U^T(\Phi^T\Phi + \bar{R})\Delta U. \end{aligned}$$

Taking the first derivative of the cost function J and using the necessary condition for minimization yield

$$\frac{\partial J}{\partial \Delta U} = -2\Phi^T(R_s - \Gamma x(t)) + 2(\Phi^T\Phi + \bar{R})\Delta U = 0, \quad (5.22)$$

from which the optimal control trajectory is determined as

$$\Delta U = (\Phi^T\Phi + \bar{R})^{-1}\Phi^T(R_s - \Gamma x(t)). \quad (5.23)$$

Although the optimal solution vector ΔU contains the control inputs $\Delta u(t)$, $\Delta u(t+1)$, $\Delta u(t+2)$, $\ldots$, $\Delta u(t+N_c-1)$, based on receding horizon control principle, we only implement the first sample of this sequence, *i.e.,* $\Delta u(t)$ and ignore the rest of the sequence. When the next sampled data arrives, the more recent measurement is used to form the state vector $x(t+1)$ for calculation of the new sequence of control input. This procedure is iterated to provide the receding horizon control law.

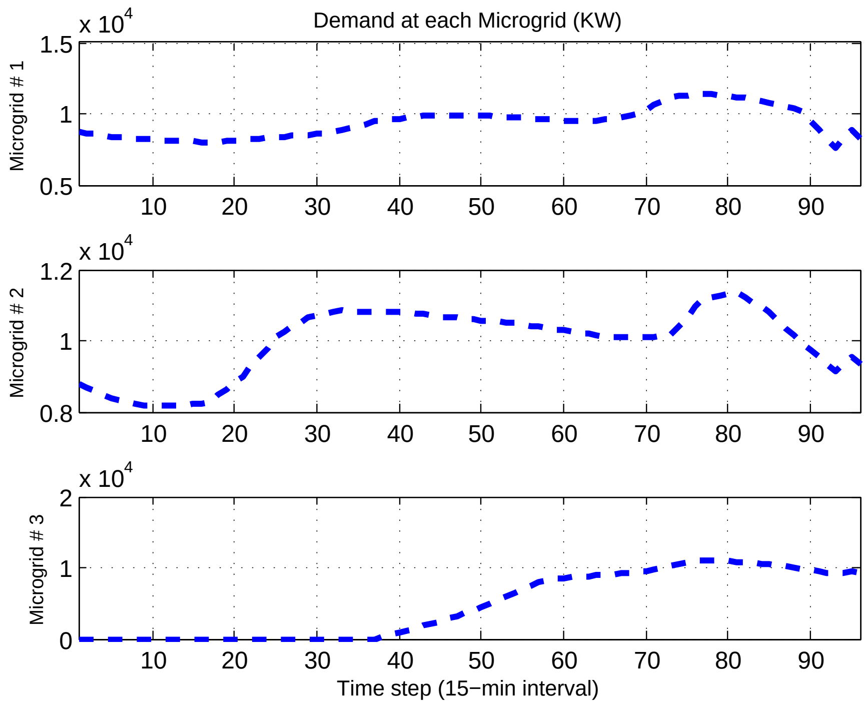

Figure 5.2: Demand profile for each microgrid of network

5.3 Simulation

In this section, the simulation results are demonstrated using a numerical example to examine the effectiveness of the proposed microgrids collaboration method described in the previous sections. In this regard, we consider a network which includes three microgrids. For each microgrid, 15-minute interval forecasted demand has been extracted based on the data from November 5^{th}, 6^{th}, and 7^{th}, 2011 provided in California ISO website [55]. We have assumed that the third microgrid has no power consumption during the first 9 hours. These load profiles are shown in Figure 5.2. In addition, 15-minute intervals prediction of the renewable power is calculated based on California ISO data for the same days [55]. This profile is shown in Figure 5.3.

If microgrids operate in islanded mode, which implies that there is no collaboration within the network, the difference between demand profile and renewable generation

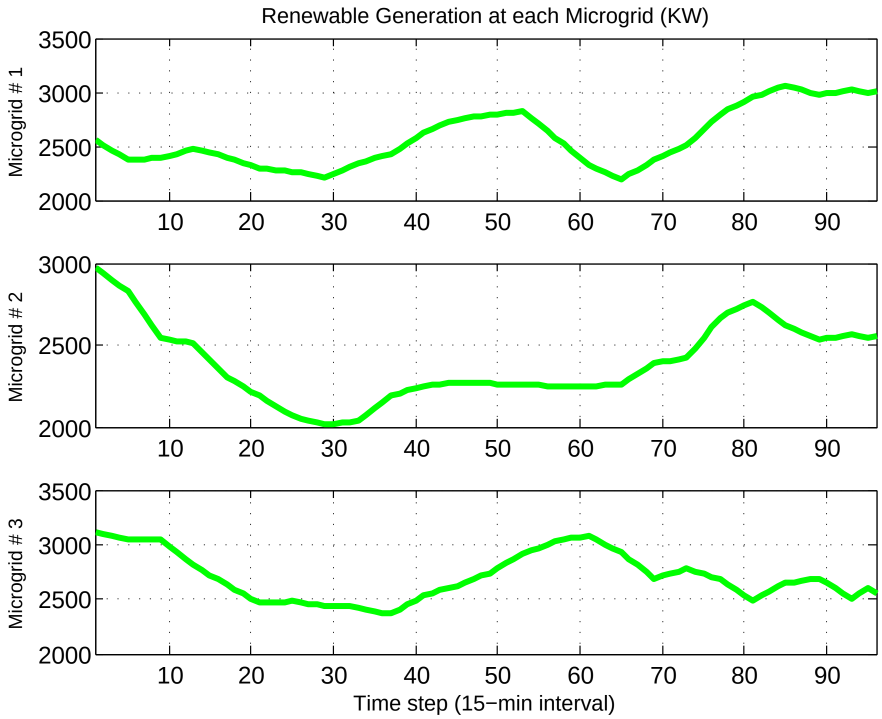

Figure 5.3: Rnewable generation at each microgrid of network

curve is used to generate the reference trajectory for each microgrid; this difference needs to be compensated for using micro gas turbine power. The reference trajectories are shown in Figure 5.4 by solid lines. Since microgrids cannot collaborate with each other, there will be no chance to utilize the surplus renewable power at the third microgrid which has been illustrated by dash dotted line. By taking advantage of the proposed method, that provides an opportunity for the microgrids to collaborate, this surplus power can be transferred to the neighbors to reduce the generated power of micro gas turbines. It is assumed that the surplus power is split equally between the neighbors, which in our case means $a_{ij} = 0.5$. The reduced power needed by micro gas turbines is shown in Figure 5.4 by dashed lines for first and second microgrid, and by solid line for the third one.

Finally, it should be noted that the length of the optimization window N_p and

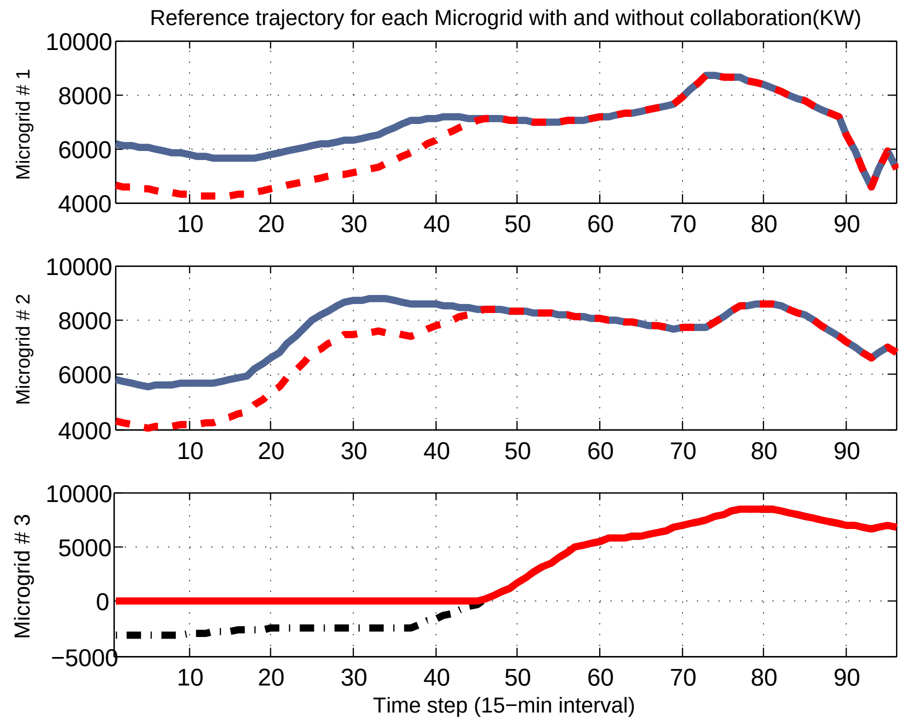

Figure 5.4: The reference trajectory of each microgrid with and without collaboration opportunity

