INVESTIGATIONS ON MICROGRID INTERCONNECTION TO DISTRIBUTION SYSTEM

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CERTIFICATE

This is to certify that the thesis entitled **"Investigations on Microgrid Interconnection to Distribution System"** submitted by **Nandkishor Gupta** (ID. No. 2012REE9030) to Malaviya National Institute of Technology Jaipur for the award of the degree of **Doctor of Philosophy** in Electrical Engineering is a bonafide record of original research work carried out by him under our supervision.

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CANDIDATE'S DECLARATION

I hereby declare that the thesis entitled **"Investigations on Microgrid Interconnection to Distribution System"** is my own work conducted under the supervision of Prof. R. A. Gupta, Department of Electrical Engineering, Malaviya National Institute of Technology, Jaipur (Rajasthan), India. I firmly declare that the presented work does not contain any part of any work that has been submitted for the award of any degree either in this University or in any other University/Deemed University without proper citation.

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ABSTRACT

Increasing penetration of renewable energy resources to the distribution system in evolving deregulated power system has great public attention, recently. Among the renewable energy sources, the penetration of wind and solar generators has been increased due to their evolved technology and wide spread availability. To integrate these renewable sources as Distributed Energy Resources (DERs) into the utility grid, Micro-Grids (MGs) play an important role. MG is a small-scale power supply network that is designed to provide power for a small community and can increase the reliability and economics of energy supply. MGs are self-sustainable and generally operated in two modes: (1) grid connected and (2) grid isolated. In grid-connected mode, MG can export its excess power to the grid and can import its deficit power from grid. MG can manage its demand independently in grid-isolated mode.

An Energy Management System (EMS) is used in MGs to optimize their operation, schedule local generation, and control all the interactions with the upstream grid. Optimizing the operation of a MG is essential to reduce fuel cost, energy unscheduled, power losses, and gas emissions. Due to random nature of demand as well as renewable sources and to operate the generators within its technical limitations, the efficient and economic management of the generators is highly recommended. The grid price volatility in deregulated environment of power system has increased the complexity of MG's EMS. Therefore, development of efficient approaches for MG management under different uncertainties is necessary. The work presented in this thesis concentrates on development of efficient approaches for MG management with an objective to minimize the total cost of operation subject to different constraints considering renewable power uncertainties.

In order to maximize the benefits of the resources available in a MG, an optimal scheduling of the power generation is considered in this work. Generation scheduling problem is an optimization problem that consists of two sub-problems: Unit Commitment (UC), and Economic Dispatch (ED). The unit commitment problem provides the on/off status of the dispatchable generation units over a daily or weekly time horizon. On the other hand, the economic dispatch problem finds the optimal output power for the units committed by the unit commitment problem over shorter time horizons: *i.e.*, hourly or in real time. The optimal solution thus obtained satisfies the operational constraint.

MG operator can solve the energy scheduling problem with an objective to minimize the total operation cost considering the day-ahead power balance constraint, real time

power balance constraint, dispatchable power constraint, imbalance constraint and grid power constraint. In grid connected mode, the total cost of operation of MG is ''The sum of operating cost of dispatchable generating unit's power, reserves and cost of power imported/exported from/to grid''. In grid isolated mode also, the objective of MO is to minimize the total cost of operation, similar to the grid connected mode. However, the cost of exchange of power between main grid & MG is replaced by the cost of demand shedding. Since, the cost of demand shedding is very high, it is generally avoided till the complete utilization of the reserve capacity. In grid connected mode, the MG is connected to the utility grid thereby facilitating the power transaction between the MG and the utility grid. In the deregulated environment, MG can earn revenue by selling its excess power to the spot market. Additionally, MG can also earn revenue by selling its reserve capacity to the spot market if prices are higher than its marginal cost. On the other hand the cost of operation can be minimized by meeting its deficit power from the utility grid when grid power is cheaper than MG's reserve cost.

One of the benefits of establishing MGs is increasing the penetration of renewable resources in the distribution system but a major problem is the intermittent nature. The amount of power generated by renewable resources solely depends on the weather parameters such as wind speed and solar radiation. Therefore, these generators can neither be dispatched nor committed like conventional thermal generators. Furthermore, renewable generators can cause load mismatch and voltage instability in the system. These problems are more significant in the case of MG due to higher penetration level of renewable generators compared to large power systems. Uncertainties associated with renewable generators must be taken into consideration when scheduling the power generation in MGs in order to achieve reliable solutions. Hence, reformulating the scheduling problem and developing new models is necessary to produce efficient and robust commitment schedules. In the proposed work, wind and solar power are considered as uncertain parameters.

Random nature of wind and solar power can be modeled by stochastic process. ARIMA model is a popular approach for modeling any stochastic process and is widely used for forecasting electricity prices & demand. As the wind and solar power vary with atmospheric conditions, the time series variation of wind power is non-stationary, since, ARIMA model is applicable for only stationary data series, the wind and solar power are converted into stationary series by differentiation. In proposed work, ARIMA model is used for forecasting upper and lower limit of wind power and solar power on 95%

confidence interval. These forecasted limits are used in proposed robust optimization based MG scheduling approach considering wind and solar power as uncertain parameter.

A robust optimization approach has been extensively used for solving different decision making problems with different uncertainties. For modeling of these problems, Robust Optimization (RO) provides a solution that is guaranteed to be “good” for all or most possible realization of the uncertain parameter. In any decision making problem there are three types of robustness in optimization problem (i) constraint robustness (ii) objective robustness (iii) combinational robustness. If uncertainty is present in only constraint parameter then problem is defined as constrained robustness and if uncertainty is present in only objective function parameter then problem is defined objective robustness, and if uncertainty is present in both, it is defined as combinational robustness. Due to effective modeling of uncertain parameters, the problem formulated by the robust optimization is tractable and has low computational burden. In this work, since wind and solar are considered as uncertain parameters in the constraints, it is formulated as a constrained robustness problem.

A comparative analysis on MG operation is carried out. For this purpose, the same problem is simulated using deterministic and stochastic programming approach. In deterministic approach, wind power output is forecasted using ARIMA model and the forecasted value of wind power is considered to compute the scheduling of MG.

The impact of degree of robustness on operation cost, in both cases has been evaluated by varying the degree of robustness. Per unit cost of operation, at any degree of robustness is obtained by dividing its actual value by the reference value, which represents the cost of operation at zero degree of robustness. From the analysis, it was observed that the optimal value of degree of robustness is 24, where per unit cost of MG operation is minimum. At this degree of robustness, optimal condition is obtained because the uncertainty of wind power is considered for 24 hours. This degree of robustness takes into account all possible deviations of the uncertain parameter for whole day. Additionally, at zero degree of robustness the cost of operation obtained using proposed robust optimization based approach is equal to the cost of operation obtained using deterministic approach.

Further in this work the solar power uncertainty is considered in MG generation scheduling problem. The Modeling of solar power uncertainty has been done through Time series based ARIMA model. Robust optimization based formulation of MG generation scheduling problem in both grid connected and isolated mode considering solar power uncertainty has been proposed. The results obtained through robust optimization approach has been compared with traditional stochastic and deterministic approach and the impact of degree of robustness on the optimal generation scheduling through robust optimization based approach has been evaluated through realistic case studies. A study of multiple uncertainties considering wind power and solar power uncertainty is incorporated in MG generation scheduling problem and the results obtained through robust optimization approach have been compared with traditional stochastic and deterministic approaches.

A robust optimization based approach has been proposed for optimal generation scheduling of MG in both grid-connected and grid-isolated modes. Wind power and solar power uncertainties have been modeled through interval forecasting using ARIMA model. A comparative analysis on daily cost of operation of MG using proposed robust optimization based approach with deterministic and stochastic approach has been performed. A significant reduction in cost of operation in the proposed approach shows the strength of proposed robust optimization based approach in MG generation scheduling in the deregulated environment. The impact of degree of robustness on the cost of operation in both cases has also evaluated and compared with existing methods. The proposed approach is more advantageous in incorporating different type of uncertainties. The consideration of correlation between different uncertainties is also an important extension of this work. This work may also be enhanced by incorporating multiple-micro grids, different type of consumers and considering different technical environmental constraints.

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NANDKISHOR GUPTA

CONTENTS

LIST OF ABBREVIATIONS

The abbreviations used in the text have been defined at appropriate places, however, for easy reference, the list of abbreviations is given below.

Abbreviation	**Explanation**
MG	Micro Grid
DG	Distributed Generation
DER	Distributed Energy Resource
EMS	Energy Management System
ESS	Energy Storage System
ACF	Auto Correlation Function
PV	Photo Voltaic
ARIMA	Auto Regressive Integrated Moving Average
ARMA	Auto Regressive Moving Average
AMI	Advanced Meter Infrastructure
DSM	Demand Side Management
ANN	Artificial Neural Network
LP	Linear Programming
MILP	Mix Integer Linear Programming
QP	Quadratic Programming
MADS	Mesh Adaptive Direct Search
MR-CGA	Matrix Real-Coded Genetic Algorithm
DP	Dynamic Programming
ADP	Advance Dynamic Programming
SR	Spinning Reserve
SMES	Smart Energy Management System
RH	Rolling Horizon
RO	Robust Optimization
CVaR	Conditional Value at Risk
PACF	Partial Autocorrelation Factor

LIST OF FIGURES

LIST OF SYMBOLS

The symbols used in the text have been defined at appropriate places, however for easy reference, the list of principle symbols is given below.

Symbol	**Explanation**
A. Sets or Indices	
j	Index of conventional dispatchable units running from 1 to N_j
t	Index of time period running from 1 to N_t
w	Index of wind power units running from 1 to N_w
k	Index of robustness running from 1 to N_k
B. Constants or Parameters	
N_j	Number of dispatchable units
N_t	Number of time periods
λ_{grid},t	Grid power price at time t $(\$/kWh)$
λ_d^{shed}	Load shedding price $(\$/kWh)$
$P_{d,t}$	Forecasted system's demand at time t (kW)
$P_{w,t}^f$	Forecasted wind power generation at time t (kW)
PV_t	Forecasted solar power generation at time t (kW)
$P_w^{\max}$	Total Installed capacity of wind units (kW)
$P_j^{\min}$	Minimum output power of unit j (kW)
$P_j^{\max}$	Maximum output power of unit j (kW)
$P_{grid}^{\max}$	Capacity of the line linking the upstream grid and the MG (kW)
$R_j^{u,\max}$	Maximum upward reserve capacity of conventional generating units
$R_j^{d,\max}$	Maximum downward reserve capacity of conventional generating units
C. Variables	
$P_{j,t}$	Power generated by dispatchable unit j at time t (kW)
$P_{grid,t}$	Power imported/exported from/to the grid at time t (kW)
$P_{d,t}^{Shed}$	Demand shedding at time t (kW)
$r_{j,t}^u$	Scheduled upward reserve of unit j at time t (kW)
$r_{j,t}^d$	Scheduled downward reserve of unit j at time t (kW)
$\Delta P_{w,t}$	Expected wind power deviation at time t (kW)

Symbol	Explanation
$\Delta PV_{v,t}$	Expected PV power deviation at time $t\left(kW\right)$
$\Delta P_{d,t}$	Expected demand deviation at time $t\left(kW\right)$
$P_{w,t}^{a}$	Actual wind power generated at time $t\left(kW\right)$
$W_{t,k}$	Expected value of wind power at k^{th} iteration at time $t\left(kW\right)$
$PV_{v,t}^{a}$	Actual PV power generated at time $t\left(kW\right)$
$P_{d,t}^{a}$	Actual demand of MG at time $t\left(kW\right)$
G^{k}	Incremental factor at k^{th} iteration

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Chapter 1

Introduction

THIS chapter explains the background, context, and motivation for this work. It also explains main contributions of this research and then organization of the thesis chapters.

CHAPTER – 1

INTRODUCTION

1.1 General

Due to increase in electricity demand, scarcity of fossil fuel sources and environmental concerns with greenhouse gas emissions, integration of environment friendly renewable power sources in electric power system is increased throughout the world. Among the renewable power sources, integration of wind and solar power sources has been increased rapidly due to their mature technology and widespread availability. Integration of such renewable power sources in the electric power system at both transmission and distribution level causes several technical and financial challenges for designers and operators of electric power system due to their random nature. Therefore power generation at the consumer center is required to be distributed locally, which is also referred as Distributed Generation (DG).

DG's fuel source type can be selected on the basis of its local availability, operating cost, technological advancement of conversion system and environmental impact. In standby mode gas power generation sets or large diesel generators can be used to power up large load centers such as hospitals, telecommunication centers and large industries etc. Solar/PV cells, wind turbines and fuel cells etc. are the new comers in energy sector that are competing with many available generating sets in terms of size, efficiency and per kW cost. Today's DGs cost rate ($/kWhr) is becoming more and more competitive as efficiency/technology behind the modern energy conversion units is continuously being improved and diversified. By combining a variety of dispersed DGs, a distributed energy resource (DER) domain is developed. Various mixtures of different energy sources are then controlled under a central energy management system (EMS) in order to improve efficiency and reliability of the operation. As incorporated the modern concept of DER and EMS theory, the Micro-Grid (MG) concept is put forwarded [1].

As newly created concept, there are various definitions existing for the MG. In recent literature, MG defines in different ways. A MG is a group of interconnected loads and distributed energy resources within clearly defined electrical boundaries that acts as a single controllable entity with respect to the grid. A MG can connect and disconnect from the grid to enable it to operate in both grid- connected and island-mode.

As another important entity which leads lots of MG research, Department of Defense (DOD), UK also provided their specific definition of MG [4] as follows:
"A MG is an integrated energy system consisting of interconnected loads and energy resources which, as an integrated system, can island from the local utility grid and function as a stand- alone system."

It can be observed from those three definitions that although different entities have various perspectives on MG, the common concept can be extracted that MG is a bunch of electrical loads within certain geographic boundary powered by local distributed energy resources (DER) which include DGs and energy storage system (ESS). In such a system, wind turbines, PV panels and other renewable generations can be used as DGs and the stability and reliability should be maintained by the system itself with the help of modern operation and control techniques. Furthermore, such a system can be either connected to the utility grid or operated in an islanded mode. In this dissertation, both operation modes are investigated and the corresponding decision- making model is proposed respectively.

1.2 Motivation for the Presented Work

One of the benefits of establishing MGs is increasing the penetration of renewable resources in the distribution system but a major problem is the intermittent nature of these sources. The amount of power generated by renewable resources solely depends on the weather parameters such as wind speed and solar radiation. Therefore, these generators can neither be dispatched nor committed like classical thermal generators. Furthermore, renewable generators can cause load mismatch and voltage instability in the system [3]. These problems are more significant in case of MG due to higher penetration level of renewable generators compared to large power systems. Uncertainties associated with renewable generators must be taken into consideration when scheduling the power generation in MGs in order to achieve reliable solutions. Hence, reformulating the scheduling problem and developing new models is necessary to produce efficient and robust commitment schedules.

MGs can operate under two different modes of operation *i.e.* grid connected mode and grid isolated mode. The major difference being the sources of power generation used to supply the demand and the reserve requirement. This has a direct impact on the generation scheduling problem making it more challenging. Therefore, the formulation must be updated to account for the objectives and constraints in each mode of operation. This will result in a better distribution of the available generation capacities in the MG and will allocate the required amount of spinning reserve to maintain the system's stability and to mitigate the effects of uncertainties. Developing more accurate and reliable scheduling models that account for the effects of uncertainties and modes of operation is the main motivation behind this research. The work presented in this thesis examines the impacts of these added difficulties on the day-ahead unit commitment problem which is the first stage of the generation scheduling problem in a MG in distribution system. Two optimization models are presented; one for each mode of operation. The proposed models will tackle uncertainties by integrating uncertainty handling techniques in the problem formulation. Case studies are presented to study MG operation, and to evaluate the uncertainties and spinning reserve's effect.

In grid-connected mode, MG can export its excess power to the grid and can import its deficit power from grid. On the other hand, MG can manage its demand independently in grid-isolated mode. Due to uncontrollable nature of demand and generators' technical limitations, efficient and economic management of these generators is necessary. With increasing penetration of renewable sources like wind and solar in the distribution power system MG management system may become complex. The complexity of MG's energy management is further increased by the deregulation of power systems due to grid price volatility in MG management [4]-[5]. The work in this thesis focuses on overcoming these complex issues in MG operation. Further High cost of imbalance penalties and generation uncertainty in wind power generation in pool based day-ahead electricity markets provides a great challenge in the operation of MG. This research concentrates on the development of a new robust optimization based approach for optimal MG operation in deregulated environment considering renewable power uncertainties.

Several approaches have been proposed for MG's energy management considering renewable resources. Some of them are focused on control and scheduling of DERs, including renewable generation in MG [6]-[8]. A simple optimization based approach has been used for MG operation considering different market policies [9]. However, renewable power and market price uncertainties are modeled deterministically. A Lagrangian Relaxation along with genetic algorithm approach can optimally schedule generators of isolated MG [10]. However, the uncertainty in renewable generation is still modeled deterministically. Stochastic programming based approaches considering wind and solar power uncertainties suggested for the optimal operation of MG [11], [12]. The impact of network losses and network constraints has also been investigated in [12]. Renewable power uncertainties have been modeled through different scenarios. An artificial intelligence based methodology can solve MG generation scheduling problem with an objective minimization of operation and emission cost considering renewable power and demand uncertainties. These uncertainties are modeled using artificial neural network [13].