control horizon N_c are assumed to be the same and equal to 5. Figure 5.5 illustrates the power generated by micro gas turbines in each microgrid calculated using MPC design strategy versus reference trajectory. As it can be inferred, the generated power, *i.e.,* supply, compensates for the residual load reasonably well. In addition, the marginal cost for a gas unit has been considered to be \$130/MWh, and we have assumed the marginal cost for a renewable source is free. Therefor, the total cost of generation of microgrids in network is $\$5.4872 \times 10^4$ when each microgrid is in islanded mode. By adopting the developed MPC based cooperation method, we could reduce the generation cost to $\$5.1346 \times 10^4$. It implies an approximately 6.43% reduction in electricity cost of generation which is the result of utilizing inherent capability of employing future system behavior and providing the collaboration opportunity

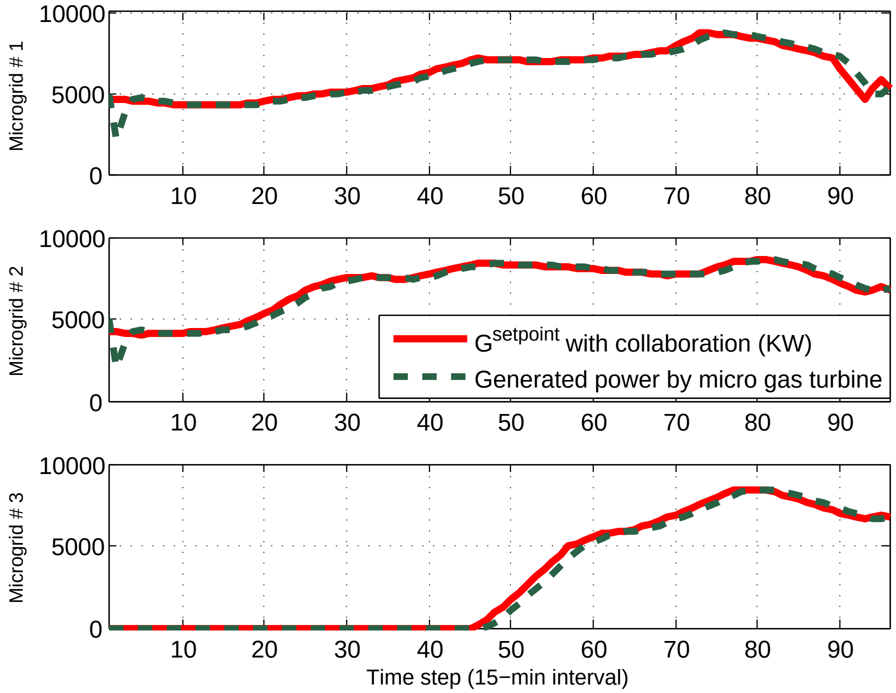

Figure 5.5: The generated power from the micro gas turbine in the three microgrids vs. the residual demand

between the microgrids in the network.

Chapter 6

Power System Dynamic Scheduling with High Penetration of Renewable Sources

The scheduling problem in power systems is defined as *determining the outputs of power generation units to balance supply and demand considering the power network constraints*. In economic scheduling, an optimization problem is solved by system operator (SO) to minimize the generation cost. Utilizing concepts from control theory, dynamic economic scheduling was first introduced in 1970's [56], in which the demand prediction over a period of time was taken into consideration at each optimization step. Moreover, the method was shown to handle the ramp rate constraint of generators which is a dynamic constraint [57]. Obviously, dynamic economic scheduling (DES) can be more realistic and useful in long term compared to the solution obtained from a static economic scheduling problem [58, 59].

There have been several approaches proposed to address the DES problem. In [60], dynamic programming has been suggested for solving the optimization problem corresponding to DES. However, the computational time and dimension of scheduling problem based on dynamic programming would increase with the dimension of the power system. In 1980's, DES problem was transformed into the minimization of entire generation cost on a particular period of time interval, known as dynamic economic dispatch (DED) [61, 62]. Different methods were proposed to solve the DED problem including gradient projection method, Lagrange relaxation, etc. [63, 64]. Unfortunately, DED violates the ramp rate constraint of generation units [65]. More importantly, DED strategy is an open-loop control policy, and hence, there will be no control over any deviation from the forecasted demand or any disturbance affecting the generation units' outputs. In this chapter, MPC strategy is employed to solve the DES problem.

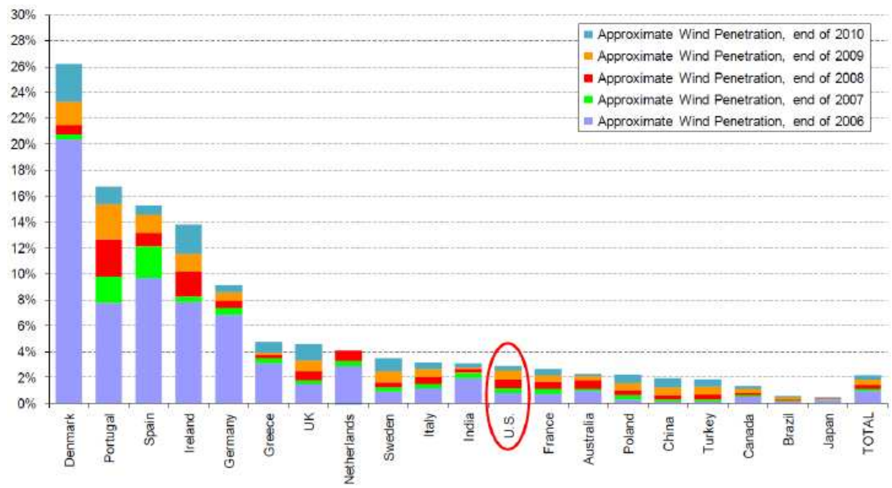

Figure 6.1: Estimated wind generation as a proportion of power consumption [66]

Renewable energy sources affect the operation of the power systems. Intermittency and uncontrollability of these sources have made them different from traditional power generation sources from the operation point of view. Similar to the demand profile, renewable sources production should be predicted ahead of the operation. Power generation from renewables is currently counted as a small portion of supply; for example, the estimated wind generation in the United States as a proportion of power consumption was less than 2.5% in 2010 (see Figure 6.1). Due to this low percentage, the most common approach in using renewable production in power system operation is to consider them as a negative load; some examples can be found in [67], [68], and [37]. On the other hand, the fossil fuels' price and the trend for reducing the carbon footprint are increasing. Due to these reasons, many countries have officially targeted the goal of increasing the renewable energy generations. For example, United States has targeted to raise its power generation from wind source to 20% by 2030 [69]. The State of California has also passed a renewable electricity mandate to reach 33% by 2020 [70]. The renewable portfolio and goals for different states is shown in Figure 6.2.

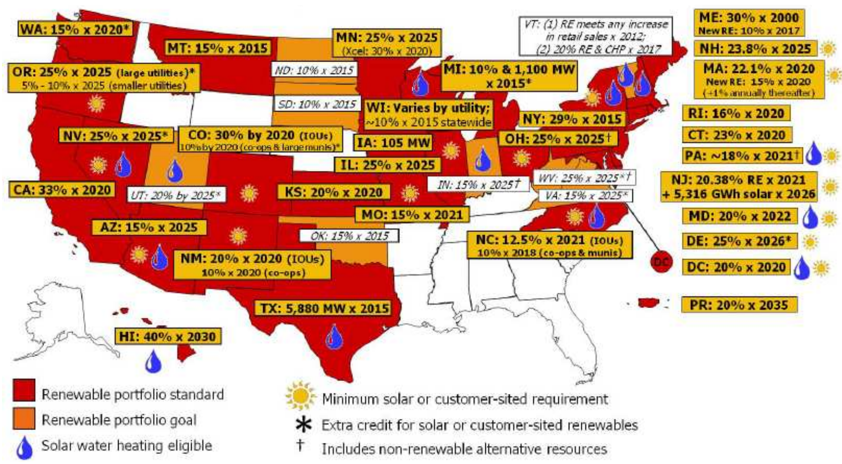

Figure 6.2: United States renewable portfolio [66]

With an increase in penetration of the renewable sources in supplying power, the use of negative load approach will not be appropriate anymore. There are a number of reasons that prohibit SO from fully utilizing renewable generations. In [28], authors have illustrated that it is not efficient to dispatch the maximum capacity of renewable generations when 30% of the total power is provided by wind power. They have shown that by considering intermittent sources as dispatchable units, the efficiency of economic dispatching problem can be improved since they can increase the generation of cheap and slow-response units such as coal and nuclear power and decrease the generation of expensive but fast-response units such as gas power plants. This advantage arises from the almost cost-free generation and high ramp rate characteristics of renewable sources and in particular wind power.

In this chapter, we examine the impact of high penetration of renewable generation sources on the future generation of smart grids from different points of view. We will show that due to the constraints on capacity of the transmission lines, SO can no longer interpret renewable sources as negative loads and dispatch their total power generated. Instead, we show that this issue can be handled by considering the renewable sources to be dispatchable units in the underlying optimization problem. In addition, we study the effect of integrating storage devices (and in particular batteries) with renewable sources on power scheduling problem. The use of storage devices will not only enable us to schedule the power from intermittent sources but also utilize their maximum capacity of production. It is noted that, here, the impact of market, *e.g.*, price bidding won't be considered. Instead, the objective is for SO to only minimize the cost of production of the generation units. Following the rationale and power scheduling principles proposed in this chapter, the problem of economic dispatching in a day-ahead market can be addressed, in which locational marginal pricing (LMP) for each generation unit will be among the decision variables. In the latter case, renewable sources might not be allowed to offer their total generations in financial day-ahead market due to the transmission congestion constraints; but they can offer major portion of their generation and act as dispatchable units. Moreover, they can schedule to store the uncommitted portion of their generation and offer it in the same day-ahead market.

6.1 Power System Economic Scheduling: Problem Statement and Formulation

In power scheduling problem, SO's primary objective is to schedule the generators' output to reliably and efficiently supply power requested by the end users. This scheduling that aims to minimize the cost of generation should be implemented in a cost-efficient way. To this purpose, we first consider an objective function defined as

$$J := \sum_i C_i(G_i(t)), \tag{6.1}$$

where $C_i(G_i(t))$ is a general cost function corresponding to i^{th} generator at time instant t that depends on its generation $G_i(t)$. The relation between generator output at time instant $t+1$ and time instant t is described as a state equation

$$G_i(t+1) = G_i(t) + u_i(t), \tag{6.2}$$

where $G_i(t)$ is the system state and $u_i(t)$ is the generator ramp rate considered to be the system input. The objective function is often assumed to be affine or quadratic to ensure the convexity of the underlying problem.

We next describe the typical constraints imposed on the power systems.

Constraint 1: *Supply-demand constraint* illustrates the balance of demand and supply at each time instant as

$$\sum_i G_i(t) = L(t), \tag{6.3}$$

where $L(t)$ is the total load consumed at time instant t.

Constraint 2: *Generators' capacity constraint* is considered as

$$G_i^{min}(t) \leq G_i(t) \leq G_i^{max}(t). \tag{6.4}$$

For conventional suppliers such as coal and gas units, the minimum and maximum capacities, denoted respectively by $G_i^{min}(t)$ and $G_i^{min}(t)$, are constant; however, for renewable generation sources, these values change based on their forecasted profile.

Constraint 3: *Ramp-rate constraint*: A substantial mechanical stress in the prime mover can be created due to over increasing or decreasing the output of the generators. This immoderate stress can cause a serious long term harm to the unit and eventually leads to a shorter life span [58]. To avoid this, a dynamic constraint is imposed on the rate, at which a generator can increase or decrease its output as

$$\begin{aligned} G_i(t+1) - G_i(t) &\leq R_i^u \\ G_i(t) - G_i(t+1) &\leq R_i^d, \end{aligned} \tag{6.5}$$

in which R_i^u and R_i^d represent ramp-up and ramp-down limits, respectively. We next describe the problems we will address in this paper.

Problem 1 *Scheduling problem with infinite-capacity transmission network*: Assuming that there is no transmission loss and no restriction on the capacity of transmission lines, one can interpret that all the suppliers and consumers are connected to the same bus. To pursue the discussion, we divide generators into two sets: (i) conventional generators such as coal and gas units represented by $\mathcal{C}$, and (ii) renewable generation sources such as wind and photovoltaic units represented by $\mathcal{R}$.

Problem 1.1 *Renewable generation as fully dispatched resources*: Considering that renewable sources are treated as fully dispatched resources acting like negative loads, the power scheduling problem can be addressed by solving the following optimization problem

$$\begin{aligned}
&\min_{u_i(t)|_{i\in\mathcal{C}}} J := \textstyle\sum_{i\in\mathcal{C}} C_i(G_i(t)) \\
&\text{subject to:} \\
&G_i(t+1) = G_i(t) + u_i(t), \qquad i \in \mathcal{C} \\
&\textstyle\sum_{i\in\mathcal{C}} G_i(t) = L(t) - \sum_{i\in\mathcal{R}} G_i(t) \\
&G_i^{min}(t) \leq G_i(t) \leq G_i^{max}(t), \quad i \in \mathcal{C} \\
&G_i(t+1) - G_i(t) \leq R_i^u, \qquad i \in \mathcal{C} \\
&G_i(t) - G_i(t+1) \leq R_i^d, \qquad i \in \mathcal{C}.
\end{aligned} \tag{6.6}$$

Problem 1.2 *Renewable generation as dispatchable resources*: Considering renewables as dispatchable generation sources, the power scheduling problem can be addressed by solving the following optimization problem (for any $i \in \mathcal{C} \cup \mathcal{R}$)

$$\begin{aligned}
&\min_{u_i(t)} J := \textstyle\sum_i C_i(G_i(t)) \\
&\text{subject to:} \\
&G_i(t+1) = G_i(t) + u_i(t) \\
&\textstyle\sum_i G_i(t) = L(t) \\
&G_i^{min}(t) \leq G_i(t) \leq G_i^{max}(t) \\
&G_i(t+1) - G_i(t) \leq R_i^u \\
&G_i(t) - G_i(t+1) \leq R_i^d.
\end{aligned} \tag{6.7}$$

It is noted that in Problem 1.2, maximum and minimum values corresponding to the renewable generations come from forecasted daily profile. The dependency of these upper and lower bounds on time is an implication of the power variability of the renewable sources.

The next problems we formulate correspond to the cases, where the transmission lines are constrained in terms of the allowable line capacity.

Problem 2 *Scheduling problem with finite-capacity transmission network*: This constraint imposed by the limitation of transmission lines can be represented by

$$|F_{ij}(t)| \leq F_{ij}^{max}, \tag{6.8}$$

where F_{ij} is the power transmitted through the line between buses i and j and is a function of power injected by contributing buses in the network, and F_{ij}^{max} is the maximum capacity of the transmission line between buses i and j. The relation between the lines' power vector denoted by $F(t)$ and buses' power vector denoted by $P(t)$ can be expressed as

$$P(t) = AF(t), \quad P \in R^N, \ F \in R^K \tag{6.9}$$

where N is the number of buses, K is the number of lines and A is a constant matrix. Notice that each element in vector $P(t)$ equals to generated power in the bus corresponding to that element minus its demand at time instant t. For instance, if bus i generates $G_i(t)$ and consumes $L_i(t)$, we have $P_i(t) = G_i(t) - L_i(t)$.