All the above studies focus on minimizing the generation cost in MG using deterministic and stochastic based approaches. However scheduling in both modes i.e. grid connected and grid isolated is not considered and complexity of optimization problem in both deterministic and stochastic approach is not justified. These approaches have mainly two difficulties: (i) knowledge of the exact distribution of the data, and (ii) the size of the resulting optimization model. Difficulties in solving the problem drastically increase as a function of the number of scenarios, which is subjected to substantial computational challenges.

As mentioned in previous section, there are numbers of benefits of incorporating MG in distribution system. However, it is necessary for MG to maintain a stable and reliable operation to achieve those benefits. Due to its unique characteristics, there are multiple challenges for the MG operation.

Considering the penetration level of renewable generation, the volatility of renewable energy resources can impact the MG operation significantly. Those types of volatilities pose uncertainties in MG operation, especially in the MG resource scheduling. Currently, most of the large power system operators try to use renewable generation forecasting to alleviate the uncertainties in their scheduling. However, it is almost impossible to achieve a no-mismatch forecasting results with current techniques due to stochastic nature of renewable energy resource. For example suppose in an hour ending at 19:00, the day-ahead forecasting predicted about 1300 MW from the wind generation while the actual output is as 400 MW during the operation hour. The shortage of 900MW may lead to severe reliability problems. Due to the geographic scale of MG, the prediction for the renewable generation in a MG are particularly difficult thus the forecasting errors are more significant than those for bulk power system. This kind of uncertainties brings considerable challenges for the resource scheduling of MG operation.

Another challenge faced by MG operation is the mismatch between renewable generation and load pattern. This phenomenon is observed more in wind power and solar power production. In MG, similar type of mismatch occurs due to the same reason since the penetration level of renewable generation in MG might be even higher than bulk power system. This type of mismatch can lead to operational challenges when MG trying to integrate large amount of renewable energy like wind and solar energy. Consequently, the utilization factor of renewable energy resources would be jeopardized. Also, this type of mismatch also shows uncertain behaviors. It can be difficult to fully capture the mismatch in the day- ahead forecasting results [14].

Moreover, MG operation is challenged to optimally participate in the deregulated market under the current market framework. For a grid-connected MG, it is assumed as a 'modern citizen' from the bulk power system point of view [5]. Consequently, there are numbers of opportunities for MG to participate in the power market. For example, in current ERCOT market the offer price cap keeps increasing since the nodal market opened in 2010 [15], The optimal operation scheme should be developed to help the stakeholders of MG harvest the maximum economic benefit by strategically participating in the power market.

1.3 Contributions of the Presented Work

The research work in this thesis starts by addressing MG interconnection issues under renewable power generation uncertainties. And after addressing the issues a better solution for MG generation scheduling problem under renewable power uncertainties is achieved. The main contributions of thesis are follows:

(i) On the basis of literature review pertaining to MG operation under renewable power uncertainties, an overview of MG's generation scheduling problem along with associated issues is presented. The detail study helps to understand the considered problem in MG operation under penetration of DERs in the distribution system.

(ii) On part of research work contributes by formulating MG generation scheduling problem for both modes i.e. grid connected and isolated mode in robust framework considering renewable power uncertainties. The proposed formulation help to understand applications of robust optimization based approaches in the MG operations.

(iii) Wind and solar power are two major sources of uncertainties faced by the MG operator during the scheduling of generation in MGs. These uncertainties are modeled through interval forecasting using a Time series based Autoregressive Integrated Moving Average (ARIMA) model in the presented thesis.

(iv) Robust optimization based approach is developed for optimal MG scheduling considering renewable power uncertainties.

(v) Proposed algorithms and approaches are illustrated through realistic case studies.

(vi) Wind and solar power uncertainties affect the optimal MG generation scheduling in deregulated power system. Therefore, comparative study is presented to evaluate the impact of wind, solar and both uncertainty individually and simultaneously on the optimal operation of MG in both grid connected and isolated mode.

(vii) A comparative study is presented to compare the robust optimization approach with traditional stochastic and deterministic approach.

(viii) An analysis is presented to evaluate the impact of degree of robustness on the optimal generation scheduling obtained through robust optimization based approach.

1.4 Organization of the Thesis

Chapter organization is an important part of thesis that provides a complete overview of the thesis. Current chapter introduces major issues involved in microgrid interconnection to distribution system. It analyses the involved problems in this area that motivated the work, and further contributions of the presented thesis. The rest of chapters of this thesis are organized as follows:

Chapter 2 provides a comprehensive literature review on issues pertaining to generation scheduling in distribution system, including those of uncertainty modeling like wind power uncertainty and solar power uncertainty and robust optimization approaches . It offers details on causes, models and solutions approaches of the associated issues.

Chapter 3 provides an overview of uncertainty modeling approaches and robust optimization framework. This chapter deals strength and limitations of different approaches for modeling uncertainties and formulating decision making problems in robust framework.

Chapter 4 presents algorithms for MG generation scheduling considering wind power uncertainty in robust optimization framework. Proposed algorithms are illustrated through different case studies based on MG operation. Comparative analysis helps to validate the proposed algorithms for MG generation scheduling considering wind power uncertainty.

Chapter 5 proposes a robust optimization based generation scheduling solution for MG operation considering solar power uncertainty. Proposed algorithms are illustrated through different case studies based on MG operation. Comparative analysis helps to validate the proposed algorithms for MG generation scheduling considering solar power uncertainty. The impact of degree of robustness is also carried out on the proposed algorithm.

Chapter 6 enhances the proposed robust optimization based MG generation scheduling algorithm by modeling multiple uncertainties in single problem. Here both solar power and wind power are modeled in uncertain environment simultaneously. And proposed algorithm is tested on MG generation scheduling problem considering multiple uncertainties.

Chapter 7 concludes the main findings of the work presented in this thesis and suggests directions for future research in this area.

Chapter 2

Literature Review

THIS chapter begins with fundamental thought of MG operation and underlining the major issues involved in MG operation in distribution system. Further, uncertainty characterization in renewable power generation in stochastic and RO framework and identified research challenges are discussed.

CHAPTER – 2

LITERATURE REVIEW

2.1 Introduction

Increasing penetration of renewable energy resources in evolving deregulated power system has great public attention, recently. Among the renewable energy sources, the penetration of wind and solar generators has increased due to their much evolved technology and wide spread availability. To integrate these renewable sources as Distributed Energy Resources (DERs) into the utility grid, Micro-Grids (MGs) play an important role [1]. MG is a small-scale power supply network that is designed to provide power for a small community and can increase the reliability and economics of energy supply [2]. A typical architecture of MG is shown in Fig. 1, which consists of dispatchable, non dispatchable generating unit and consumers. MG can be operated in two modes: grid connected and grid isolated. In grid-connected mode, MG can export its excess power to the grid and can import its deficit power from grid. MG can manage its demand independently in grid-isolated mode [3].

Due to uncontrollable nature of demand and to operate the generators within its technical limitations, the efficient and economic management of the generators is highly recommended. With increasing penetration of renewable sources like wind and solar in the distribution power system, MG management system may become complex. The grid price volatility in deregulated environment of power system has further increased the complexity of MG's energy management system. Therefore, development of efficient approaches for MG management under different uncertainties is necessary.

This chapter presents a theoretical background and review of literature pertaining to challenges for MG operation in distribution network. Initially, a fundamental background on MG operation in terms of generation scheduling problem has been provided. Next, issues pertaining to renewable power uncertainty (wind power and solar power uncertainty) have been analyzed. This is further supported by a discussion on uncertainty characterization, which is present in wind power and solar power through interval forecasting. Modeling of such uncertainties can help MG operator in optimal generation scheduling for total cost of MG operation minimization. Approaches developed to model MG generation scheduling problem considering renewable power uncertainties in competitive distribution system have been discussed to identify the research gaps.

Since uncertainty present in renewable power generation, it is necessary to model uncertainty in an effective manner to solve MG generation scheduling problem. Thus, the last part of the chapter discusses Robust optimization based approach for uncertainty characterization and associated potential issues to model uncertainty through robust optimization based approach.

2.2 Microgrid Operation

As MG can be defined as a small-scale power supply network that is designed to provide power for a small community. A typical MG consists of dispatchable units, non dispatchable units and consumers. MG can be operated in two modes: grid connected mode and grid isolated mode. In grid-connected mode, MG can export its excess power to the grid and can import its deficit power from grid. MG can manage its demand independently in grid-isolated mode [1-3].

Benefits of Implementing Microgrid (MG)

It can be summed up from the designing principle and all those on-going and demonstration projects that MG brings lots exciting benefits and opportunities. Those merits of implementing MGs are summarized as the following.

The dependency on imported fuel sources can be reduced by implementing MG and prime fuel market competition can be regulated easily. The increased interest in DERs, which includes multiple types of energy sources, has the potential to influence the market and competition level for prime energy sources. Developing countries like India and China have initiated a rapidly moving production infrastructure of energy that records a higher growth in global fuel markets.

Current MG technologies can able to compete with the traditional generation facilities with the help of local government encouragement and public support following with the dynamically changed fuel prices and environmental concerns over global warming. Available local prime fuel sources can be used to fuel up profitable MGs instead of imported ones. The MG market thrust is obviously driven by positive impact of environment by using local resources along with the economic benefits.

Further, implementing MG can improve the utilization of renewable generation resources. Although renewable energy conversion systems are having their intermittent energy nature and minimal environmental impact, most of developing countries like India and China have an abundance of natural renewable resources, that can be definitely integrated to meet a portion of the demand. Due to its innovative architecture and intelligent interface, MG can be a good entity to integrate high penetration level of renewable energy. Also, the grid-connected MG, which in cooperated with ESS and responsive load, can make the power flow on the point of common coupling (PCC) smoother thus reduce the generation fluctuation caused by intermittence nature of renewable generation from the utility point of view.

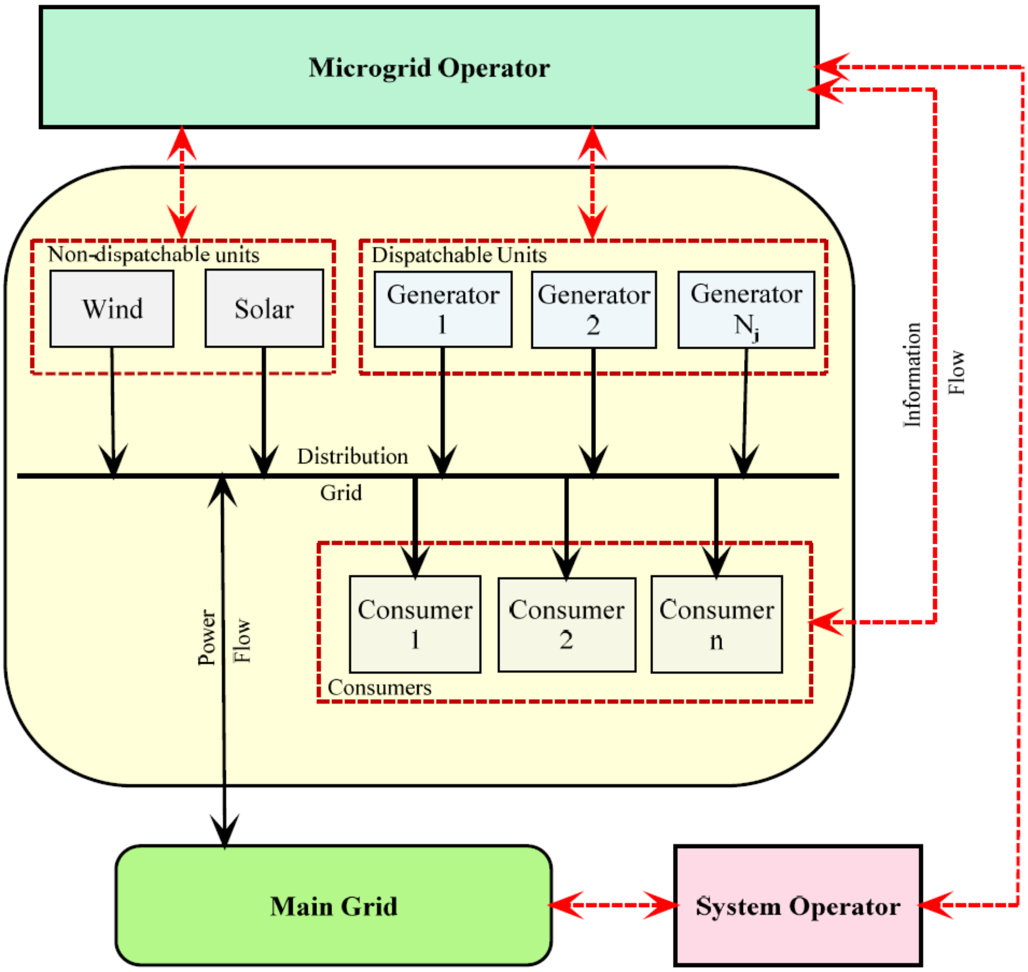

Fig. 2.1 Typical architecture of MG

Moreover, implementing MG can be able to enhance the demand side management (DSM) considering the deployment of modern communication system and advanced meter infrastructure (AMI). MG is capable of optimally managing its demand side without requiring further investment. The AMI system installed in the MG can be a useful tool for load pattern recognition and demand forecasting [16]. Also, the relatively small scale makes MG operators easier to categorize different load groups based on their load characteristics and price responsiveness. In such a manner, the managing of demand side for MG can be further improved.

Furthermore, implementing MG can be able to defer the transmission lines construction or extension. MG can be the best option to support peak period demand. Therefore, the need of peak generation unit installation can be eliminated and security benefits are enhanced [16]. MG can also be useful in nearby commercial and industrial areas to meet the heat and electricity demand. It is helpful to relieve the centralized power plant from long distances power dispatching.

Last but not the least, implementing MG can help rural electrification, especially for under-developed areas. Currently, electrification resolution is needed in many developing and third world countries like as India and China. There are Over 1.2 billion peoples without electricity access and more than 2.8 billion people are dependent on solid fuels for their daily life activities like heating and cooking. Further largest percentage of rural darkness is present in African and southeastern countries [17]. In such type of rural darkness countries a very less resources to build large centralized generation plants or transmission infrastructure are present. In these countries MG can be considered as an important solution with availability of local renewable resources like ad wind power and solar power. As incorporated with modern EMS, dispersed MGs can be the best solution with less financial burden to meet out the local demand in that particular area of rural communities.

Due to uncontrollable nature of demand and generator's technical limitations, efficient and economic management of the generators is highly desirable. With increasing penetration of renewable sources like wind and solar in the distribution power system MG management system may become complex. The grid price volatility in deregulated environment of power system has further increased the complexity of MG's energy management system.

When a MG has more than two DERs, the energy management system (EMS) is needed to impose the power allocation among DER, the cost of energy production and emission. The EMS in a MG is shown in the Figure 2.2. As can be seen from this Figure, the forecast values of load demand, the distributed energy resources and the market electricity price in each hour on the next day are denoted as inputs. Furthermore, the operation objectives are considered to optimize the energy management, are given as follows:

- Economic option
- Technical option
- Environmental option
- Combined objective option.

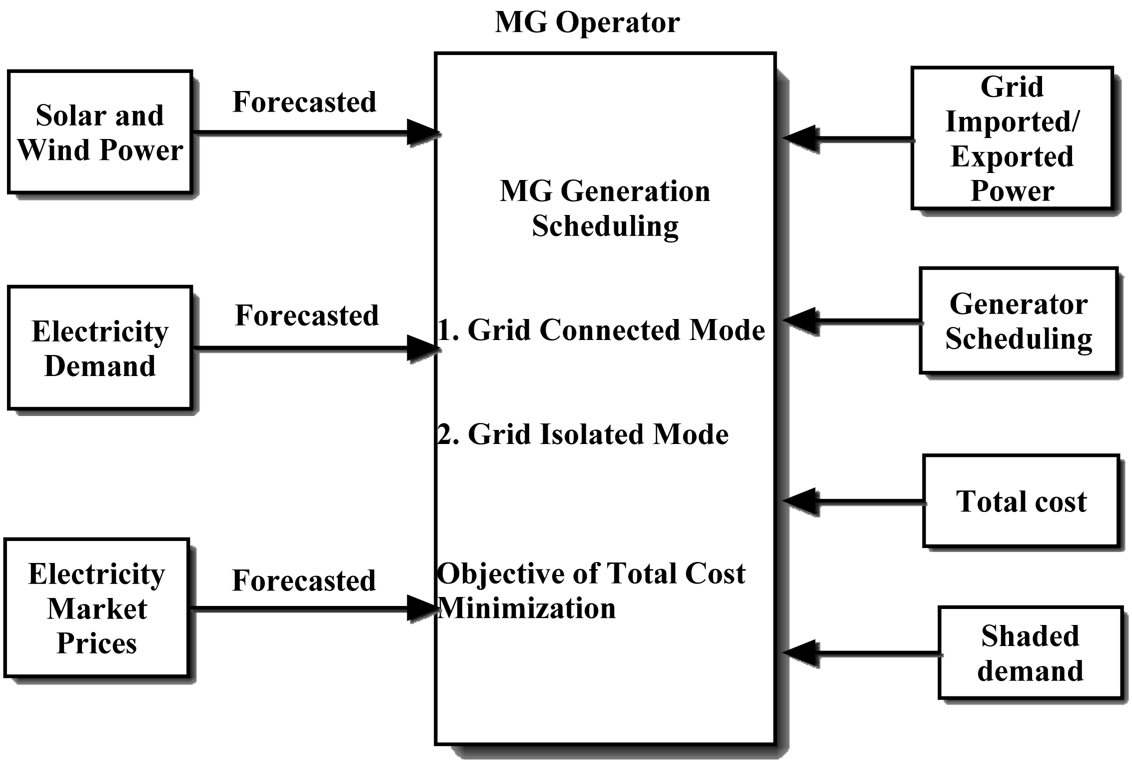

Fig. 2.2 The energy management system (EMS)

2.3 Critical Review

This section represents the critical review on generation scheduling in MG operation, uncertainty characterization in both stochastic frame work and robust framework .