Problem 2.1 *Renewable generation as fully dispatched resources (negative load) with transmission constraint*: This problem can be formulated similar to Problem 1.1 by adding the line capacity constraint. The optimization problem we solve in this case is given by

$$
\begin{aligned}
&\min_{u_i(t)|_{i\in\mathcal{C}}} J := \textstyle\sum_i C_i(G_i(t))\\
&\text{subject to:}\\
&G_i(t+1) = G_i(t) + u_i(t), \qquad i \in \mathcal{C}\\
&\textstyle\sum_{i\in\mathcal{C}} G_i(t) = L(t) - \sum_{i\in\mathcal{R}} G_i(t),\\
&G_i^{min}(t) \le G_i(t) \le G_i^{max}(t), \quad i \in \mathcal{C}\\
&G_i(t+1) - G_i(t) \le R_i^u, \qquad i \in \mathcal{C}\\
&G_i(t) - G_i(t+1) \le R_i^d, \qquad i \in \mathcal{C}\\
&|F(t)| \le F^{max}.
\end{aligned}
\tag{6.10}
$$

Problem 2.2 *Renewable generation as dispatchable resources with transmission constraint*: The optimization problem corresponding to this case can be described similar to Problem 1.2 by adding the line capacity constraint as (for any $i \in \mathcal{C} \cup \mathcal{R}$)

$$
\begin{aligned}
&\min_{u_i(t)} J := \textstyle\sum_i C_i(G_i(t))\\
&\text{subject to:}\\
&G_i(t+1) = G_i(t) + u_i(t),\\
&\textstyle\sum_i G_i(t) = L(t),\\
&G_i^{min}(t) \le G_i(t) \le G_i^{max}(t),\\
&G_i(t+1) - G_i(t) \le R_i^u,\\
&G_i(t) - G_i(t+1) \le R_i^d,\\
&|F(t)| \le F^{max}.
\end{aligned}
\tag{6.11}
$$

The last problem we address in this chapter corresponds to the integration of the renewable generation sources with storage devices. To mathematically formulate the problem, we first develop a model to represent the dynamics of the battery as the storage device. It is noted that the model considered here is a simple one that can capture the dominant characteristics of a battery. We use the following equation to describe the dynamics of the battery state of charge (SOC) for j^{th} battery ($j \in \mathcal{R}$):

$$\begin{aligned} SOC_j(t+1) &= SOC_j(t) + \left(G_j^{max}(t) - G_j(t)\right)\eta_j \\ &- u_j^{dch}(t)(1/\eta_j), \qquad j \in \mathcal{R}, \end{aligned} \tag{6.12}$$

in which $SOC_j(t)$ is the state of charge at time instant t, $u_j^{dch}(t)$ is discharged power that is injected to the grid, and the difference $G_j^{max}(t) - G_j(t)$ is the charging power that represents the undispatched portion of the j^{th} renewable source, which would be stored. Finally, η_j is the round-trip efficiency of j^{th} battery, which we assume is split between charging and discharging. It should be noted that $SOC_j(t)$ (for all the batteries) will be augmented with $G_i(t)$ (for all the generation sources) as the new state vector in the underlying optimization problem. Also, $u_j^{dch}(t)$ will be augmented with $u_i(t)$ as the new vector of decision variables. The battery capacity is limited by:

$$SOC_j^{min} \leq SOC_j(t) \leq SOC_j^{max}, \tag{6.13}$$

in which SOC_j^{min} and SOC_j^{max} denote minimum and maximum capacity, respectively.

Remark 1: There are two additional constraints on charging and discharging limits as

$$
\begin{aligned}
0 &\leq G_j^{max}(t) - G_j(t) \leq P_j^{ch} \beta_j^c(t) \\
0 &\leq u_j^{dch}(t) \leq P_j^{dch} \beta_j(t),
\end{aligned}
\tag{6.14}
$$

in which P_j^{ch} and P_j^{dch} are maximum values for charging and discharging limits, respectively. In addition, in discharge mode, $\beta_j(t) = 1$, and in idle and charge modes, $\beta_j(t) = 0$. Also, in charge mode, we have $\beta_j^c(t) = 1$, and in idle and discharge modes, $\beta_j^c(t) = 0$. To avoid the battery charging and discharging at the same time, we impose an additional constraint as

$$
\beta_j^c(t) + \beta_j(t) \leq 1. \tag{6.15}
$$

The aforedescribed constraints should be checked to ensure that they always hold true.

Problem 3 *Scheduling problem considering renewable generation as dispatchable resources, transmission line constraints and storage devices*: Considering storage devices integrated with the renewable sources, the power scheduling problem can be addressed by solving the following optimization problem as follows:

$$
\begin{aligned}
&\min_{u_i(t)|_{i\in\mathcal{C}\cup\mathcal{R}},\; u_j^{dch}(t)|_{j\in\mathcal{R}}} J := \textstyle\sum_i C_i(G_i(t))\\
&\text{subject to:}\\
&G_i(t+1) = G_i(t) + u_i(t),\\
&\textstyle\sum_{i\in\mathcal{C}\cup\mathcal{R}} G_i(t) + \sum_{j\in\mathcal{R}} u_j^{dch}(t) = L(t),\\
&G_i^{min}(t) \le G_i(t) \le G_i^{max}(t),\\
&G_i(t+1) - G_i(t) \le R_i^u,\\
&G_i(t) - G_i(t+1) \le R_i^d,\\
&|F(t)| \le F^{max},\\
&SOC_j(t+1) = SOC_j(t) + \big(G_j^{max}(t) - G_j(t)\big)\,\eta_j\\
&\qquad\qquad - u_j^{dch}(t)(1/\eta_j), \qquad j\in\mathcal{R}\\
&SOC_j^{min} \le SOC_j(t) \le SOC_j^{max}, \qquad j\in\mathcal{R}.
\end{aligned}
\tag{6.16}
$$

6.2 Model Predictive Control

In the economic scheduling problem under study in this chapter, the system model is described by a linear difference equation for each generator and for each storage device. These equations represent the relation between generator outputs and battery state of charge as described by (6.2) and (6.12), respectively. In addition, the states and control inputs are restricted to belong to a set that satisfies the equality and inequality constrains corresponding to the optimization problems introduced in Section 6.1 such as (6.16).

The MPC problem can be solved to ensure that the states of the controlled system, generators' output, converge to a reference trajectory, demand profile, by minimizing the power generation cost, which is assumed to be an affine function of the generation unit powers. The cost function is optimized at each prediction horizon step. Consequently, based on the current information about generations' power and SOC for the storage devices, a control input sequence would be obtained that determines the generators' ramp rate and storage devices' output at each sampling time. Based on receding horizon policy, only the first sample of the control sequence is implemented as the input to the system difference equations (6.2) and (6.12) at time instant t to give the updated states at time instant $t+1$. Figure 6.3 is the flowchart showing the steps involved in implementing MPC algorithm and the corresponding steps for the DES problem under study here. For the simulation results shown in the next section, we use MATLAB command *linprog* to solve the underlying optimization problems.

6.3 Numerical Examples

To examine the effectiveness of the proposed scheduling policy using MPC method, we employ a 12-bus power network, which is modified from an IEEE 14-bus system [71] shown in Figure 6.4. Five-minute intervals of the forecasted total demand have been extracted based on the data from November 1st., 2011 provided in California ISO website [55]. This load profile is shown in Figure 6.5(a). In addition, 5-minute intervals prediction of the total renewable power consisting of wind and photovoltaic units generation is calculated based on California ISO data for the same day [55]. This profile is shown in Figure 6.5(b). Calculations from the data in Figure 6.5 show that, over the 24-hour period, the average amount of renewable production is 10.2% of the load average considering a balance in supply and demand. Table 6.1 shows the specifications of the power generation sources used in Figure 6.4 [28]. Based on the

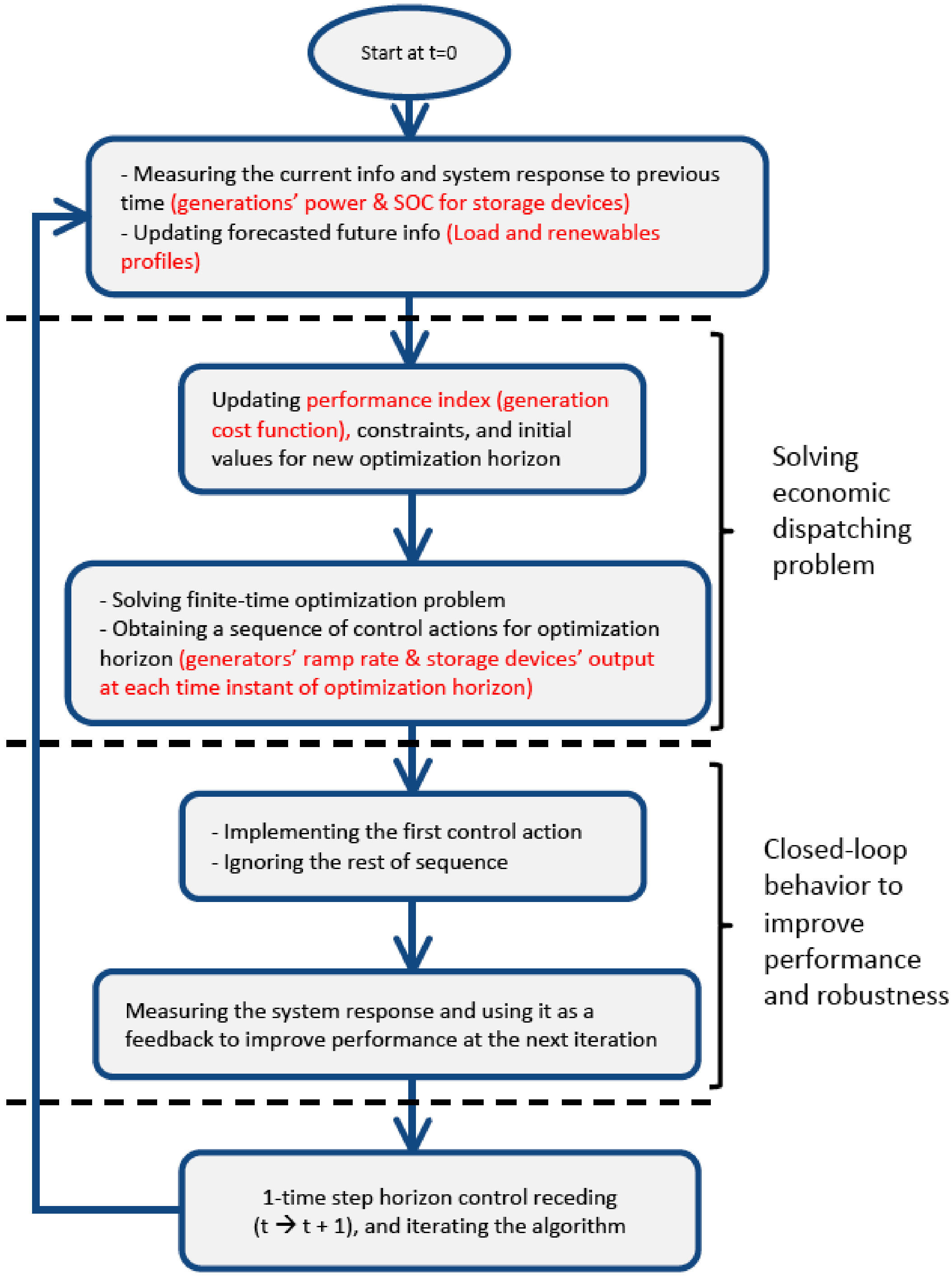

Figure 6.3: Flowchart of MPC implementation as applied to the DES problem

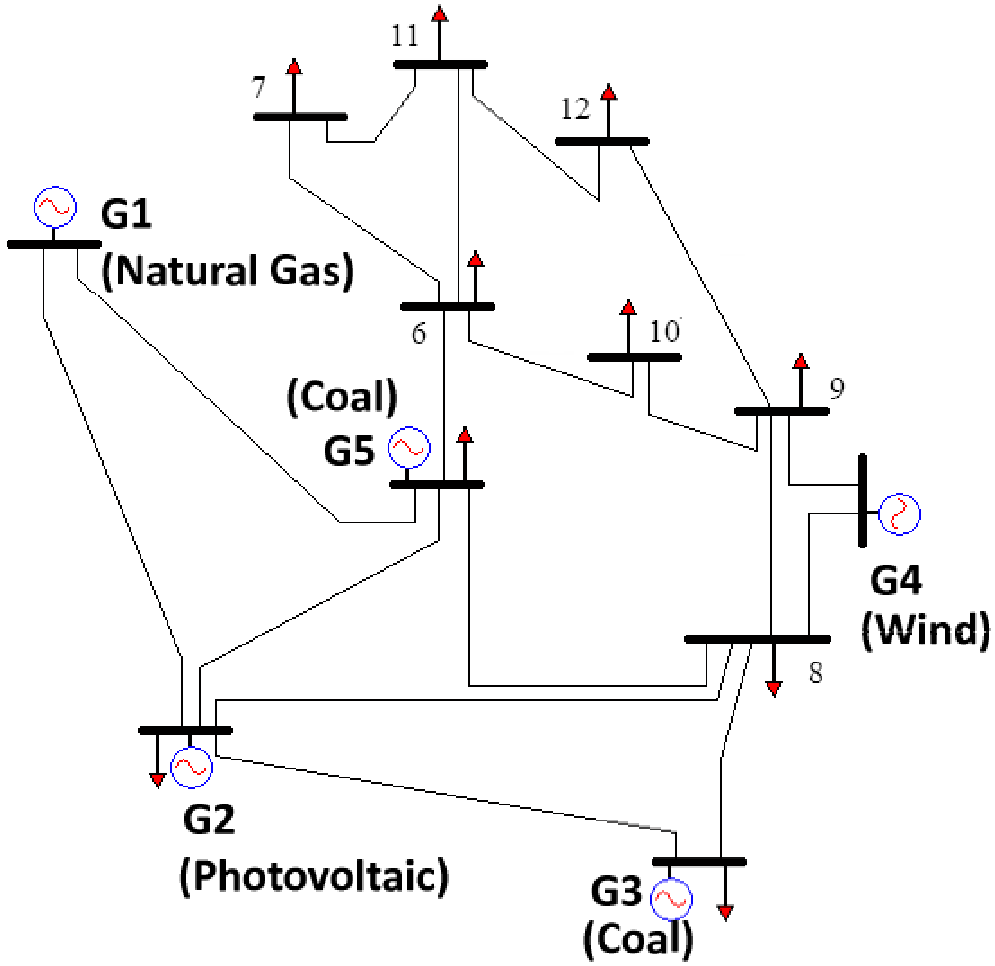

Figure 6.4: Configuration of a 12-bus power network [71]

information provided above, we examine the dynamic power scheduling for different scenarios discussed in the previous section considering two cases, where the generation from the renewable sources is either 10% or 20% of the total power demand.

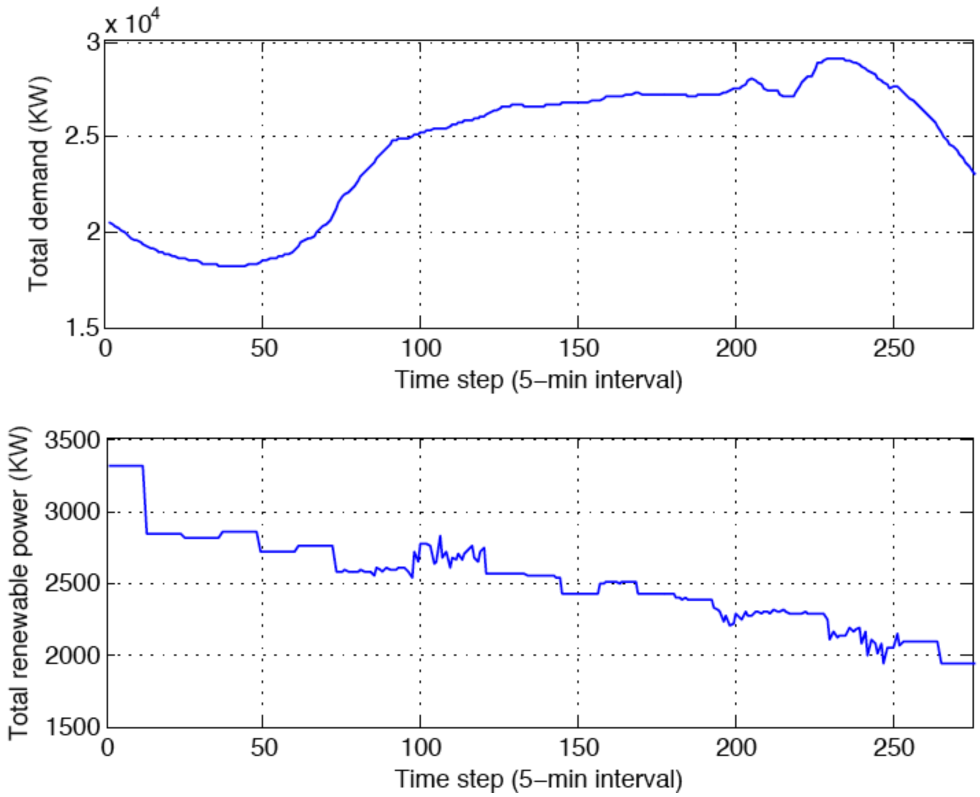

Figure 6.5: (a) Total demand in KW, (b) Total renewable generation in KW

Table 6.1: Characteristics of the generation sources

Bus #	Type	Capacity (KW)	Marginal Cost ($/MWh)	Ramp-up (KW/5min)	Ramp-down (KW/5min)
1	Natural Gas	5000	130	150	180
2	PV	1000	10	100	120
3	Coal	10000	50	50	60
4	Wind	3000	10	180	220
5	Coal	9000	50	50	60