2.3.1 Generation Scheduling in Microgrid Operation

In recent studies several approaches have been proposed for MG's energy management considering renewable resources. Most of them are based on DERs scheduling and control, including renewable generation in MG. A simple optimization based approach has been used for MG's operation considering different market policies [9]. A Lagrangian Relaxation along with genetic algorithm approach has been incorporated for optimally scheduling of generators in isolated MG system [10]. Agent-Based heuristic approach has been used for MG management [18]. In above studies, uncertainty involved in renewable power sources is modeled deterministically. Due to lack of accurate forecasting models, such type of uncertainty modeling is not reasonable for MG management.

Some algorithms for the optimization of MG energy management are proposed [9-27]. An ANN model has been used to solve optimal MG generation scheduling problem to minimize operation and emission cost considering renewable power and demand uncertainties [11, 12, 13]. For islanded MG operation optimal Energy Management system (EMS) has been presented in [19], by using a rule-based management. The MG operation depends upon developed rules, therefore, constraints are always satisfied but the optimization does not contain global results. Further to improve rule-based technologies in MG operation, fuzzy logic based estimated rules are proposed in [20]. Although, linear programming (LP) and mix integer linear programming (MILP) based technologies used to solve MG operation in [21] gives good results but the main limitation is known as the need of a specific mathematical solver. Quadratic programming (QP) based approaches have been addressed for optimal EMS in grid connected power system having Solar-PV/battery and electrical vehicle system in [22]. The results obtained through QP approach are better; however this method has a limitation of convex objective function. In [23], MG's optimal EMS is solved by using Game Theory and multi-objective optimization. The operating cost and the emission level are given as two objectives functions. Optimization of MG's total operating cost function has been achieved by Mesh Adaptive Direct Search (MADS) algorithm in [24], while to search the optimal generation schedule in MG operation MRC-GA (matrix real-coded genetic algorithm) is proposed in [25]. Further, the PSO (Particle Swarm Optimization) techniques [26] and dynamic programming (DP) approaches and advance dynamic programming (ADP) approaches [27] has been developed to optimize EMS in MG operation.

All of the above studies focus on MG operation and consists of algorithms that are used to solve the MG generation scheduling optimization problem. However these methodologies are having some limitations for solving optimization problem in MG operation, but this has provided better platform to MG researchers to overcome these critical issues of MG operation such as uncertainties involvement in renewable generation and demand side management etc.

2.3.2 Microgrid Operation Considering Renewable Power Uncertainties

Over the last couple of decades, worldwide power systems have experienced high growth in renewable power generation. Among the available renewable power generation technologies, generation from renewable sources is increasing rapidly due to its widespread availability and mature technology. Thus, renewable power is an encouraging alternative to fossil fuel power generation for mitigating climate changes. Availability of wind generation depends on atmospheric and geographical conditions. Due to inherent randomness of these conditions, renewable power like solar and wind power is highly uncertain [28]. Due to the intermittent nature of these renewable energy sources, their huge penetration may affect the reliable and secure MG operation. So accurate prediction of renewable power such as solar and wind power generation is required for secure and reliable operation of MG. However, prediction of Solar and wind power is never perfect, thus modeling of solar and wind power uncertainty is important for MG operators or system operators [28].

The main challenge for MG operator is to manage renewable generation uncertainties and demand uncertainties. Therefore it is necessary for MG operators to consider the effect of these uncertainties while determining the spinning reserve (SR) for protection against sudden change in generation and load [29]. In some literature MG reserve requirement has been determined without considering the probabilistic behavior of renewable generators before the scheduling in MG operation [30]. This type of approach is known as deterministic approaches in MG operation. To minimize total operation cost of MG operation quantum genetic algorithm [31] has been introduced without considering the uncertain nature of renewable generation. Further with consideration of probabilistic behavior of renewable generation and demand, stochastic methods are proposed for getting optimal solution in MG operation [32-33]. In stochastic methods renewable generation uncertainties are modeled through a number of scenarios [11]. It is evidenced in literature that stochastic methods have lower operating cost in comparison to deterministic methods.

Wind power and solar power are characterized by location constraints, low marginal cost, generation variability, limited dispatchability and difficulties in available resource forecasting [34-37]. Due to these, wind power and solar power integration in existing MG strongly affects its economic operation. Economic challenges relevant to MG operation include total operating cost MG generation scheduling problem and demand response [38-44].

Despite these problems, solar power and wind power generation are rapidly growing due to consistently decreasing cost of solar power and wind power generation and continuously improving accuracy of available forecasting tools. MG's generation scheduling problem can be treated as a decision-making problem due to uncertainty of wind power and solar power availability and load demands [45-48]. Modeling of involved uncertainties is necessary to solve these decision-making problems. Uncertainties are generally modeled using deterministic forecasting models, which focus on the use of point prediction. Point prediction provides single value of expected wind power or market price for a given lead-time, without any information about the possible deviation from forecasted value. Use of deterministic forecast for modeling decision-making problems may not provide the desired accuracy in solutions [49-52].

Decision-making problems are generally formulated using stochastic optimization. In this formulation, randomness of input parameters can be described by stochastic process. Stochastic process can be characterized via scenarios. Scenarios are possible outcomes of random input with corresponding occurrence probabilities [53,54].

As a large numbers of scenarios are required for accurate modeling of any stochastic process. Therefore, the computational efforts are required to reduce the original scenario set to solve scenario-based optimization models. Reduced scenarios are obtained in such a manner that the reduced set has a smaller number of scenarios, with minimally changed statistical properties [55-58].

Based on recent studies, scenario generation methods can be classified as: movement matching [59-60], conditional sampling [61] and path-based methods [62-65]. Movement matching and conditional sampling generate scenarios, which are based on direct sampling from distribution of stochastic process. Path-based methods generate scenarios using different statistical forecasting models such as ARMA and ARIMA. For a given lead-time, scenarios can be generated by repeated simulations of these forecasting models, with different confidence intervals.

These methods can be used for load, price, and wind speed scenario generation [66-68]. Monte Carlo simulation with path-based scenario-generation method has been used for generation of electric load scenarios in power management problems [66]. The wind speed scenario-generation method can use statistical time-series ARMA model for scenario generation of different sites [67]. This approach shows the relation of generated scenarios by autocorrelation plots between every two sites. Thermal rating of transmission lines have been forecasted by the time-series ARIMA model, considering the effect of weather uncertainty [68]. Bidding strategy problem using a stochastic programming approach is simulated by generating price scenarios of the Nordic market using ARMA model [69].

For wind power scenario generation, all methods assume that wind power forecasting error density function follows Gaussian or normal distribution. Statistical analysis shows that due to variable kurtosis, wind power forecasting error probability density function cannot be characterized by normal distribution [70]. Therefore, this assumption is not valid for practical applications. Generated scenario set is assumed to be stable, if several scenario sets are randomly obtained using a method to provide the same solution for a considered decision-making problem. Quality of scenarios is defined in terms of small bias that can crop up between true value and solution of scenario based optimization. A consideration of stability and quality of generated scenario set can improve modeling of wind power uncertainty [71].

To reduce computational burden for solving decision-making problems through scenario based optimization models, generated scenarios need to be reduced *via* scenario reduction techniques. Scenarios can be reduced by using fast forward selection and simultaneous backward reduction methods [72-75]. These methods can be used for reducing electric load, price and wind power scenarios. Forward and backward scenario-reduction algorithms have been proposed for price and load scenarios [74]. Recursive backward scenario-reduction technique has also been used for wind scenario reduction [76]. These methods are iterative and their mathematical formulation is complicated. Iterative elimination of scenario requires large computational time, when the preserved scenarios are mini scale as compared to generated scenarios.

Further an efficient and simplified algorithm for scenario generation and reduction has been proposed for application to multi-stage stochastic programming [77]. The scenario-generation algorithm is based on a time-series ARMA model, while the reduction algorithm utilizes the concept of probability distance. Both algorithms are implemented for next-day scenario generation of a wind farm located at Barnstable, Massachusetts, USA. The results clearly showcase the strength of the proposed algorithms in wind uncertainty modeling. Owing to quantum scenario reduction, stochastic properties of the generated scenarios are maintained with minimal variation in the mean and standard deviation.

For solving MG generation scheduling problem a smart energy management system (SMES) has been presented in [78], which considered PV output with different weather conditions and different hourly prices of main grid. Here reserve allocation is not done for renewable power generation uncertainty and load participation is also not considered. Further rolling horizon (RH) based strategy for renewable energy based energy management system (EMS) has been proposed in [79], which minimizes the total operational cost of MG. In [80] MG operation for generation scheduling has been done by considering economic and emission objectives, where to minimize the cost function, a mesh adaptive direct search algorithm has been proposed, but here wind power and solar power forecasting errors and demand side participation in energy market have not been considered. For economical MG operation, application of HRDS (High Reliability Distribution System) has been considered. HRDS has been applied to loop networks in distribution system which has higher operational reliability and fewer outages in MG.

In [81] spinning reserve requirement is ensured by estimation model, where wind power and solar power generation uncertainty, unreliability of units and uncertainty caused by load demand are considered. Various uncertainties are aggregated to reduce computational burden in this approach. Further MG generation scheduling problem is optimized in consideration of multi-period islanding constraints. Where, the objective of MG generation scheduling problem is to minimize the total operation cost of MG operation. For decoupling of grid connected and grid isolated problem bender decomposition method has been employed. Here MG components such as generating units, loads, and energy storage system etc. are modeled through mixed integer linear programing (MILP) approach. In consideration of renewable energy generation uncertainties and demand uncertainties in MG operation a fuzzy logic based EMS (Energy Management System) has been proposed, which solves the cost and emission minimization problem. Further MG operation in stochastic framework has been proposed in grid connected mode operation of MG operation, which considers the uncertain nature of wind turbine generation, load forecast error, PV generation and market prices. Uncertainties of these uncertain parameters have been modeled by generating a number of scenarios through roulette wheel mechanism. However, the reserve scheduling has not been considered in this methodology.

Another stochastic programming based approaches for MG operation considering renewable power uncertainties and network constraints has been developed in [82-83]. In this approach, uncertainties are modeled through different scenarios. A large number of scenarios are required for accurate modeling of any uncertainty. However, with large number of scenarios, the size of optimization problem drastically increases leading towards computational complexity. Additionally, stochastic programming approaches are based on knowledge of distribution of historical data of uncertain parameters. If the knowledge of the distribution of historical data is unavailable, the approach could lead wrong results.

2.3.3 Robust Optimization Based Uncertainty Characterization

Robust Optimization (RO) is an approach which is used to protect decision maker against data uncertainty and parameter ambiguity. At a high level, decision maker must have to ensure that solution is a robust solution in such a way, whose feasibility can always be guaranteed for any type of realization of uncertain parameters. To obtain robust solution the main approach relies on worst case analysis in which a solution is obtained when realization of uncertainty is most unfavorable.

In RO to compute the worst case is always a challenging task to researchers when uncertainty is involved. In some of literature the worst case realization uses a finite number of scenarios of uncertain parameter such as convex/continuous uncertainty set or historical data. While some literature states that worst case realization must be chosen in such a way that it should be neither too small nor too large *i.e.* it will trade off between system performance and protection against uncertainty.

2.3.3.1 Static Robust Optimization

In static RO framework, decision maker take decision on the basis of uncertainty. And after realization of uncertainty no recourse action would be possible. Therefore two types of uncertainty like uncertainty on feasibility of solution and uncertainty on objective value must be distinguished. Regarding infeasibility and sub optimality, decision maker have different opinions which justifies the need of separate realization of these two settings.

(a) Uncertainty on Feasibility

When solution feasibility is affected by uncertainty than RO seeks to obtain a feasible solution at any realization of uncertain parameter by unknown coefficients. However, in objective function the complete protection from adverse realization is rare. In some engineering applications of robustness this approach may be justified properly but in operational research it is less reliable because in operational research low customer demand adverse event may not be able to produce high profile repercussions. Robust methodology in MG operation may become an important solution if it will produce feasible solution for any kind of realization of an uncertain parameter for unknown coefficient within an uncertainty set. Uncertainty set is nothing but it is the smaller realistic set which belongs to uncertain parameter. The specific realization of an uncertain parameter within uncertainty set must be taken carefully by decision maker because it plays an important role for ensuring computational tractability of robust problem.

In recent literature RO based approaches are used by considering worst case optimization in which worst case is being determined on the basis of convex uncertainty set of an uncertain parameter. Convex uncertainty set is nothing but it represents the limit which bounds the maximum allowable deviation from nominal value of an uncertain parameter. In worst case optimization approaches the main objective is to derive the tractable reformulation which is able to provide optimal solution along with probabilistic guarantee against constraint violation. In order to understand RO a unified treatment under data uncertainty has been studied in [84], where convex inequalities of system represent the uncertainty set. Further heuristic based approaches have been investigated in [85] to model uncertainty, which couples RO with simplified stochastic approaches. Results obtained through this approach exhibit high flexibility towards optimization and simplicity of uses.

Further an optimization model has been presented in [86], which represent robust counterpart as a convex quadratic constraint, which is having ellipsoidal implementation error equivalent to quadratic conic constraint. The difference between local and global robustness has been analyzed in [87]. Global robustness is represented as 'Black Swans' which is the severe uncertainty faced by decision maker. Further safe tractable algorithm based on RO has been presented in [88], where approximations of chance constraints under data uncertainty are satisfied with high probability functions.

(b) Uncertainty on Objective Value

RO may be used to obtain a solution in such case when solution optimality is affected by uncertainty. In such cases results obtained from RO based approaches are good for any realization of an uncertain parameter within the uncertainty set. In RO based approaches generally worst case realization is to be optimized. Uncertainties on objective function can be better approached by worst case realization techniques by creating a new inequality set in such a manner that brings the objective function in feasibility sets. In [89] cost uncertainty, which present in objective function, has been considered with linear robust optimization. The problem is solved with single robustness by losing the objective value.

Further multi-objective RO has been investigated [90], where the assessment of robustness has been done through evolutionary algorithms within multi-objective optimization. Further multi expert multi criterion robust weighed approaches are presented in [91], which uses robust pareto decision to minimize worst case weighted sum in problem.

More over a new robust criterion is proposed in [92], which seems great due to its simplicity of use and practical relevance. In this method, which is also known as *bw*-robustness, the decision maker is allowed to identify guaranteed solution of an objective value. Here maximization problem has been considered and constraint condition has been created by taking two variables *'b'* and *'w'* in such a way that at least 'w' is present in all scenarios of uncertainty set and it maximizes the probability of reaching at 'b', which is targeted value provided 'b>w'. Further this criterion is extended in [93] by using interval in uncertainty modeling instead of finite set of scenarios. Laxicographic robustness has been presented in [94], which is defined over finite set of uncertainty scenario. Here the primary role of worst case realization has been mitigated. Further, RO framework considering combinational optimization has been proposed in [95], which uses the dempster-shafer theory with portfolio tracking and sensor placement.

2.3.3.2 Multi-Stage Decision-Making

The earliest work on RO approach is based on static decision making framework, where decision makers are authorized to take decisions at once of all values that are take by all decision variables. And if multiple decision stages are incorporated in robust problem then problem is solved by incorporating the decision taken of only current stage. Since, it is difficult to incorporate multi stage decisions in RO framework, so most theoretical approaches are based on two-stage decision RO framework. In [96], two stage robustness based tractable algorithm has been developed with minimization of worst case regret in both scenario and interval based uncertainty set. Further Kelley's algorithm based cutting plane method has been proposed in [97] with adjustable convex robust optimization problem. Additional preliminary results based on two stage robustness with robust linear program and equivalent second order conic program have been presented in [98]. With considering right hand side uncertainty two stage linear robust problem has been analyzed in [99].

Further, for a class of multi-stage chance constrained LPP, a tractable approximation has been proposed in [100]. In this method, original optimization problem has been converted into second order conic optimization problem. RO based framework has been described in [101] to extend affinely adjustable robust counterpart framework. In [102], one dimensional RO based has been described, which established the optimality of policies within uncertainty set. This methodology further explored in [103] by incorporating polynomial policies. To observe uncertainty parameter polynomial policies have been parameterized and after parameterization of policies optimal solution can be efficiently calculated by semi definite optimization methods.