6.3.1 Considering 10% renewable generation with no transmission congestion

First, we consider that about 10% of the total power needed to ensure a balance in supply and demand comes from the renewable sources and that there is no limitation on transmission lines. Using the profiles shown in Figure 6.5. We discuss the results obtained by solving the optimization problems associated with the two power scheduling problems introduced in the previous section. The two problems are solved using the MPC method considering renewable generations as negative load (Problem 1.1) or as dispatchable sources (Problem 1.2). Figure 6.6 demonstrates that both methods are capable of meeting the demand. The total cost of generation is also calculated and for both methods turns out to be the same and equals to $\$4.3822 \times 10^5$.

The total renewable power available, which is considered as negative load in Problem 1.1 and as dispatchable in Problem 1.2, is shown in Figure 6.7. As observed, the dispatched amount is almost equal to total power when there is no constraint on transmission line.

6.3.2 Considering 20% renewable generation with transmission congestion constraint

Next, we investigate the effect of transmission line constraints on power scheduling problem in the presence of a higher penetration of renewable sources among electricity providers. For this purpose, we assume a distribution of the total load among buses. The configuration we study in this example is shown in Figure 6.8. It should be noted that all the values shown in the figure are in per unit (pu). We first show the

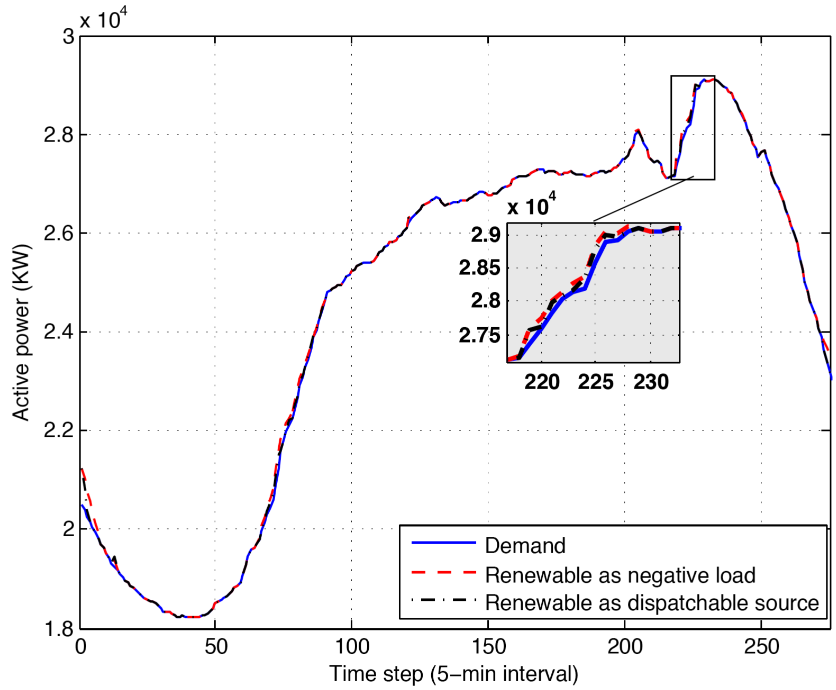

Figure 6.6: Profiles of demand (solid line), total supply power considering renewable generation sources at buses 2 and 4 as negative loads (dashed line), and total supply power considering renewable generation sources to be dispatchable (dash-dotted line)

details for representing the transmission line constraint in terms of the optimization variables. Considering bus 2, the second row of equation (6.9) becomes

$$P_2(t) = F_{21}(t) + F_{23}(t) + F_{25}(t) + F_{28}(t), \tag{6.17}$$

based on Figure 6.8. It is noted that we also have $P_2(t) = G_2(t) - L_2(t)$. Next, it is assumed that 20% of the demand is supplied using renewable sources. For this purpose, we doubled the renewable generation numbers shown in Figure 6.5(b). Considering the transmission line constraints, we solve MPC problems corresponding to problems 2.1 and 2.2. Because of violating the transmission constraints, Problem 2.1 *does not provide a feasible solution*, and hence we would not be able to consume the

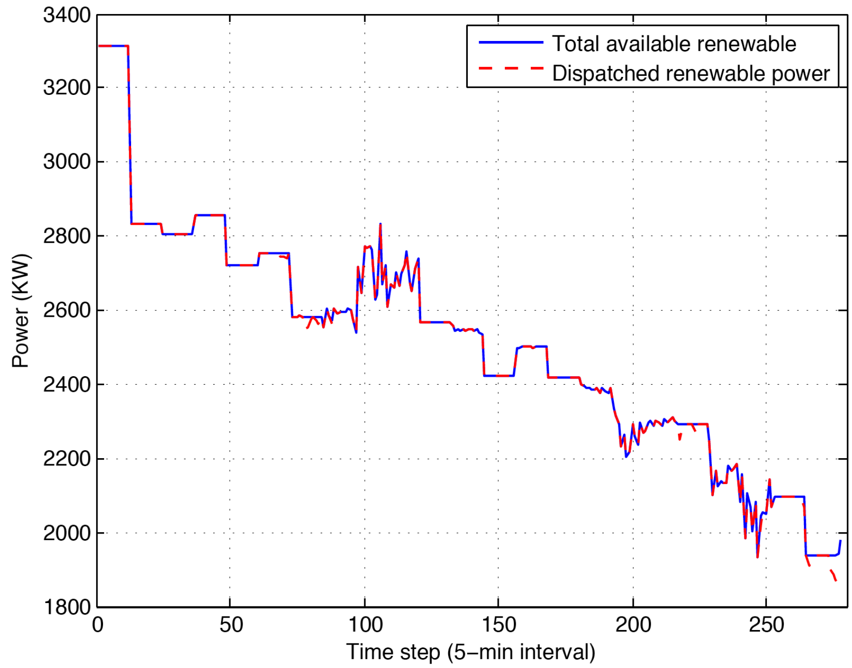

Figure 6.7: Total available and dispatched amount of renewable power

total available renewable generations at each time instant when they are considered as a negative load. On the other hand, Problem 2.2 gives a feasible solution, implying that treating renewable sources as dispatchable could successfully handle the transmission constraints and schedule the available sources to supply the requested power. Figure 6.9 shows the total supplied power and demand.

Figure 6.10 illustrates the amount of power from renewable sources that is dispatched from the total available renewable power. This figure clearly shows the effect of transmission line capacity constraint on scheduling the renewable generations. It is inferred that a portion of available renewable generations cannot be scheduled due to the transmission limits. The total cost of generation in this case is calculated to be \$$4.0217 \times 10^5$. It is noted that if we could fully dispatch renewable generations, the total cost would have been \$$3.7591 \times 10^5$.