Further decision rule policies have been considered in [104]. These policies are based on stochastic framework for both primal and dual version of problem. Here loss of optimality is analyzed with RO approximation approach. Further min max approach has been presented in [105], where dynamic policies are characterized by min max algorithm and discrete dynamic system is perturbed by noise. In continuation with multistage approaches on RO framework, adjustable multistage RO dynamic problem has been presented in [106]. Convex multi stage RO problem has been considered in [107], which approximate the decision of decision maker with finite linear combinations of prescribed uncertain functions. Here it is described how constraint randomization is utilized to optimize problem at low computation time and cost.

Further considering limited information of distribution process constrained stochastic linear system has been investigated in [108], in which only first two moments of distribution are known. Here two types of distributional robust constraints are used, one is the constrain that is come through known moments of given probability for all disturbance distribution and another one is CVaR (Conditional Value at Risk) constraint. CVaR constraint is used to bind expected constraint violation with given moment information for all disturbances consistent. A new deviation measure method has been used in [109] to construct uncertainty set for RO. The asymmetry of the distribution can be captured by these deviations measures. These are also known as improved approximations for chance constrained problem. In [110] uncertainty set formulation in Robust LP framework has been described with coherent risk measures. Further, for risk measures in finance, uncertainty set has been constructed in [111] with consideration of opposite perspective. For generating coherent risk measures a specific approach has been proposed in [112] with risk adverse optimization and developed sufficient and necessary condition for optimality of RO approach in convex set. Further considering smoothness assumptions necessary sufficient conditions are derived in non-convex uncertainty set with ambiguous and inconsistent utility assessment of a decision making framework has been investigated and pareto efficiency to RO approach has been incorporated in [113].

Further RO formulations to non-linear problems have been provided in [114], which is valid in robust approach to first order and nominal parameter. Further robust non-convex optimization approach has been presented in [115] with arbitrary objective function. It will move iteratively in descent directions with termination at robust local minima. Uncertain quadratic programing based conic quadratic constraint has been analyzed in [116] by formulating approximate robust counterpart. Robust geometric programing with tractable approximations has been studied in [117], where pricewise linear convex approximation is used for each non-linear constraint. In [118] geometric programing has been investigated with injected robustness at algorithm level and seeks to get feasible solution.

Further Robust convex optimization has been proposed in [119], where optimization problem is solved with passimizing oracles. Robustness for uncertain convex quadratic programing problem has been discussed in [120] with consideration of ellipsoidal uncertainties. Here realization technique with consideration of robust deviation random sampling has been utilized. Further unconstrained non-convex problem has been considered in [121], which uses arise in partial differential equation. Here any specific structures are not assumed to solve the problem. Further with considering constraints non-linear problem is solved in [122].

In [123] a special type of optimization approach has been formulated, which has linearity in decision variables and convexity in uncertainty. Here worst case has been maximized and exact & tractable robust counterpart has been derived. Further a special class for non-convex set of uncertain parameter in RO has been analyzed in [124]. RO based approach which uses intervals of uncertainty, for both non convex and convex quadratic programing problem has been discussed in [125], while min max and robust model for polynomial optimization has been used in [126].

Further demand uncertainty in capacity vehicle routing problem has been considered in [127] with uses of interval of uncertain parameter. Robust salesman problem has been presented in [128]. Combinational robustness has been utilized in [129] for different bidding behaviors of combinatorial auctions. Min-max regret and two stage analysis has been done in [130], which consider a solvable polynomial under uncertain demand interval sets. Further in transportation services combinatorial auctions have been considered in [131] with taking shipment as uncertain variable.

Further robustness has been analyzed in [132] by considering scheduling stability measures. Scheduling has been done through tabu search algorithm. Discrete time/cost trade off problems for robustness measurement in robust scheduling problem has been considered in [133]. With non-linear objective functions an efficient and effective algorithm has been developed that gives most nearer optimal solution [134]. Network flow under travel time uncertainty and demand uncertainty has been considered in [135] as robust capacity expansion problem. Here tractable reformulation has been provided with considering broad set of assumptions. Further demand uncertainty has been considered in network flow and design problem [136]. Here two stage network topology is considered to solve problem. Considering transportation cost and demand uncertainty in network design a tractable approximation has been discussed in [137] for each commodity at single origin and destination.

Further facility location problem has been discussed in [138], where optimal location and optimal time both are determined. Optimal time is determined to establish capacitated facility with consideration of demand and cost variation. Problem is solved by heuristic approach like bender decomposition method or local search algorithm. Robust network design has been proved in [139] with uncertain parameter. Deviation in robustness has been analyzed in [140]. Further RO has been applied in location facility problem for network design over multi period in [141], where different uncertainty model are used in different network topologies. A dual based local search algorithm has been investigated in [142] for all deterministic, stochastic and robust study. Further robust version of transportation problem has been discussed in [143], where local transportation problem with uncertain demand has been reformulated using two stage formulation and non-linear convex cutting plane method.

Further RO in energy systems has been discussed in [144] with investigation of two stage unit commitment problem where demand uncertainties have been considered and tractable solutions are obtained. Strategic planning model has been proposed in [145] for oil supply chain problem. Further integer programing model has been proposed in [146] for robust power grid optimization problem. Two stage adaptive robust optimization model has been proposed in [147], which uses security constrained unit commitment problem. Here nodal net injection uncertainty has been considered and bender decomposition method is used. Further daily operation of pumping station has been optimized in [148] considering demand uncertainty with the help of adaptive RO.

RO applications in RE (Renewable Energy) field have been investigated with considering wind and solar power uncertainties. Robust unit commitment has been proposed in [149], which uses thermal generators scheduling and minimizes the total operational cost under wind power uncertainty. However results obtained through this method are some where tractable but represent confusions on selecting sites and larger system is unable to give feasible solution.

2.4 Research Challenges and Objectives

On the basis of critical review of literature pertaining to approaches or algorithms that have been used for modeling uncertainties through scenarios, following challenges are identified. Existing algorithms for scenario generation as well reduction has been used for modeling electric load and financial market uncertainties and their application need to extend for modeling wind power and electricity market price uncertainties. Additionally, existing algorithms are complicated and not well explanatory, thus need to be simplified for modeling wind power and solar power uncertainties. Quality and stability of generated scenarios needs to be considered for improving uncertainty modeling.

Renewable power integration in MG operations in deregulated environment poses several challenges for MG operators. Development of efficient generation scheduling algorithm for MG operator under uncertainties is a major challenge considered for further investigations in this thesis. Excellent bibliographical surveys and research reviews on such challenges published in recent years indicate that MG generation scheduling under uncertainty environment is a potentially interesting decision-making problem for MG operators in distribution system. Uncertainties of renewable power have generally been modeled through a number of scenarios, which are generated and reduced using different approaches. On the basis of critical review of literatures pertaining to considered problem, following challenges are identified.

I. Development of MG generation scheduling problem in both grid connected and isolated mode.
II. Development of wind and solar power uncertainty in the MG generation scheduling problem using a Time series based Autoregressive Integrated Moving Average (ARIMA) model.
III. Development of robust optimization based approach for optimal MG scheduling considering renewable power uncertainties.

IV. Impact of renewable power uncertainties on optimal MG generation scheduling in deregulated power system.

On the basis of research challenges following objectives are created in this thesis

(i) To formulate MG generation scheduling problem in both grid connected and isolated mode.

(ii) To model wind and solar power uncertainty in the MG generation scheduling problem using a Time series based Autoregressive Integrated Moving Average (ARIMA) model.

(iii) To develop robust optimization based approach for optimal MG scheduling considering renewable power uncertainties.

(iv) To evaluate the impact of renewable power uncertainties on optimal MG generation scheduling in deregulated power system.

(v) To compare the robust optimization approach with traditional stochastic and deterministic approach.

(vi) To evaluate the impact of degree of robustness on the optimal generation scheduling obtained through robust optimization based approach.

(vii) To illustrate the proposed work through realistic case studies.

2.5 Summary

This chapter presents an overview of MG operation in distribution system. Further working modes of MG operation are discussed. The benefits of implementing MG have been discussed. The critical review on MG operation, uncertainty characterization in MG operation, uncertainty characterization in stochastic framework and robust optimization based uncertainty characterization have been carried out. On the basis of critical review research challenges are identified and on the basis of research objectives are made.

Chapter 3

Uncertainty Characterization

THIS chapter presents the basics of uncertainty characterization. Different types of uncertainties presented in MG operation have been illustrated. Further basics of ARIMA model for modeling of an uncertain parameter have been discussed in non-stationary time series signals. Further on the basis of ARIMA model, ACF and PACF formulation has been discussed.

UNCERTAINTY CHARACTERIZATION

3.1 Introduction

Occurring phenomena in the quantitative analysis related to engineering applications is first developed with mathematical models which are converted into simulation computer codes. A mathematical model can represent a real system, which is dependent on a number of parameters and hypotheses. The mathematical model can be represented in either deterministic or stochastic way. If occurring phenomena's underlying knowledge is incomplete than under analysis system cannot be characterized. This represents the uncertainty in the analysis of system. The uncertainty in quantitative analysis is due to the (i) occurring phenomenon's intrinsic variability and (ii) lack of information or knowledge of occurring phenomena. Such uncertainties within the model can propagate, which results in intrinsic variability in output. Therefore, the quality and characterization of resulting output are different that defines the scope of uncertainty analysis.

The aim of uncertainty analysis is to determine the behavior of uncertainty in quantitative result analysis [33]. Analysis of uncertainty can be illustrated with introduction of a new model $f(x)$, which is dependent on input quantities x as $y = f(x)$. With uncertainty in x, the uncertainty analysis of model y can be computed with propagation of model f.

Generally, both the uncertainties i.e. uncertainty in data structure x and uncertainty related to model structure f, are treated separately due to the existence of plausible hypothesis. In recent literature the first source of uncertainty i.e. the uncertainty in data structure x is widely investigated and improved by researchers, while, the uncertainty in model structure f is less investigated. So to handle-out the uncertainty in model structure f, effective and agreed methods are to be required [33]. Therefore, uncertainty analysis is an unavoidable component to model occurring phenomena and to study the behavior of system under their limits of operation. The uncertainty analysis of any system can be done by incorporating the understanding of uncertain system components, behavior of uncertain data, appropriate characterization of uncertain data etc.

The characterization of data uncertainty set using *ARIMA* model is described in next section of this chapter. And uncertainty characterization through stochastic and robust framework has been described in section 3.3 and 3.4 of this chapter. Fig. 3.1 shows the different possible uncertainties that may affect the smooth MG Operation.

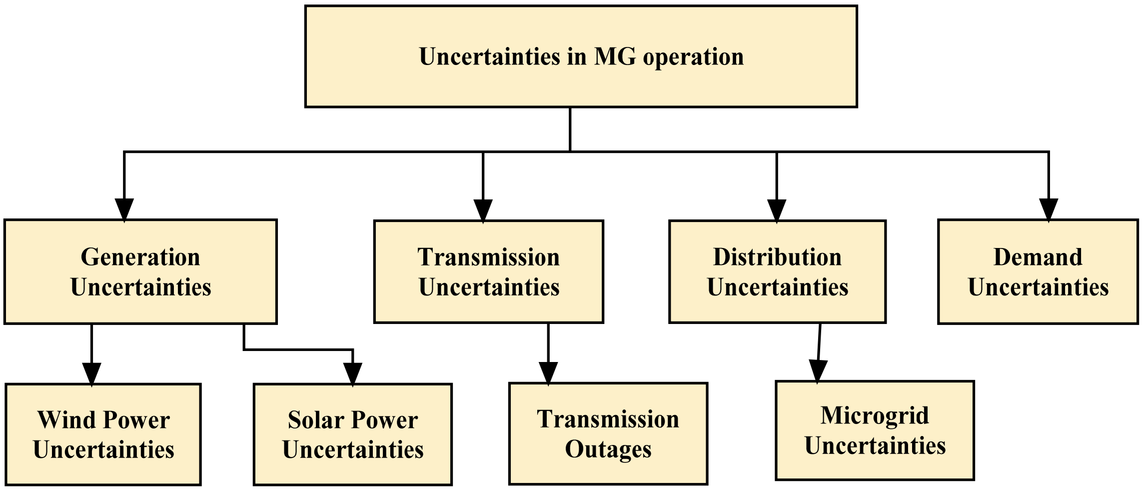

Fig. 3.1 Possible uncertainties in MG operation

3.2 ARIMA Model

In a particular realization of time series analysis an ARIMA (Autoregressive Integrated Moving Average) model is defined as a generalization of an ARMA (Autoregressive Moving Average) model. To predict future points in time series analysis, these models (i.e. ARIMA and ARMA) can be fitted. The prediction of future points are also known as forecasting, which is used for better understanding of data. These models (ARIMA and ARMA) are applied in stationary time series models, while in some cases, where data time series model is non-stationary, the non-stationarity is removed by an initial differencing step. This step is corresponding to the "integrated" part of the non-stationary model. Therefore, before describing the ARIMA model, the concept of stationarity and the technique of differencing time need to be discussed.

(i) Stationarity

Any time series model can be said stationary if properties of that system do not depend upon time. The time series model with seasonality and trends cannot be considered as stationary time series models because the value of time series model with seasonality or trends will be affected at any time. Similarly white noise series can be considered as stationary as its value will not depend upon time. The value of white noise series model is similar at any time period.

Some more confusing examples like cyclic behaviour time series model is considered stationary if there is no trend or seasonality. Since the length of cycle is not fixed, so before observing the series, it cannot be sure about peaks and troughs of cycle. In a stationary time series model no predictable pattern for a long term is observed. The time plot of time series model is considered of roughly horizontal with constant variance of time series models.

(ii) Differencing

Differencing is nothing, but it is the way to make stationary time series from the non-stationary time series to compute the consecutive observation differences. Differencing is used to stabilize the mean of a time series model. It is done by removing the time series model level changes to eliminate the present trend and seasonality.

Non-stationarity of the time series model can be identified with ACF plot as well as time plot of data. ACF (autocorrelation factor) in stationary time series is required to drop to zero relatively, while in non-stationary time series model ACF of data decreases slowly.

(iii) Second-Order Differencing

If the differenced data of time series model is again non-stationary than it is required to go forward for second order differencing to obtain a stationary time series:

$$y_t'' = y_t' - y_{t-1}' \tag{3.1}$$

$$= (y_t - y_{t-1}) - (y_{t-1} - y_{t-2}) \tag{3.2}$$

$$= y_t - 2y_{t-1} + y_{t-2} \tag{3.3}$$

Where,

y_t' Represents first differentiation of time series

y_t'' Represents second differentiation of time series

(iv) Seasonal Differencing

Seasonal differencing is nothing but it is used to represent the difference of current time observations to same time observations of previous year as shown in equation (3.4)

$$y_t' = y_t - y_{t-s} \tag{3.4}$$

Where,

s = number of seasons

These are also called "lag–s differences" as we subtract the observation after a lag of s periods.

3.2.1 Non-Seasonal ARIMA Models

If differencing is combined with AR (Auto regression) and a MA (moving average) model, an ARIMA model with non-seasonality is obtained. ARIMA is an acronym for Autoregressive Integrated Moving Average model ("integration" in this context is nothing but it is the reverse of differentiating). The full model representation of a time series model can be given as

$$y_t^{'} = c + \phi_1 y_{t-1}^{'} + ... + \phi_p y_{t-p}^{'} + \phi_1 e_{t-1} + ... + \theta_q e_{t-q} + e_t \qquad (3.5)$$

Where,

c is constant term, included in forecasting

ϕ_i is AR parameters

θ_i is MA parameters

e_i is Error term

$y_t^{'}$ represents the differenced series, which might have been differenced more than once. The "predictors" on the right hand side include both lagged values of y_t and lagged errors (e_i). This is referred as an ARIMA (p,d,q) model where, p represents the order of the autoregressive part, d represents the degree of first differencing involved, and q represents the order of the moving average part.

Once combining of components is done in this way to form more complicated models, it is much easier to work with the backshift notation. Then above equation can be written as

$$\left(1-\phi_1 B - ... - \phi_p B^p\right)\left(1-B\right)^d y_t = c + \left(1+\theta_1 B + ... + \theta_p B^q\right) e_t \qquad (3.6)$$

Where,

B is backshift operator

d is differentiation operator

3.2.2 Seasonal ARIMA Models

Non-stationary series can be converted into stationary ones with regular differences, *i.e.*, the difference from one period with respect to the next. Similarly to remove seasonality seasonal differences can be used. Non-stationary time series model with seasonality can be converted into a stationary time series model by using equation (3.7) as

$$w_t = \nabla_S^D \nabla^d z_t \qquad (3.7)$$

Where,

D is the number of seasonal differences (if there is seasonality)

D is 1; if there is no seasonality

d is the number of regular differences $(d \leq 3)$

∇ is differentiation operator

z_t is non stationary time series model

w_t is stationary time series

When seasonality in non-stationary time series model is present than the ARMA model can be generalized by incorporating both the differencing i.e. measurement intervals as well seasonal dependence of time series model separated by s seasonal periods.