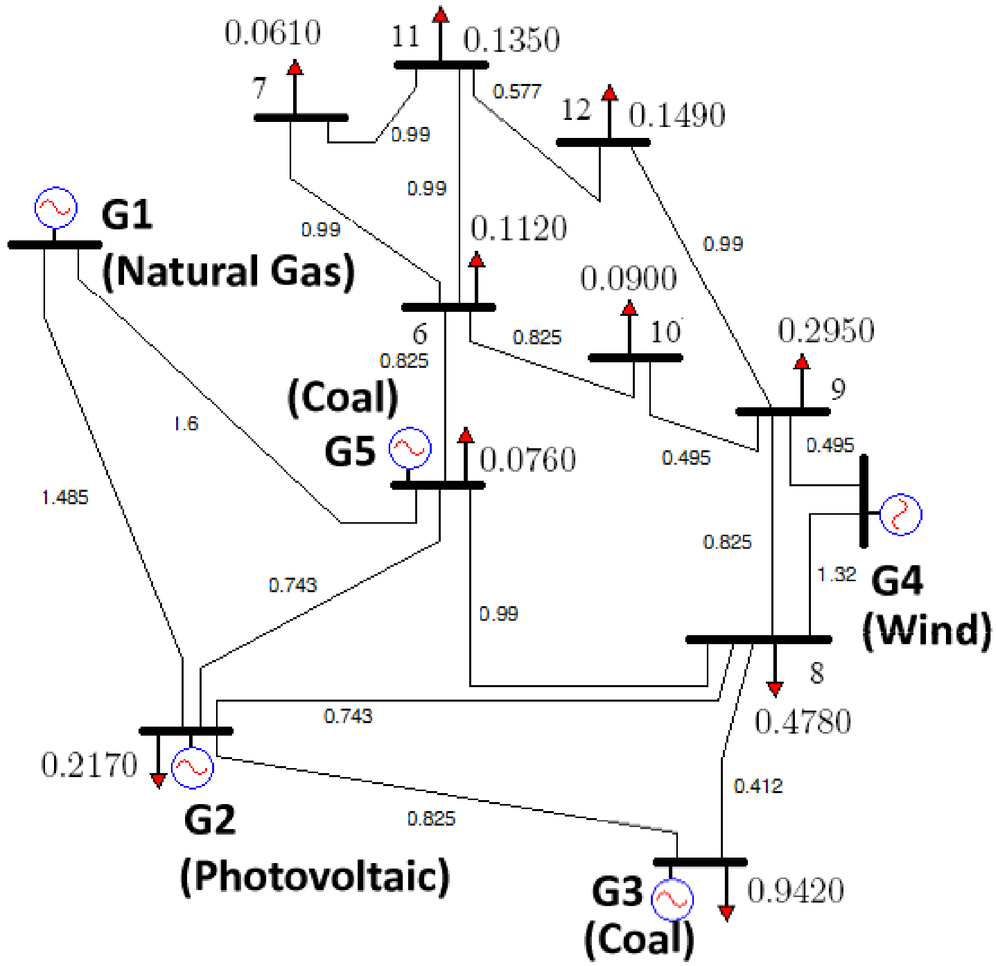

Figure 6.8: Configuration of a 12-bus power network considering transmission line constraints and distributed loads

To avoid the loss of undispatched power from the renewable sources, we use storage devices at buses, in which there are renewable resources installed. We assumed a round-trip efficiency of 90% for the batteries, which is split between charging (95%) and discharging (95%), and charging and discharging rates of 250 KW/5-min and 300 KW/5-min, respectively. This approach has been described by Problem 3 in the previous section. The solution to this problem leads to a demand and supply profile similar to the one shown in Figure 6.9 that illustrates a balance in supply

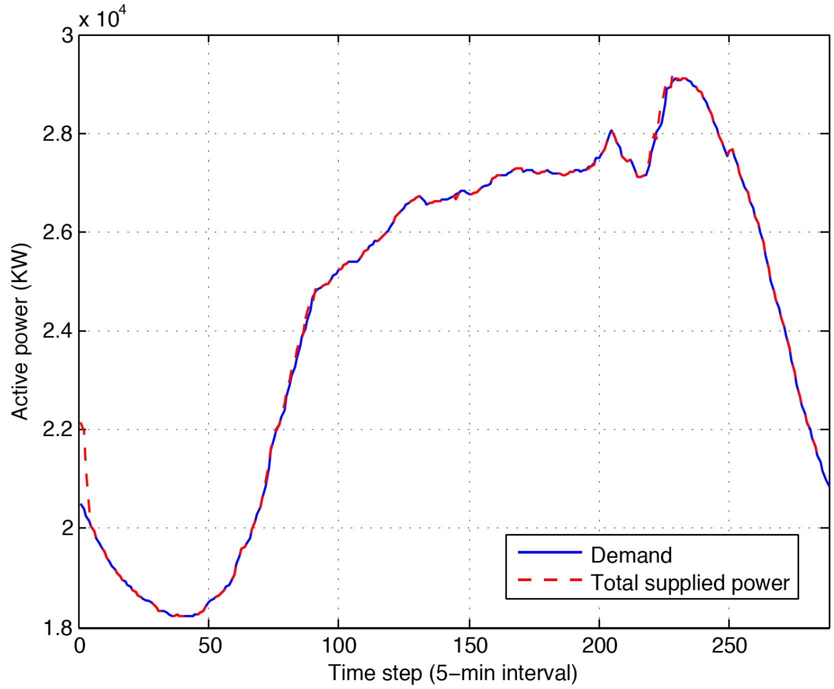

Figure 6.9: Profiles and demand and total supply considering transmission capacity constraints

and demand. In Figure 6.11, we have shown three profiles. Solid line shows the 24-hour total power available from the renewable sources generated at bus numbers 2 (photovoltaic) and 4 (wind). Dashed line shows the amount of dispatched renewable power. Due to the transmission congestion limits, the dispatched renewable power is lower than the maximum power available for time range between midnight and around 10 AM. Therefore, the difference between these two profiles is scheduled to be saved in storage devices. After 10 AM, transmission capacity allows system operator to dispatch not only the maximum available renewable power but also the stored power in storage devices. The total dispatched power from renewables and battery outputs is shown by the dash-dotted line. As observed, this profile is higher than the maximum generation of renewables. The accumulated difference between these two profiles is slightly less than the amount of power stored in batteries before 10

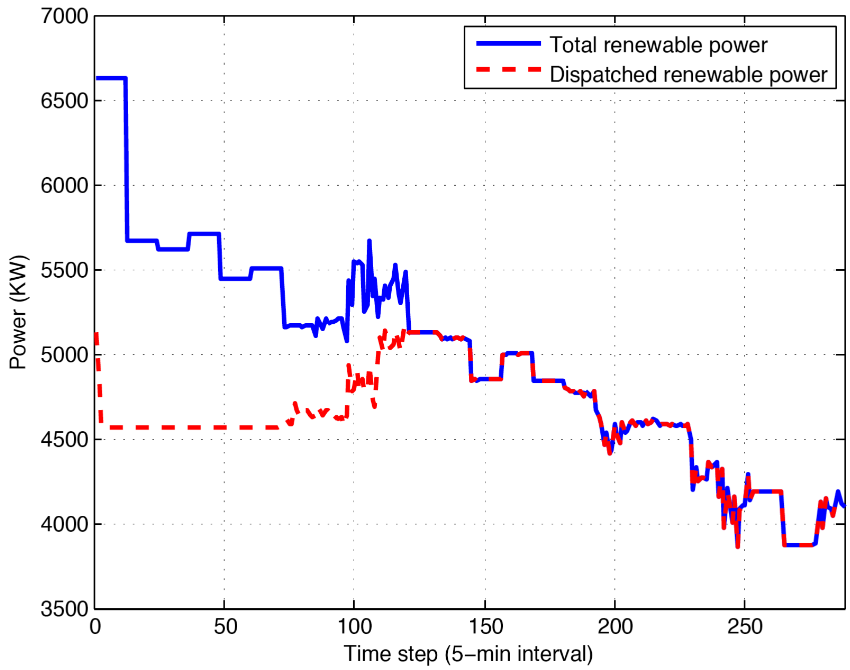

Figure 6.10: Total available and dispatched amount of renewable generation

AM. Shown in Figure 6.12 is the profile of SOC for the battery installed in the 4^{th} bus integrated with the wind turbine. The plot shows the trend of charging and discharging that is consistent with the profiles shown in Figure 6.11 since the battery is charged until 10 AM, after which it begins to discharge. We note that due to the low power production from the photovoltaic cell and the presence of a large load at 2^{nd} bus, battery integrated with this generation source is never charged, and hence SOC corresponding to this battery is always zero.

Finally, we summarize the simulation results obtained by solving the power scheduling associated with Problem 3. We observed that when there is a constraint on transmission lines, by utilizing the storage devices, unscheduled renewable power can be stored and later dispatched as shown in Figure 6.11. The adopted strategy in using storage devices reduces the generation cost from $\$4.0217 \times 10^5$ to $\$3.9288 \times 10^5$, implying an approximately 2.3% reduction in the cost of generation.