Further it is important to discuss, how to model these two types of dependence:

- In first solution, seasonal dependence is incorporated in regular time series model by using B operator. In B operator AR or MA are incorporated to represent the dependence between observations separated by s periods.
- This formulation represents complexity in system solutions as it leads to very large polynomials in AR and MA. For example, if a monthly data with seasonality s = 12, is related to the same month in three previous years, then an AR or MA of 36 order is required to represent the seasonal dependence.

Therefore, it is needed to model a simpler approach for separately seasonal and regular dependence. The multiplicative seasonal ARIMA model is given as equation (3.8)

$$\Phi_P\left(B^S\right)\phi_P\left(B\right)\nabla_S^D\nabla^d z_t = \theta_q\left(B\right)\Theta_Q\left(B^S\right)e_t \tag{3.8}$$

Where,

$\Phi_P\left(B^S\right)=\left(1-\Phi_1 B^S-.......-\Phi_P B^{sP}\right)$ is the seasonal AR operator of order P

$\phi_P=\left(1-\phi_1 B-.......-\phi_P B^P\right)$ is the regular AR operator of order P

$\nabla_S^D=\left(1-B^S\right)^D$ represents the seasonal differences and $\nabla^d=\left(1-B\right)^d$ the regular differences

$\Theta_Q\left(B^s\right)=\left(1-\Theta_1 B^s-.....-\Theta_Q B^{sQ}\right)$ is the seasonal moving average operator of order Q

$\theta_q\left(B\right)=\left(1-\theta_1 B-.....-\theta_q B^q\right)$ is the regular moving average operator of order q

e_t is a white noise

This class of models, introduced by Box and Jenkins (1976), offers a good representation of many seasonal series that this model can be written as (p,d,q) in simplified form as the ARIMA model $(P,D,Q)_s \times (p,d,q)$. Where, p,d,q are used for non seasonal arima model while P,D,Q are used for seasonal ARIMA model.

In above equation 3.8, to represent the seasonal part of model uppercase notations are used, while to represent the non-seasonal parts of the model lowercase notation are used. The modeling of seasonal part and non-seasonal parts are very similar except involving of backshifts of the seasonal period.

3.2.3 Statistical Features

Characteristics of time series model can be represented by adding the following additional features:

(i) Mean

Generally the mean is represented by $\bar{x}$. The mean is given by the arithmetic average of observation sets. It is mathematically calculated by the total sum of the observation sets divided by the number of observation sets as shown in equation (3.9):

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{3.9}$$

Where x is the value of observation sets and n is the number of observation sets.

(ii) Mean Absolute Deviation

Variability is measured by the Mean absolute deviation (*Mad*). The *Mad* for a sample size n is defined as equation (3.10):

$$Mad(x_1.....x_n) = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2 \tag{3.10}$$

Where, $\bar{x}$ is the distribution mean

(iii) Variance

Dispersion is widely used by another term variance, which estimates the squared mean deviation of x from its mean value $\bar{x}$ as sown in equation (3.11)

$$Var(x_1.....x_n) = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2 \tag{3.11}$$

(iv) Skewness

The degree of asymmetry around mean is measured by skewness. The skewness gives the idea of variation data set's direction. There are two types of skewness, one is positive skewness and another one is negative skewness. Positive skewness tells that the distribution tail of the time series model is more stretched above the mean side, while negative skewness tells that the distribution tail of the of the time series model extends out below the mean side. In normal distribution of time series model, the skewness is treated as zero. Skewness is defined as equation (3.12)

$$Skew(x_1.....x_n) = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{x_i - \bar{x}}{\sigma}\right)^2 \tag{3.12}$$

Where $\sigma = \sigma(x_1.....x_n) = \sqrt{Var(x_1.....x_n)}$ is the standard deviation of the distribution.

3.2.4 ACF and PACF

The autocorrelation factor (ACF) at lag k is computed by equation (3.13)

$$ACF(k) = \frac{E\left[\left(y_t - E[y_t]\right)\left(y_{t-k} - E[y_{t-k}]\right)\right]}{\sqrt{Var[y_t]Var[y_{t-k}]}} \tag{3.13}$$

The relationship between Y_t and Y_{t-k} is to be measured in time series model when effects of other time lags are removed. Because correlation does not measure the effect of other time lags. To measure the effect of other time lags partial autocorrelation is used. ACF is a plot of correlation as a function of lag. The autocorrelation is simply the ordinary Pearson product-moment correlation of a time series with itself at a specified lag. The autocorrelation at lag 0 is the correlation of the series with its unlagged self, or 1. The autocorrelation at lag 1 is the correlation of the series with itself lagged one step, the autocorrelation at lag 2 is the correlation of the series with itself lagged 2 steps, and so forth. The partial autocorrelation factor (PACF) of a time series at lag k is denoted a_k and is found as follows:

$$y_t = \phi_0 + \phi_1 y_{t-1} + \phi_2 y_{t-2} + ... + \phi_k y_{t-k} + e_t \tag{3.14}$$

Then $a_k = \phi_k$ represents the fitted value of ϕ_k from the regression (Least Squares).

At different lags, the set of partial autocorrelations is called the PACF (partial autocorrelation function) and is plotted like the ACF *i.e.* PACF is a plot of partial autocorrelations with functions of lag. The partial autocorrelation at a given lag is the autocorrelation that is not accounted for by autocorrelations at shorter lags.

The principle way to determine appropriate AR /MA model is to look at the ACF and PACF of the time series model. Table 3.1 shows the principle way to find out the AR /MA with shapes of ACF and PACF.

Table 3.1: Shapes of ACF and PACF to identify AR or MA

MODEL	ACF	PACF
AR(1)	Exponential decay: on +ve side if $\varphi_1 > 0$ and alternating in sign, starting on –ve side, if $\varphi_1 < 0$.	Spike at lag 1, then 0; +ve spike if $\varphi_1 > 0$ and −ve spike if $\varphi_1 < 0$.
AR(p)	Exponential decay or damped sine wave. The exact pattern depends on the signs and sizes of φ_1 , . . . , φ_p .	Spikes at lags 1 to p , then zero.
MA(1)	Spike at lag 1, then 0; +ve spike if $\psi_1 < 0$ and −ve spike if $\psi_1 > 0$	Exponential decay: on +ve side if $\psi_1 < 0$ and alternating in sign, starting on +ve side, if $\varphi_1 < 0$
MA(q)	Spikes at lags 1 to q , then zero.	Exponential decay or damped sine wave. The exact pattern depends on the signs and sizes of ψ_1 , . . . , ψ_q .

3.2.5 White Noise

A stationary time series ε_t is said to be white noise if

$$Corr(\varepsilon_t - \varepsilon_s) = 0 \qquad \forall t \neq s \tag{3.15}$$

Where,

ε_i = White noise term

t = Time period 1,2,......,n

s = Seasonality

Thus white noise can be a sequence of uncorrelated random variables with both constant mean and constant. White noise series plots are very jumpy, erratic and unpredictable in behavior. Since white noise is uncorrelated, hence future values of white noise cannot be forecasted on the basis of previous values. The results of successive spins of a roulette wheel provide an example of a white noise series.

In economic time series, the white noise series is often thought of as representing innovations, or shocks. That is, ε_t represents those aspects of the time series of interest which could not have been predicted in advance.

3.3 Uncertainty Characterization in Stochastic Optimization Framework

Uncertainty is subjected to most of decision-making problems due to the natural phenomena's inherent randomness nature or to the input information's inaccurate knowledge. So, to overcome the effect of uncertainty decision makers are eager to develop such methods and tools which are less sensitive to influences or imprecise data. Besides developing models, decision makers are simultaneously working for increasing profit, reducing cost and improving reliability. Most of the decision-making processes based on optimization problems, where a set of the decisions (control variables) is to be obtained to optimize a certain objective like maximization of profit or minimization of total cost. The range of possible solution values of decision can take the value within economical, physical, technical and environmental limitations. Fig. 3.2 shows the Computational framework for stochastic MG operation in deregulated environment.

The following linear optimization problem equation (3.16) without loss of generality is considered for modeling

$$\begin{aligned} &Max. \;\; C^{'}x \\ &S.t. \;\; Ax \le b \\ &\qquad\; l \le x \le u \end{aligned} \tag{3.16}$$

Where x is the decision variable vector, and matrix A and vectors b and c are input data. Solution algorithms for linear optimization problems can be solved by the famous simplex method, if the parameters A, b and c are perfectly known. The decision variable vector x is best suitably optimized by simplex method. Now assume that some of these input parameter data are dependent on a certain random vector λ with a realization of λ_ω. Mathematically, this can be written as $A_\omega = A(\lambda_\omega)$, $b_\omega = b\ (\lambda_\omega)$, and $c_\omega = c\ (\lambda_\omega)$. If the decision variable vector x is required to be determined before the random parameter vector λ with realization of λ_ω in the decision-making process, then to determine the optimal solution for decision variable vector x of problem equation (3.16) will be more intricate in the following aspects:

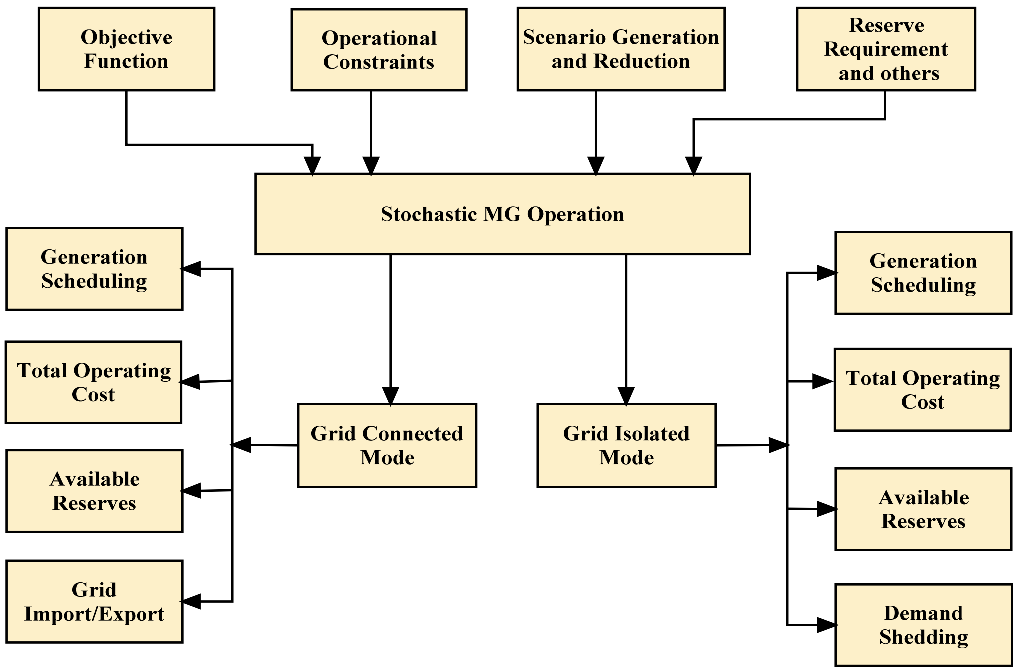

Fig. 3.2 Computational framework for stochastic MG operation

(i) Feasibility: First of all, it is the main question for decision maker to make completely satisfied constraint while the matrix A and vector b are the unknown parameters. And similarly another question is about of guarantee of feasibility of decision variable vector x in optimal solution under uncertainty. In decision making problems, the way of feasibility can be measured by using uncertainty modeling approach.

(ii) Optimality: If in above problem equation (3.16) uncertainty parameter is cost vector c, then objective function in equation (3.16) may not be a real-valued function. Now equation (3.16) becomes a random variable's family as $f(x,\omega) = C_{\omega}^{'} x$. To get feasible decision vector $x, f(x, \omega)$ can be obtained as a function of random variable $f(x, \cdot)$ at an argument of ω. Hence, decision variable vector x is found through optimization under uncertainty, that belongs to the *best* random variable $f(x, \omega)$. Therefore, it is required to discriminate the goodness of each family member of the uncertainty set U. Ranking of random variables in function $f(x, \omega)$ is a common practice in stochastic programming framework. Ranking of random variables is done according to their expectations by picking the biggest in a maximization problem.

(iii)Solution algorithm: in stochastic programing framework, the problem equation (3.16) of optimization problem is required to be recast for getting optimal solution of linear

programming problems. The most used method for solving LP problem is the simplex method to get the optimal value of decision vector x. Let the random parameter vector λ is continuously affecting the optimization problem equation (3.16), then in stochastic framework, a discrete approximation is required to make such a problem solvable. For this, random vector λ is modeled as a set of Ω, which are the plausible outcomes of different scenario set ω, where each scenario $\omega \in \Omega$ has a probability π_ω of occurrence as such that $\sum_{\omega \in \Omega} \pi_\omega = 1$.

In decision making problems with uncertain data parameter, stochastic programming provides the required tools and concepts with optimize solutions. Uncertainty parameters using distribution functions have been traditionally characterized in optimization problem. These distribution functions are describing most plausible realization of the uncertain parameter by generating a number of scenarios. Further these scenarios using probabilistic distribution functions are used in stochastic programming based optimization to make optimal decision regarding decision variable vector x. The approach exhibits two drawbacks:

(i) There are difficulties to characterize some uncertain parameters using distribution functions; for example, offering behavior of rival producers.

(ii) Generally, to describe the most plausible outcomes of the uncertain parameters, there are a large number of scenarios are needed. This may lead to large-scale optimization problems which become intractable or very difficult to solve.

3.4 Uncertainty Characterization in Robust Optimization Framework

Robust optimization is nothing but it addresses those uncertain parameters in optimization problems with uncertain parameters which are not described by using probability distributions but uncertainty sets [84]. An uncertainty set has set structure which is used to characterize the uncertain parameter's possible outcomes. In a robust optimization the aim is to determine a solution to an optimization problem in such a way that the obtained solution is feasible for any realization of the uncertain parameters within the uncertainty set and for the worst-case realization of these uncertain parameters, solution is optimal.

To formulate Robust Optimization, uncertainty set is to be properly defined, so that uncertain phenomenon presented by uncertain parameters can be described properly. Uncertainty set can have either highly risky or conservative solution. Further complexity in uncertainty sets may lead to damage the tractability which characterizes the robust optimization with elliptical or polyhedral sets.

Fig. 3.3 shows the Computational framework for robust MG operation in deregulated environment.

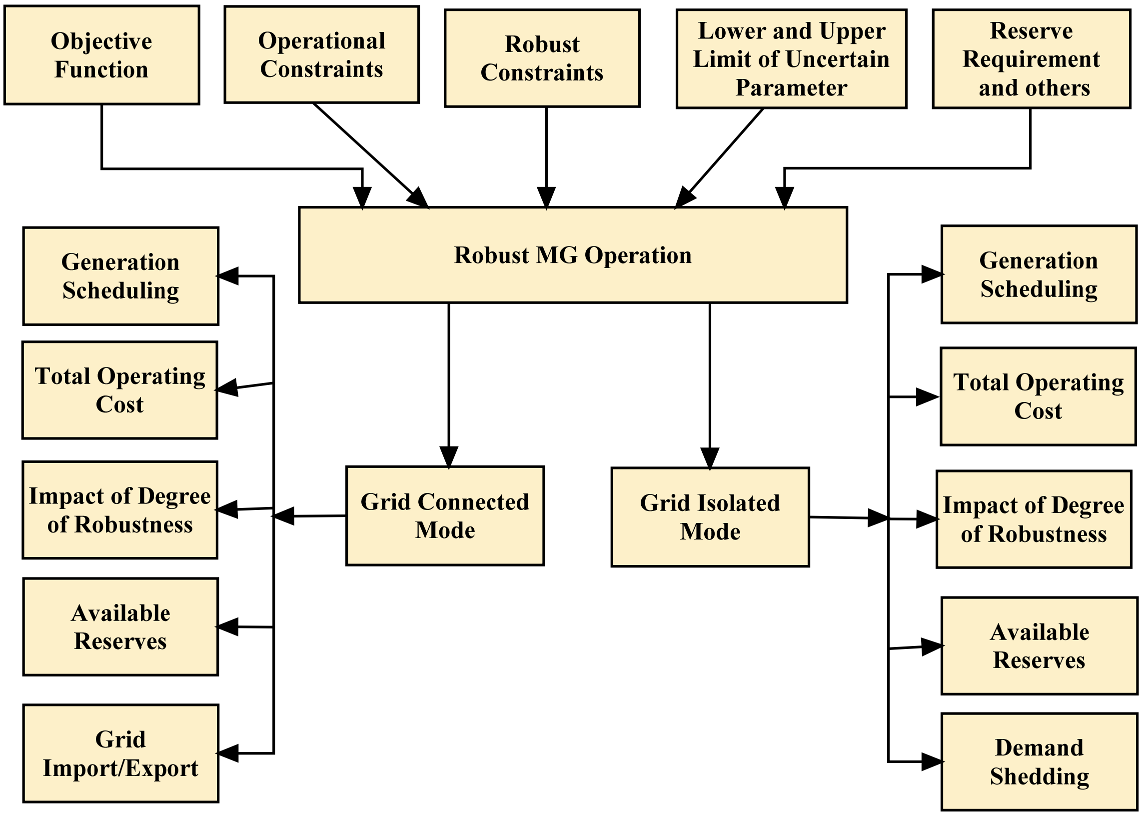

Fig. 3.3 Computational framework for robust MG operation

Robust optimization is used to provide an alternative and compact manner to describe the uncertain parameters within the uncertainty set at the cost of reduced flexibility. Optimal results obtained from such approaches are generally more computationally efficient than their stochastic programming counterparts, while preserving sufficient modeling flexibility.

The following nominal linear optimization problem has been considered as similar to problem considered in stochastic optimization equation (3.16) for better understanding:

$$\begin{aligned} &Max.\ \ C'x \\ &S.t.\ \ \ Ax \le b \\ &\qquad\ \ \ l \le x \le u \end{aligned} \tag{3.16}$$

In any decision making problem there are three types of robustness (i) constraint robustness (ii) objective robustness (iii) combinational robustness. If uncertainty is present in only constraint parameter, then the problem is defined as constraint robustness problem. If uncertainty is present in only objective function parameter, then the problem is classified as objective robustness problem. If uncertainty is present in both constraints parameter and objective function parameter then it is defined as combinational robustness. Due to effective modeling of uncertain parameters the problem formulated by the robust optimization is tractable and has low computational burden. In the above formulation, it is assumed that data uncertainty only affects the elements in matrix *A*. it is assumed without loss of generality that the objective function *C* is not subject to uncertainty. Therefore the problem is solved as constraint robustness problem.

A robust formulation of optimization problem equation (3.16) is able to withstand the parameter uncertainty under data uncertainty set *U.* further RO formulation is linear without affecting the value objective function and ready to extend discrete optimization problems. The equivalent RO based formulation of equation (3.16) is given as follows:

$$
\begin{aligned}
&Max.\ C^{'}x\\
&Subject\ to\\
&\qquad \sum_{j} a_{ij}x_j + z_i\Gamma i + \sum_{j\in J_i} p_{ij} \le b_i && \forall i\\
&\qquad z_i + p_{ij} \ge \hat{a}_{ij}\, y_j && \forall i \ne 0, j \in J_i\\
&\qquad p_{ij} \ge 0 && \forall i, j \in J_i\\
&\qquad y_j \ge 0 && \forall j\\
&\qquad z_i \ge 0 && \forall i\\
&\qquad -y_j \le x_j \le y_j && \forall j\\
&\qquad l_j \le x_j \le u_j && \forall j\\
&\qquad x_i \in Z && \forall i = 1,2,3.......k
\end{aligned}
\tag{3.17}
$$

In above reformulation of problem Γi has been introduced for robustness purposes, the values of Γi lies in the interval of [0, $|J_i|$], where $J_i = \left\{ j\,; \hat{a}_{ij} > 0 \right\}$. The value of Γi is assumed to be an integer. The role of the parameter Γi in the constraints is to adjust the degree of robustness of the proposed method against the level of conservatism of the solution. Consider the i^{th} constraint of the nominal problem $a_i^{'} x \le b_i$. Let J_i be the set of coefficients a_{ij} , $j \in J_i$ that are subject to parameter uncertainty, i.e., a_{ij}, $j \in J_i$ independently takes values according to a symmetric distribution with a mean equal to the nominal value a_{ij} in the interval $\left[a_{ij} - \hat{a}_{ij} , a_{ij} + \hat{a}_{ij} \right]$. It is unlikely that all of the a_{ij} , $j \in J_i$ will change. The parameter Γi controls the level of robustness in the objective. As an optimal solution is needed that optimizes against all scenarios under which a number Γi of the constraint coefficients can vary in such a way as to maximally influence the objective. Let $J_i = \left\{ j ; \hat{a}_{ij} > 0 \right\}$. If $\Gamma i = 0$, the influence of the uncertain parameter deviations can be completely ignored, while if $\Gamma i = |J_i|$, all possible uncertain parameter deviations are considered, which is indeed most conservative. In general a higher values of Γi increases the level of robustness at the expense of higher nominal cost.

3.5 Summary

In this chapter basics of uncertainty characterization have been discussed. Different types of uncertainties presented in MG operation have been illustrated. Further basics of ARIMA model for modeling of an uncertain parameter have been discussed in non-stationary time series signals. Further on the basis of ARIMA model, ACF and PACF formulation has been discussed. Uncertainty characterization in both stochastic framework and robust optimization framework has been discussed and problem formulation considering uncertain parameter in both stochastic framework and robust optimization framework has been derived.

Chapter 4

Robust Microgrid Operation in Deregulated Environment Considering Wind Uncertainty

THIS chapter presents proposed robust optimization based approach for optimal generation scheduling of MG in both grid-connected and grid-isolated modes. Wind power uncertainty has been modeled through interval forecasting using ARIMA model. A comparative study on daily MG cost of operation using proposed robust optimization based approach with deterministic and stochastic approach has been performed.

CHAPTER - 4

ROBUST MICROGRID OPERATION IN DEREGULATED ENVIRONMENT CONSIDERING WIND UNCERTAINTY

4.1 Introduction

Increasing penetration of renewable energy resources in evolving deregulated power system has great public attention, recently. Among the renewable energy sources, the penetration of wind and solar generators has increased due to their much evolved technology and wide spread availability. To integrate these renewable sources as Distributed Energy Resources (DERs) into the utility grid, MGs play an important role [1]. MG is a small-scale power supply network that is designed to provide power for a small community and can increase the reliability and economics of energy supply [2]. A typical architecture consists of dispatchable, non dispatchable generating unit and consumers. MG can be operated in two modes: grid connected and grid isolated. In grid-connected mode, MG can export its excess power to the grid and can import its deficit power from grid. MG can manage its demand independently in grid-isolated mode [3].

Due to uncontrollable nature of demand and to operate the generators within its technical limitations, the efficient and economic management of the generators is highly recommended. With increasing penetration of renewable sources like wind and solar in the distribution power system, MG management system may become complex. The grid price volatility in deregulated environment of power system has further increased the complexity of MG's energy management system. Therefore, development of efficient approaches for MG management under different uncertainties is necessary.

This chapter presents robust optimization based approach for optimal MG operation in deregulated environment considering renewable power uncertainties. Proposed approach is formulated for generation scheduling problem of MG in both grid-connected and grid-isolated mode. Wind uncertainty can be modelled through interval forecasting using time series based Autoregressive Integrated Moving Average (ARIMA) model. Other uncertainties (like PV generation uncertainty, demand uncertainty and grid prices uncertainty) are modelled using deterministic point forecasting method. The proposed approach is illustrated through a case study having both dispatchable and non-dispatchable generators through different modes of operation. Further the impact of degree of robustness is analyzed in both cases on the total cost of operation of the MG. A comparative analysis between obtained results using proposed approach and other existing approach shows the strength of proposed approach in cost minimization in MG management.

4.2 Problem Description

MG operator can solve the MG energy scheduling problem with an objective to minimize the total cost of operation considering various constraints. Parameters in both grid-connected and isolated mode are slightly different. The detailed basic formulation of MG energy management formulation is described below:

4.2.1 Grid Connected Mode

In this mode, the MG is connected to the utility grid therefore, MG can Import/Export its deficit/excess power from/to the utility grid. In the deregulated environment, MG can earn revenue by selling its excess power to the spot market. Additionally, MG can also earn revenue by selling its reserve capacity to the spot market if prices are higher than its marginal cost. On the other hand the cost of operation can be minimized by meeting its deficit power from the utility grid when grid power is cheaper than MG's reserve cost. In grid-connected mode, the basic problem is formulated as follows:

(i) Objective Function

$$\min \sum_{t=1}^{N_t} \left[\sum_{j=1}^{N_j} C_j \left(P_{j,t} + r_{j,t}^u - r_{j,t}^d \right) + P_{grid,t} * \lambda_{grid,t} \right] \tag{4.1}$$

MO solves the generation scheduling problem with an objective to minimize the total cost of operation. The total cost of operation of MG is "The total sum of operating cost of dispatchable generating unit's power, reserves and cost of power imported/exported from/to grid", is termed as total operation cost of MG.

(ii) Power Balance Constraint

The Power balance constraint states that "the sum of scheduled power of dispatchable generating units, wind power units and PV generation must be equal to day-ahead forecasted demand at any time t". Wind power, PV generation and demand can be forecasted using any existing approach.

$$\sum_{j=1}^{N_j} P_{j,t} + \sum_{w=1}^{N_w} P_{w,t}^{f} + \sum_{v=1}^{N_v} PV_{v,t}^{f} = Pd_t^{f}, \quad \forall t \tag{4.2}$$

(iii) Real time Power Balance Constraint

$$\sum_{j=1}^{N_j} \left(r_{j,t}^{u} - r_{j,t}^{d} \right) + \sum_{w=1}^{N_w} \left(\Delta P_{w,t} \right) + \sum_{v=1}^{N_v} \Delta PV_{v,t} + P_{grid,t} - \Delta Pd_t = 0, \quad \forall t \tag{4.3}$$

Due to error in existing forecasting approaches, the actual values of wind power, PV generation and demand may be different from their forecasted values. The system imbalance created due to the error in forecasting in real-time can be compensated by the reserve capacity of dispatchable units or by the power from the main grid depending on the cost of compensation.

(iv) Imbalance Constraints

$$\Delta P_{w,t} = P_{w,t}^{a} - P_{w,t}^{f}, \qquad \forall w, \forall t \tag{4.4}$$

$$\Delta PV_{v,t} = PV_{v,t}^{a} - PV_{v,t}^{f}, \qquad \forall v, \forall t \tag{4.5}$$

$$\Delta P_{d,t} = P_{d,t}^{a} - P_{d,t}^{f}, \qquad \forall d, \forall t \tag{4.6}$$

In real-time, the deviation of wind power, PV generation and system demand from their forecasted values can be calculated by the corresponding imbalance constraints expressed in equation (4.4)-(4.6). In this work, forecasting error of wind power generation, PV Generation & demand is assumed as a random variable with zero mean and constant standard deviation. The Real value of wind power, PV power and demand is obtained by multiplying the error coefficient to their forecasted values.

(v) Dispatchable Units Power Constraint

$$P_j^{\min} \le P_{j,t} \le P_j^{\max}, \qquad \forall j, \forall t \tag{4.7}$$

$$r_{j,t}^{u} \le R_{j,t}^{u,\max}, \qquad \forall j, \forall t \tag{4.8}$$

$$r_{j,t}^{d} \le R_{j,t}^{d,\max}, \qquad \forall j, \forall t \tag{4.9}$$

$$P_{j,t} + r_{j,t}^{u} - r_{j,t}^{d} \geq 0, \qquad \forall j, \forall t \tag{4.10}$$

$$P_{j,t} + r_{j,t}^{u} - r_{j,t}^{d} \leq P_{j,t}^{\max}, \qquad \forall j, \forall t \tag{4.11}$$

Equation (4.7) maintains scheduled dispatchable generation unit power within predefined limits, while Constraints (4.8) and (4.9) define the scheduled upward and downward reserve of dispatchable generating units. It must be lesser than their maximum upward and downward reserve capacity respectively. Constraints (4.10) and (4.11) state that sum of scheduled power of dispatchable units with their respective reserves must be within their specified limits.

(vi) Grid Power constraint

$$P_{grid,t} \leq P_{grid,t}^{\max}, \qquad \forall t \tag{4.12}$$

Due to transmission network constraints, MG cannot meet the whole demand through grid power when grid prices are lower than operation cost. On the other hand, the complete reserve capacity cannot be sold in the spot market during high market prices. Constraint (4.12) ensures that the power exchange between the main grid & MG is less than predefined capacity of the connecting.

4.2.2 Grid Isolated Mode

In this mode also, similar to grid connected mode, it is also required to minimize the expenses of the MG. However, more attention is given to meet the demand within technical limits. The objective function in the isolated mode is stated as:

(i) Objective Function

$$\min \sum_{t=1}^{N_t} \left[\sum_{j=1}^{N_j} C_j \left(P_{j,t} + r_{j,t}^{u} - r_{j,t}^{d} \right) + P_{d,t}^{shed} * \lambda_d^{shed} \right] \tag{4.13}$$

Similar to the grid connected mode, the objective of MO in this mode is also to minimize the total cost of operation. However, the cost of exchange of power between main grid & MG is replaced by the cost of demand shedding. Since, the cost of demand shedding is very high, it is generally avoided till the complete utilization of the reserve capacity.

(ii) Real time Power Balance Constraint

To maintain system security and reliability, the generation is always equal to system demand at each instant.

$$\sum_{j=1}^{N_j}\left(r_{j,t}^{u}-r_{j,t}^{d}\right)+\sum_{w=1}^{N_w}\left(\Delta P_{w,t}\right)+\sum_{v=1}^{N_v}\Delta PV_{v,t}+P_{d,t}^{Shed}-\Delta Pd_t=0,\quad \forall t \tag{4.14}$$

The system imbalance created due to volatile wind power, PV generation and demand at real-time is balanced by scheduling the reserve capacities of dispatchable generating units and shedding of demand.

(iii) Demand Shedding Constraint

$$P_{d,t}^{shed}\le P_{d,t} \qquad \forall t \tag{4.15}$$

The shedding power is always less than equal to the scheduled demand in day-ahead scheduling.

(iv) Power Balance Constraint

$$\sum_{j=1}^{j}P_{j,t}+\sum_{w=1}^{N_w}P_{w,t}^{f}+\sum_{v=1}^{N_v}PV_{v,t}^{f}=Pd_t^{f},\quad \forall t \tag{4.16}$$

Similar to Grid connected mode, the power balance constraint in this mode, states that "the sum of scheduled power of dispatchable generating units, wind power units and PV generation must be equal to day-ahead forecasted demand at any time t".

(v) Imbalance Constraints

$$\Delta P_{w,t}=P_{w,t}^{a}-P_{w,t}^{f}, \qquad \forall w,\forall t \tag{4.17}$$

$$\Delta PV_{v,t}=PV_{v,t}^{a}-PV_{v,t}^{f}, \qquad \forall v,\forall t \tag{4.18}$$

$$\Delta P_{d,t}=P_{d,t}^{a}-P_{d,t}^{f}, \qquad \forall d,\forall t \tag{4.19}$$

Similar to above discussed grid connected mode, the imbalance constraints defined as real-time deviation of wind power, PV generation and system demand from their forecasted values that can be calculated by the corresponding imbalance constraints expressed in equation (4.17)-(4.19).

(vi) Dispatchable Units Power Constraint

$$P_j^{\min}\le P_{j,t}\le P_j^{\max}, \qquad \forall j,\forall t \tag{4.20}$$

$$r_{j,t}^{u}\le R_{j,t}^{u,\max}, \qquad \forall j,\forall t \tag{4.21}$$

$$r_{j,t}^{d} \leq R_{j,t}^{d,\max}, \qquad \forall j, \forall t \tag{4.22}$$

$$P_{j,t} + r_{j,t}^{u} - r_{j,t}^{d} \geq 0, \qquad \forall j, \forall t \tag{4.23}$$

$$P_{j,t} + r_{j,t}^{u} - r_{j,t}^{d} \leq P_{j,t}^{\max}, \qquad \forall j, \forall t \tag{4.24}$$

The dispatchable unit power constraints in grid isolated mode are similar to grid connected mode that defined as follows: Equation (4.20) maintains scheduled dispatchable generation unit power within predefined limits, while Constraints (4.21) and (4.22) define the scheduled upward and downward reserve of dispatchable generating units. It must be lesser than their maximum upward and downward reserve capacity respectively. Constraints (4.23) and (4.24) state that sum of scheduled power of dispatchable units with their respective reserves must be within their specified limits.

4.3 Uncertainty Modeling

The main source of uncertainty in the operation of MG in both the modes, in deregulated power systems, is random wind power. Random nature of wind power can be modelled by stochastic process. ARIMA model is the most popular approach for modelling any stochastic process and is widely used for forecasting electricity prices, demand and the prices of commodities other than electricity. As wind power varies with atmospheric conditions, the time series of wind power is non-stationary. Since, ARIMA model is applicable for only stationary data series, so wind power is converted in to stationary series by differentiation. In this work, ARIMA model is used for forecasting upper and lower limit of wind power. The typical ARIMA (p, d, q) model is expressed as

$$Y_t = \mu + \sum_{i=1}^{p} \gamma_i Y_{t-1} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-1} + \varepsilon_t \tag{4.25}$$

Where, Y_t is the forecasted limits of wind power at time t, p is the order of autoregressive coefficients, γ_i and q are the orders of moving average coefficients θ_i. The term ε_t is a normally distributed random number with mean zero and constant variance, also known as white noise or error signal. The term μ is a constant in the model. The main objective of this work is to develop a robust optimization approach for optimal generation scheduling of MG. For the sake of simplicity, modelling of seasonal impacts in the wind power uncertainty is not considered in the present work, as this work focuses on short term generation scheduling of MG.