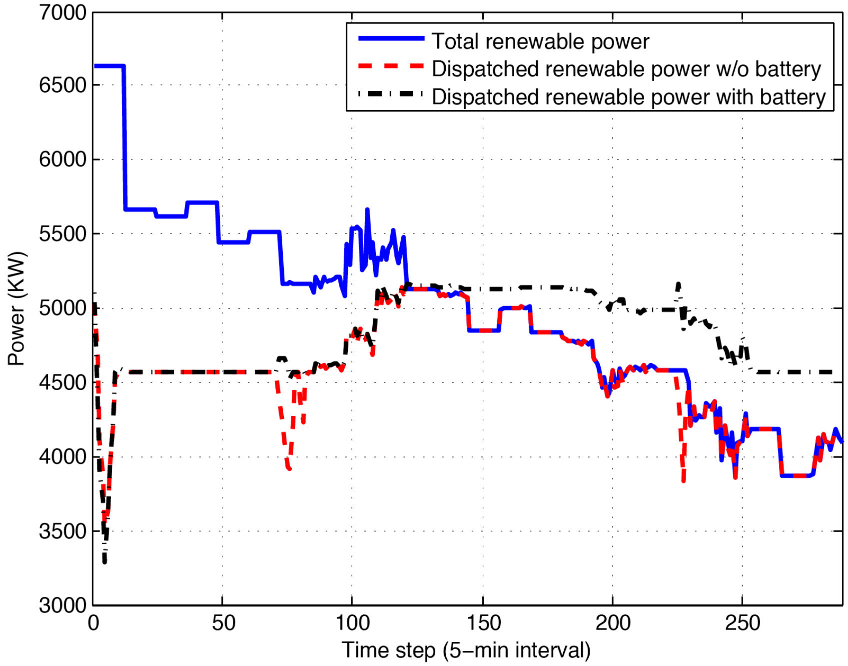

Figure 6.11: Total available and dispatched amount of power from renewable sources with and without storage devices

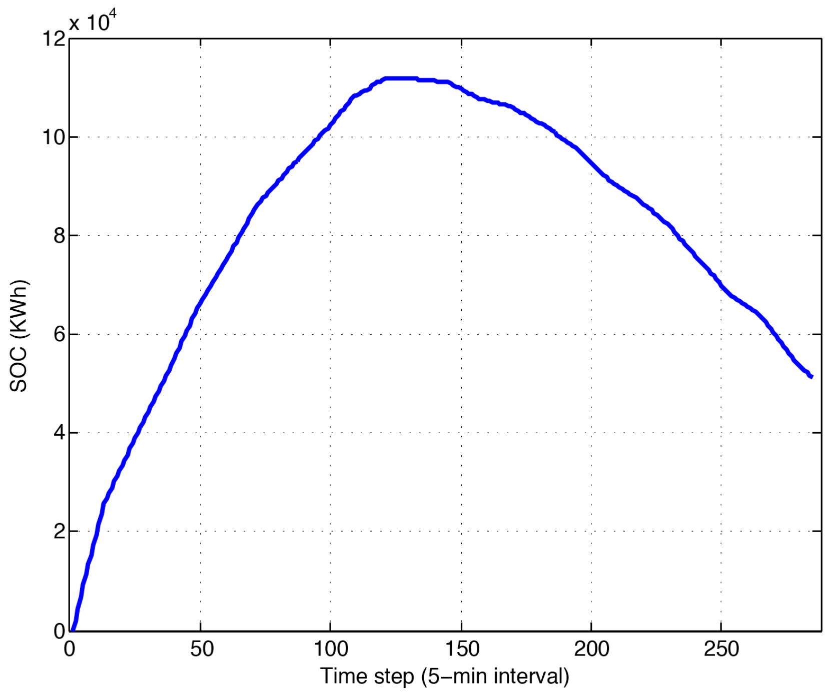

Figure 6.12: State of Charge for the storage device located at the 4^{th} bus

Chapter 7

Conclusions and Future Work

In this chapter we summarize the research that has been accomplished in this dissertation and discuss the future research that can be pursued. We describe our findings on energy management systems and significant impact that they can have on the efficiency of smart grid operation. We further discuss problems and solution methods that can be explored from the current point of research.

7.1 Current Findings

Considering the new technologies and opportunities within the concept of smart grid, we developed several energy management tools for the new generation of power systems. To this end, model predictive control strategy was utilized to formulate the management systems and different approaches were employed to solve the MPC problems. Various types of distributed generations such as PV, wind, and microgas turbine were considered besides the grid connection as electricity providers. To investigate the advantages and optimal operation of storage devices in power systems, battery units were considered in smart grid structure as well.

In chapter 3, we studied the problem of microgrid management in islanded mode. To this end, a three-node topology for the power network was considered. Due to uncertainty terms in load and renewable generation profiles, the formulated management problem became a stochastic one. We then proposed a stochastic method based on the combination of empirical mean and dynamic programming to solve the problem. The numerical example illustrated the viability of the proposed management strategy for islanded microgrids.

In chapter 4, we presented a multi-objective management system to control the operation of grid-tied microgrids. Two objectives were selected to obtain the optimal performance of the microgrid. First objective was minimization of energy operational cost; and the second one was maximization of battery lifetime. To implement the management algorithm, an MPC based approach was used to solve the underlying optimization problem. To investigate the performance of proposed management strategy, a microgrid including local renewable generations, grid connection, energy storage unit and a load was simulated in MATLAB environment. We compared the performance of MPC algorithm with static method proposed in [45]. It turned out that MPC method obtains more saving in energy cost. Also, it has been shown that by considering battery life span maximization objective, MPC is able to operate the battery for its whole rated life.

Chapter 5 investigated the problem of power flow management for a network of islanded microgrids. To this end, we defined an optimization problem, which besides achieving optimal solution for minimum generation cost allows the microgrids in a network to collaborate with each other. This collaboration minimizes the power produced by micro gas turbine as a unit with higher cost of generation, and increases the reliability of providing the required power to the costumers.

Finally, in chapter 6, we examined various power scheduling strategies adopted to handle the high penetration of renewable generation sources among energy suppliers. By investigating different power scheduling scenarios, we concluded that:

- With 10% of the total power coming from the renewable sources, these sources can be considered as either negative load, *i.e.*, fully dispatched, or dispatchable sources. In both cases, the total power produced from renewables can be fully used and cost of generation is almost the same in both cases.

- With 20% of the total power coming from the renewable sources and imposing a constraint on transmission line capacity, renewable resources cannot be considered as negative load anymore since their total generation cannot be fully dispatched. On the other hand, considering renewable sources as dispatchable, the power scheduling problem has a feasible solution that is not necessarily optimal in the sense that a portion of renewable power could be lost due to the transmission line constraints.

- In order to prevent the loss of renewable power generation, we reformulated the power scheduling problem by embedding storage devices. Using the proposed method, we showed that the undispatched portion of the renewable power could be saved and efficiently used at a later time.

7.2 Future Work

This section includes the overview of future research and possible progressions in energy management systems for smart grids. Each chapter in this dissertation can be considered as a starting point for further investigation. We itemize some of the potential topics and open problems that can be chosen for further advance research.

- In different chapters, it proved that storage devices such as battery units have important role in efficient operation of smart grids and microgrids. In addition to those applications, there are other situations that batteries can be effective. Traditionally, the frequency is regulated in the power systems by employing the fast response power plants. The power generated by these power plants is the most expensive power in the network. Since the batteries are among fast response power suppliers, they are appropriate for providing frequency regulation ancillary service as well. Therefore, technical and financial issues of battery utilization as frequency regulator is an open problem that needs to be investigated.

- The cooperation strategy proposed in chapter 5 is a central control scheme. The effect of distributed control schemes, where the microgrids exchange limited information with only other ones which have a direct connection with, is another topic which needs to be explored. Using the distributed control scheme, the need for a central processor will be removed, and consequently, the reliability of the control will be increased.

- The solution methods and results reported in the chapter 6 can be analyzed and used for making long term decisions when the power system is expected to provide a high percentage of its power through renewable sources. There are several relevant questions including:

  - Is it efficient and economical to extend the transmission network to include higher capacity?

  - Is it efficient and economical to keep the current transmission network and instead utilize storage devices?

  - If it is more efficient to utilize the storage devices, what size of storage capacity will be optimal for each device?

The optimality and advantage of the different options described above needs to be investigated in the framework of a new research.

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