4.4 Robust Optimization Approach

A robust optimization approach has been extensively used in engineering and economics field for solving different decision making problems with different uncertainties. For modeling of these problems Robust Optimization can provide a solution that is guaranteed to be "good" for all or most possible realization of the uncertain parameter. In any decision making problem there are three types of robustness (i) constraint robustness (ii) objective robustness (iii) combinational robustness. If uncertainty is present in only constraint parameter, then the problem is defined as constraint robustness problem. If uncertainty is present in only objective function parameter, then the problem is classified as objective robustness problem. If uncertainty is present in both constraint parameter and objective function parameter then it is defined as combinational robustness. Due to effective modeling of uncertain parameters the problem formulated by the robust optimization is tractable and has low computational burden [152].

When degree of robustness is zero, the problem reduces to a deterministic case which solves the problem using the nominal values *i.e.,* expected values of the uncertain coefficients. Degree of robustness can be adjusted according to the trade-off between decision maker's risk preference and the conservatism of the solution [152].

4.5 Proposed Problem Formulation

This section provides the proposed formulation of MG scheduling problem in both Grid connected and Grid isolated mode using robust optimization approach. In this problem, wind power is considered as uncertain parameter that is present in the constraints, therefore the formulated problem has constraint robustness.

4.5.1 Grid Connected Mode

In this mode, problem described in section 2.2 is reformulated by using Robust

Optimization as follows:

(i) Objective Function

Since uncertainty is present in the constraint only, the Objective function, similar to equation (4.1) in which minimization of total cost of operation is represented as the sum of operating cost of dispatchable generating unit's power, reserves and cost of power exchange between main grid & the MG.

$$\min \sum_{t=1}^{N_t} \left[\sum_{j=1}^{N_j} C_j \left(P_{j,t} + r_{j,t}^{u} - r_{j,t}^{d} \right) + P_{grid,t} * \lambda_{grid,t} \right] \tag{4.26}$$

(ii) Power Balance Constraint

$$\sum_{j=1}^{j} P_{j,t} + \sum_{w=1}^{N_w} \left(\sum_{k=1}^{N_k} W_{t,k} + z_k \Gamma_k + \sum_{k=1}^{N_k} q_k \right) + \sum_{v=1}^{N_v} PV_{v,t}^{f} = Pd_t^{f}, \quad \forall t \tag{4.27}$$

Power balance constraint is represented in equation (4.27). This constraint states that the sum of scheduled power of dispatchable generating units, wind power units and PV generation must be equal to day-ahead forecasted demand at any time t. But irrespective of the previous formulation, wind power is considered as uncertain parameter and modeled in RO framework, where variables like z_k, q_k and Γ_k are introduced to solve the problem, Where, Γ_k is the degree of robustness which controls the robustness of the problem and z_k, q_k are the dual variables to linearize the non-linearity in the problem. The PV generation and demand can be forecasted using any existing approach.

(iii) Robust Constraints

$$z_k + q_k \ge \hat{W}_{t,k} y_k, \qquad \forall k \ne 0,\ k \in N_k \tag{4.28}$$

$$q_k \ge 0, \qquad \forall k,\ k \in N_k \tag{4.29}$$

$$y_k \ge 0, \qquad \forall k \tag{4.30}$$

$$z_k \ge 0, \qquad \forall k \tag{4.31}$$

Robust constraints are represented by equations (4.28)-(4.31), Where, equation (4.28) states that dual variable z_k and q_k are taken into account as the known bounds of wind power in such a way that the sum of both variables is always greater than the wind characterization parameter $\hat{W}_{t,k} y_k$. y_k is an auxiliary variable, used to obtain the corresponding linear expressions. However, $\hat{W}_{t,k}$ is obtained as the proportionate of the difference of lower and upper bounds of wind power. Constraint (4.29), (4.30) and (4.31) show that the dual variables used in robust approach must be positive.

(iv) Real time Power Balance Constraint

$$\sum_{j=1}^{N_j}\left(r_{j,t}^u - r_{j,t}^d\right) + \sum_{w=1}^{N_w}\left(\Delta P_{w,t}\right) + \sum_{v=1}^{N_v}\Delta PV_{v,t} + P_{grid,t} - \Delta Pd_t = 0, \quad \forall t \tag{4.32}$$

Due to error in existing forecasting approaches, the actual values of wind power, PV generation and demand may be different from their forecasted values. The system imbalance created due to the error in forecasting in real-time can be compensated by the reserve capacity of dispatchable units or by the power from the main grid depending on the cost of compensation.

(v) Imbalance Constraints

$$\Delta P_{w,t} = P_{w,t}^a - P_{w,t}^f, \qquad \forall w, \forall t \tag{4.33}$$

$$\Delta PV_{v,t} = PV_{v,t}^a - PV_{v,t}^f, \qquad \forall v, \forall t \tag{4.34}$$

$$\Delta P_{d,t} = P_{d,t}^a - P_{d,t}^f, \qquad \forall d, \forall t \tag{4.35}$$

In real-time, the deviation of wind power, PV generation and system demand from their forecasted values can be calculated by the corresponding imbalance constraints expressed in (4.33)-(4.35). In this work, forecasting error of wind power generation, PV Generation & demand is assumed as a random variable with zero mean and constant standard deviation. The Real value of wind power, PV power and demand is obtained by multiplying the error coefficient to their forecasted values.

(vi) Dispatchable Units Power Constraint

$$P_j^{\min} \le P_{j,t} \le P_j^{\max}, \qquad \forall j, \forall t \tag{4.36}$$

$$r_{j,t}^u \le R_{j,t}^{u,\max}, \qquad \forall j, \forall t \tag{4.37}$$

$$r_{j,t}^d \le R_{j,t}^{d,\max}, \qquad \forall j, \forall t \tag{4.38}$$

$$P_{j,t} + r_{j,t}^u - r_{j,t}^d \ge 0, \qquad \forall j, \forall t \tag{4.39}$$

$$P_{j,t} + r^{u}_{j,t} - r^{d}_{j,t} \le P^{\max}_{j,t}, \qquad \forall j, \forall t \tag{4.40}$$

Equation (4.36) maintains scheduled dispatchable generation unit power within predefined limits, while Constraints (4.37) and (4.38) define the scheduled upward and downward reserve of dispatchable generating units. It must be lesser than their maximum upward and downward reserve capacity respectively. Constraints (4.39) and (4.40) state that sum of scheduled power of dispatchable units with their respective reserves must be within their specified limits.

(vii) Grid Power Cconstraint

$$P_{grid,t} \le P^{\max}_{grid,t}, \qquad \forall t \tag{4.41}$$

Due to transmission network constraints, MG cannot meet the whole demand through grid power when grid prices are lower than operation cost. On the other hand, the complete reserve capacity cannot be sold in the spot market during high market prices. Constraint (4.41) ensures that the power exchange between the main grid & MG is less than predefined capacity of the connecting.

4.5.2 Grid Isolated Mode

Since wind power uncertainty is involved in the constraints, the MG generation scheduling problem in this mode is formulated using Robust Optimization approach similar to Grid connected mode differing in the objective function and supply-demand equilibrium constraint. Similar to previous one, in this mode also, it is required to minimize the expenses of the MG. However, more attention is given to meet the demand with stable operation. The problem in the isolated mode is formulated as:

(i) Objective Function

Similar to previously defined grid connected mode under RO Approach, the objective of MO in this mode is also the minimization of total operation cost. However, the Objective function is same as (4.13) in grid isolated mode.

$$\min \sum_{t=1}^{N_t} \left[\sum_{j=1}^{N_j} C_j \left(P_{j,t} + r^{u}_{j,t} - r^{d}_{j,t} \right) + P^{shed}_{d,t} * \lambda^{shed}_{d} \right] \tag{4.42}$$

It states that the sum of operating cost of dispatchable generating units and cost of demand shedding should be minimized.

(ii) Power Balance Constraint

Power balance constraint is same as grid connected mode formulation in RO framework by equation (4.43). For the same, robust constraint is also similar to the previous case *i.e* equation (4.28)-(4.31).

$$\sum_{j=1}^{j} P_{j,t} + \sum_{w=1}^{N_w}\left(\sum_{k=1}^{N_k} W_{t,k} + z_k\Gamma_k + \sum_{k=1}^{N_k} q_k\right) + \sum_{v=1}^{N_v} PV_{v,t}^{f} = Pd_t^{f}, \quad \forall t \tag{4.43}$$

Power balance constraint is represented in equation (4.43). This constraint states that the sum of scheduled power of dispatchable generating units, wind power units and PV generation must be equal to day-ahead forecasted demand at any time t. But irrespective of the previous formulation, wind power is considered as uncertain parameter and modeled in RO framework, where variables like z_k, q_k and Γ_k are introduced to solve the problem, Where, Γ_k is the degree of robustness which controls the robustness of the problem and z_k, q_k are the dual variables to linearize the non-linearity in the problem. The PV generation and demand can be forecasted using any existing approach.

(iii) Robust Constraints

$$z_k + q_k \geq \hat{W}_{t,k} y_k, \qquad \forall k \neq 0,\ k \in N_k \tag{4.44}$$

$$q_k \geq 0, \qquad \forall k,\ k \in N_k \tag{4.45}$$

$$y_k \geq 0, \qquad \forall k \tag{4.46}$$

$$z_k \geq 0, \qquad \forall k \tag{4.47}$$

Robust constraints are represented by equations (4.44) - (4.47), Where, equation (4.44) states that dual variable z_k and q_k are taken into account as the known bounds of wind power in such a way that the sum of both variables is always greater than the wind characterization parameter $\hat{W}_{t,k} y_k$. y_k is an auxiliary variable, used to obtain the corresponding linear expressions. However, $\hat{W}_{t,k}$ is obtained as the proportionate of the difference of lower and upper bounds of wind power. Constraint (4.45), (4.46) and (4.47) show that the dual variables used in robust approach must be positive.

(iv) Real time Power Balance Constraint

$$\sum_{j=1}^{N_j}\left(r_{j,t}^{u}-r_{j,t}^{d}\right)+\sum_{w=1}^{N_w}\left(\Delta P_{w,t}\right)+\sum_{v=1}^{N_v}\Delta PV_{v,t}+P_{d,t}^{Shed}-\Delta Pd_t=0, \quad \forall t \tag{4.48}$$

To maintain system security and reliability, the generation is always equal to system demand at each instant. The system imbalance created due to volatile wind power, PV generation and demand at real-time is balanced by scheduling the reserve capacities of dispatchable generating units and shedding of demand.

(v) Demand Shedding Cconstraint

$$P_{d,t}^{shed} \le P_{d,t} \qquad \forall t \tag{4.49}$$

The shedding power is always less than equal to the scheduled demand in day-ahead scheduling.

(vi) Imbalance Constraints

$$\Delta P_{w,t}=P_{w,t}^{a}-P_{w,t}^{f}, \qquad \forall w, \forall t \tag{4.50}$$

$$\Delta PV_{v,t}=PV_{v,t}^{a}-PV_{v,t}^{f}, \qquad \forall v, \forall t \tag{4.51}$$

$$\Delta P_{d,t}=P_{d,t}^{a}-P_{d,t}^{f}, \qquad \forall d, \forall t \tag{4.52}$$

In real-time, the deviation of wind power, PV generation and system demand from their forecasted values can be calculated by the corresponding imbalance constraints expressed in (4.50)-(4.52). In this work, forecasting error of wind power generation, PV Generation & demand is assumed as a random variable with zero mean and constant standard deviation. The Real value of wind power, PV power and demand is obtained by multiplying the error coefficient to their forecasted values.

(vii) Dispatchable Units Power Constraint

$$P_j^{\min} \le P_{j,t} \le P_j^{\max}, \qquad \forall j, \forall t \tag{4.53}$$

$$r_{j,t}^{u} \le R_{j,t}^{u,\max}, \qquad \forall j, \forall t \tag{4.54}$$

$$r_{j,t}^{d} \le R_{j,t}^{d,\max}, \qquad \forall j, \forall t \tag{4.55}$$

$$P_{j,t}+r_{j,t}^{u}-r_{j,t}^{d} \ge 0, \qquad \forall j, \forall t \tag{4.56}$$

$$P_{j,t}+r_{j,t}^{u}-r_{j,t}^{d} \le P_{j,t}^{\max}, \qquad \forall j, \forall t \tag{4.57}$$

Equation (4.53) maintains scheduled dispatchable generation unit power within predefined limits, while Constraints (4.54) and (4.55) define the scheduled upward and downward reserve of dispatchable generating units. It must be lesser than their maximum upward and downward reserve capacity respectively. Constraints (4.56) and (4.57) state that sum of scheduled power of dispatchable units with their respective reserves must be within their specified limits.

4.6 Proposed Algorithm

The following algorithm (as shown in Fig. 4.1) is adopted to solve the formulated Robust Optimization based MG generation scheduling problem for both grid connected and isolated mode:

Step 1: Collect historical data: Collect the historical data of wind speed for a specific location where wind units are located. The wind speed is converted in power using power curve of standard turbine models.

Step 2: ARIMA model parameters estimation: From collected data, parameters of ARIMA model are estimated. Order of AR and MA terms are determined by the observation of Auto Correlation Function (ACF) and Partial Auto Correlation Function (PACF) plot, respectively. The coefficients of AR and MA terms and the variance of error signal are determined by Least Square method [159].

Step 3: Interval Forecasting: To forecast upper and lower limits of wind power, ARIMA model expressed in (16) is simulated for each time instant.

Step 4: Robust optimization Parameter Initialization: The initial output of wind unit is set to be $W_t = W_t^{\max}$, degree of robustness is $\Gamma_k = N_t$ with incremental factor G^k, which takes increasing values in the interval [0, 1] in steps of 0.01, denoted as δ [158].

Step 5: Iteration Counter Initialization: The total number of iterations N_k is defined and the counter is initialized with $k = 1$.

Step 6: Wind Uncertainty Characterization: The upper and lower limits of wind power are obtained from Step 3. The wind power is set in the iteration as $\hat{W}_{t,k} = G^k \left(W_t^{\max} - W_t^{\min} \right)$. Value of wind power is limited in the interval $[W_t^{\max}, W_t^{\max} - \hat{W}_{t,k}]$.

Step 7: Problem Solution: Formulated MG scheduling problem for both modes are solved and optimal results are obtained in the form of optimal scheduling of dispatchable units, optimal scheduling of upward and downward reserve, optimal Main grid to MG power exchange, optimal demand shedding.

Step 8: Check Iteration Counter: If iteration $k \le N_k$, update the range of incremental factor G^k by step δ and repeat Steps 6 and 7. Otherwise, go to next step.

Step 9: Published results: Show obtained optimal cost of MG along with optimal value of scheduled dispatch-able unit generation and reserves.

Step 10: End.

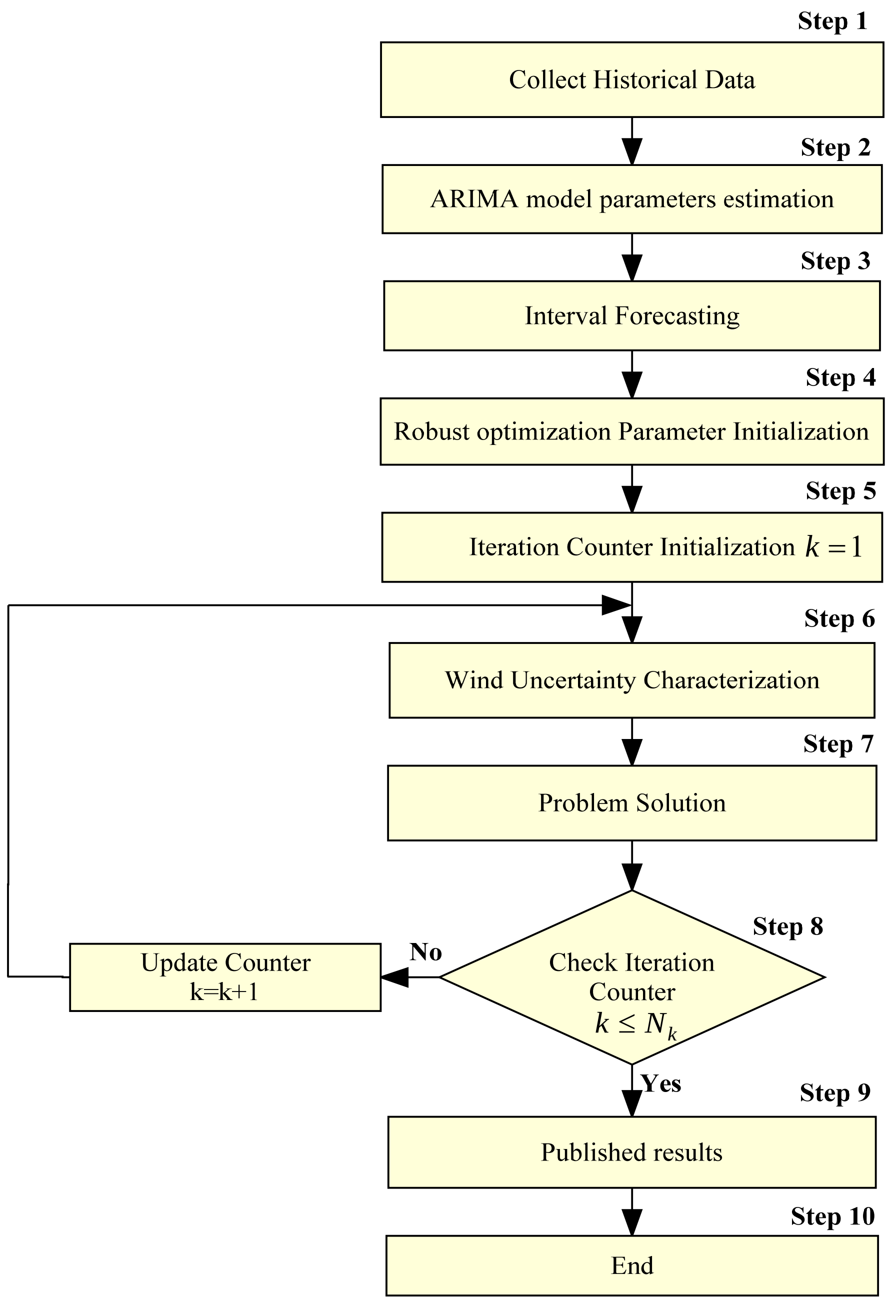

Fig. 4.1 Flow chart of proposed algorithm

4.7 Case Study

This section provides the study of test system, simulation results and discussions.

4.7.1 Data

In this study, installed capacity of PV unit and wind units are considered as 200 kW and 1.34 MW respectively. Wind units consists ENERCON turbine model whose parameters are detailed in manufacturer database [160]. The historical wind speed data of the duration of 27.04.2006 to 08.06.2007, used in this study from publically available database at Illinois Institute of Rural Affair, USA. [161]. Along with renewable units, 10 dispatchable units are considered, whose parameters are given in Table 4.1. Hourly grid price, demand profile and PV generation profile is shown in Table 4.2.

Table 4.1: Dispatchable Unit Parameters

Dispatchable unit	Installed capacity (kW)	Upward reserve	Downward reserve (kW)	Marginal cost ($/kWh)
1	600	240	240	0.0141
2	600	240	240	0.0222
3	400	160	160	0.02775
4	400	160	160	0.03375
5	300	120	120	0.0321
6	300	120	120	0.0384
7	200	80	80	0.04335
8	200	80	80	0.049125
9	100	40	40	0.04554
10	100	40	40	0.05154

The capacity of line linking the main grid and MG is considered as 5000 kW. Hourly grid price obtained for PJM electricity market is shown in [165]. Short-term generation scheduling on the basis of marginal generation cost is common in evolving electricity markets. The fixed cost has no role in short-term operation of electricity markets. This study focuses on short-term generation scheduling of MG in deregulated environment, considering the marginal cost of generators. Marginal cost of generators is calculated according to their cost functions.

4.7.2 Simulation Results

Using the above data, proposed approach is tested on a typical MG by considering two cases. In Case I, grid connected operation of MG is simulated while in Case II, grid isolated operation of MG is simulated. Both test cases are coded in GAMS platform and final LP problem is solved using CPLEX solver [163].

Table 4.2: Daily Market Prices, Load and PV Profiles

Time (h)	Price ($/kw)	Demand (pu)	PV (pu)
1	0.04836	0.784	0
2	0.04461	0.754	0
3	0.043695	0.739	0
4	0.044535	0.736	0
5	0.051765	0.756	0
6	0.069	0.814	0
7	0.08238	0.912	0.002
8	0.080115	0.977	0.008
9	0.08802	0.991	0.035
10	0.090045	0.997	0.1
11	0.09258	1	0.23
12	0.088725	0.997	0.233
13	0.0906	0.992	0.318
14	0.09054	0.989	0.433
15	0.08595	0.981	0.37
16	0.07908	0.971	0.403
17	0.07461	0.964	0.33
18	0.06552	0.956	0.238
19	0.062415	0.949	0.133
20	0.065775	0.945	0.043
21	0.07266	0.962	0.003
22	0.0609	0.950	0
23	0.05253	0.884	0
24	0.044925	0.822	0

For uncertainty modeling using ARIMA model first the order of suitable ARIMA model on the basis of collected historical data is determined. Order of AR and MA terms are obtained by the observation of ACF and PACF plot. These plots are shown in Fig. 4.2 and 4.3, respectively. Fig. 4.4 shows the forecasted wind power for 24 hours with upper and lower bounds.

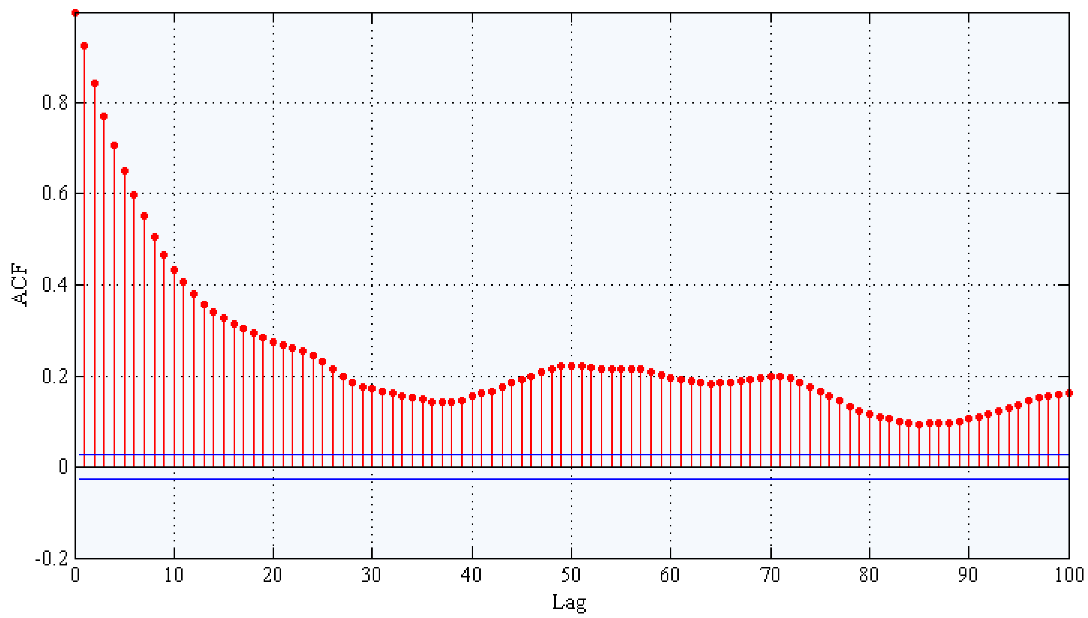

Fig. 4.2 ACF plot of sample wind power data

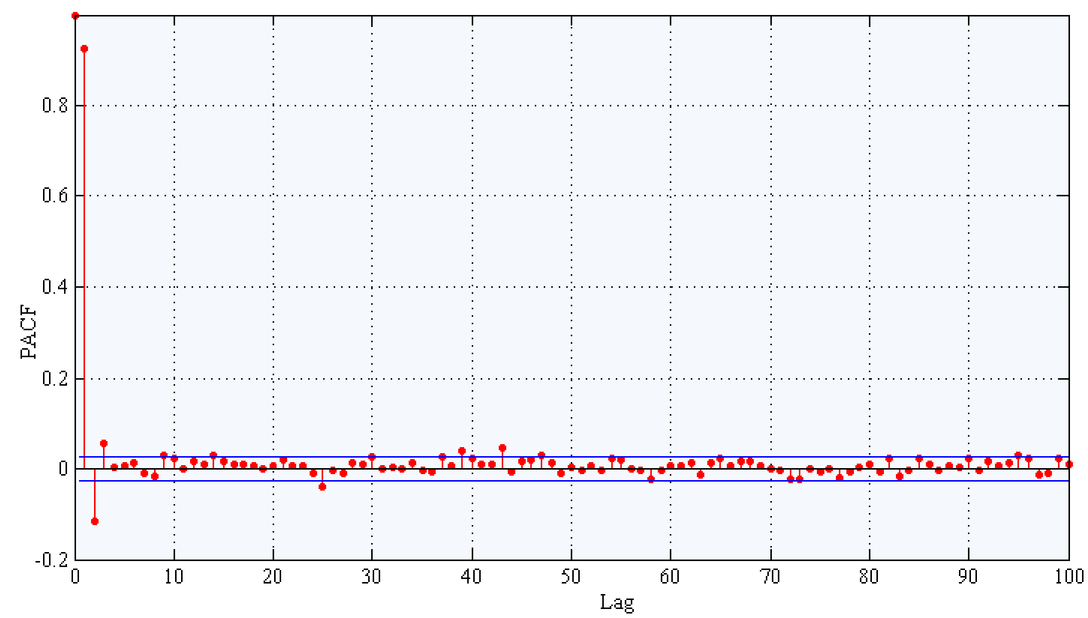

Fig. 4.3 PACF plot of sample wind power data

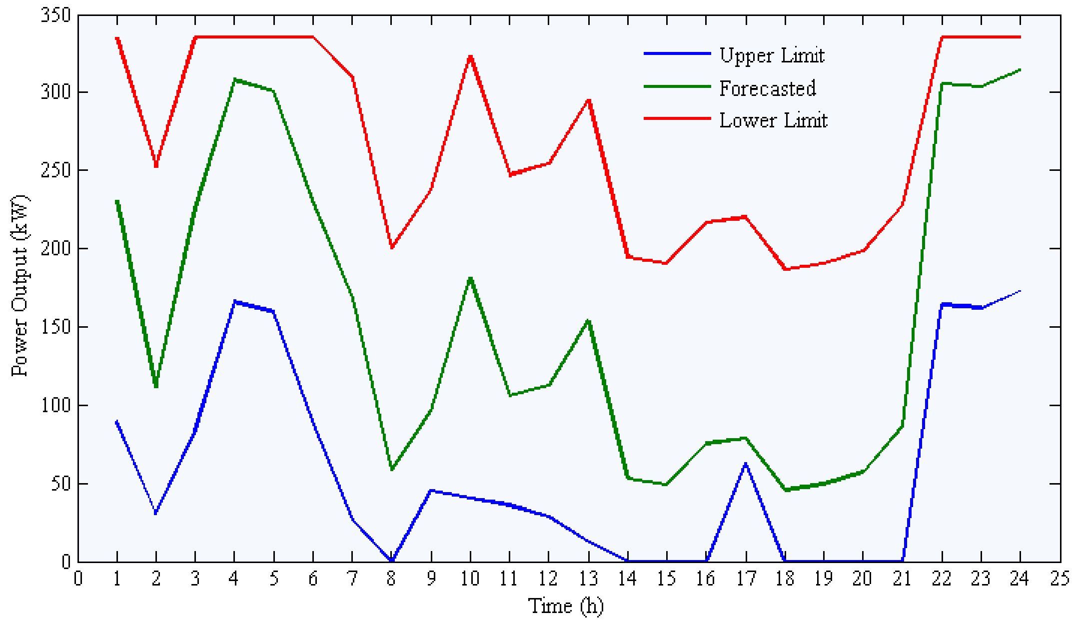

Fig. 4.4 Hourly wind power

From the Fig. 4.3 and 4.4, it is observed that ACF plot is sinusoidal and PACF for first two legs are out of bounds. Thus, ARIMA (3,0,0) is suitable for modeling wind power uncertainty. The estimated values of AR coefficients are 0.779, -0.03, and 0.039. The value of constant term and variance of white noise are 244.098 and 0.264 respectively. On a 95% confidence interval forecasted limits are used in proposed robust optimization based MG scheduling approach.

Case I : Microgrid Operation in Grid Connected Mode

In this case, MG operation in grid-connected mode is considered for simulation using proposed robust optimization method.

Fig. 4.5 shows the obtained scheduled power of dispatchable units in MG during grid connected mode of operation. From the figure, it can be observed that it will be beneficial to schedule maximum capacity from the unit with lower cost than the unit with higher cost. Further Fig. 4.6 and Fig. 4.7 show the obtained scheduled upward and downward reserves of dispatchable units respectively. From the figures, it can be observed that any dispatchable unit is scheduled for one type of reserve requirement at any particular instant of time *t*. It can be observed that at the time of exporting the power the most costly dispatchable units are scheduled to their downward reserve while in case of importing the power these units are scheduled to their upward reserve. In these figures at time axis, 1 indicates the first hour *i.e.* 00:00 AM to 01:00

AM of the day.

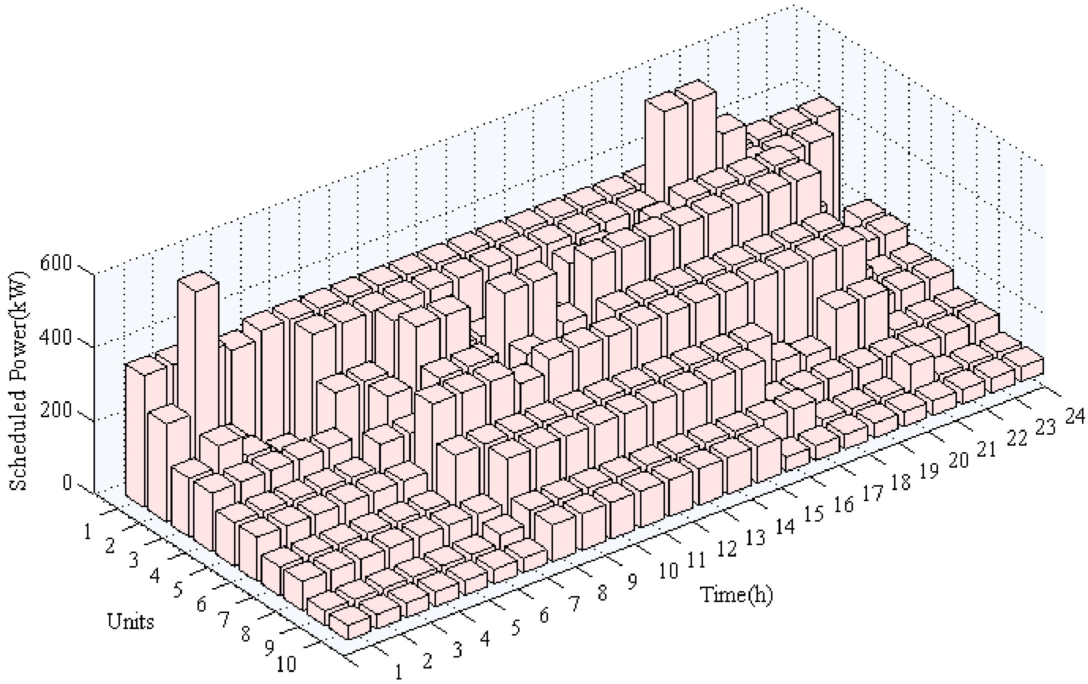

Fig. 4.5 Scheduled power of dispatchable units in Case I

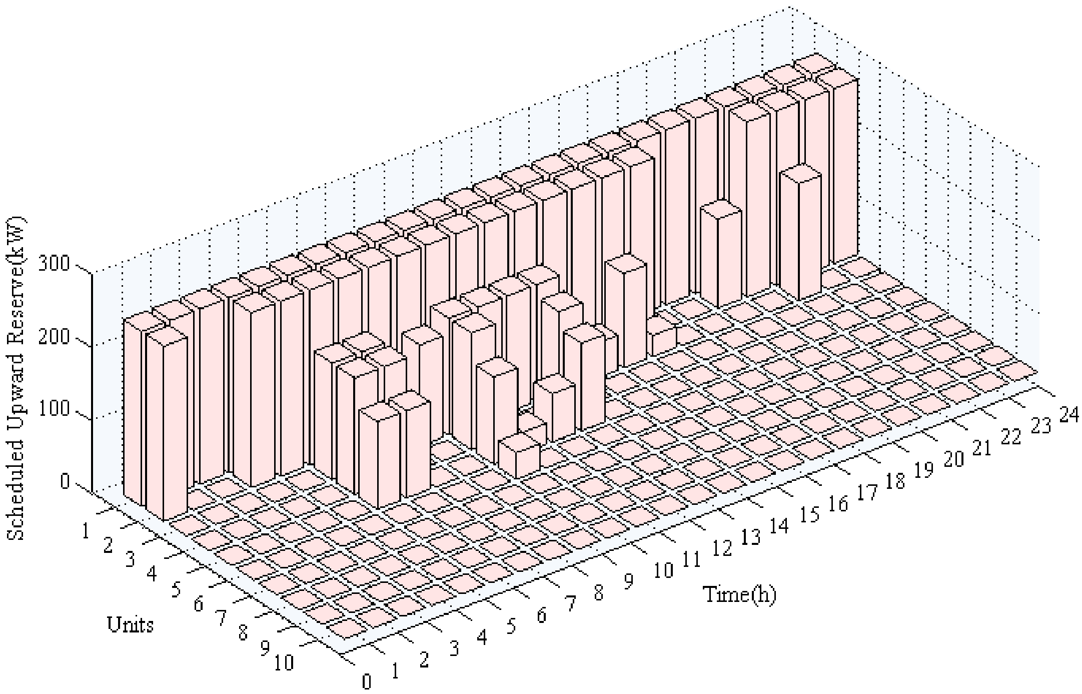

Fig. 4.6 Scheduled upward reserve in Case I

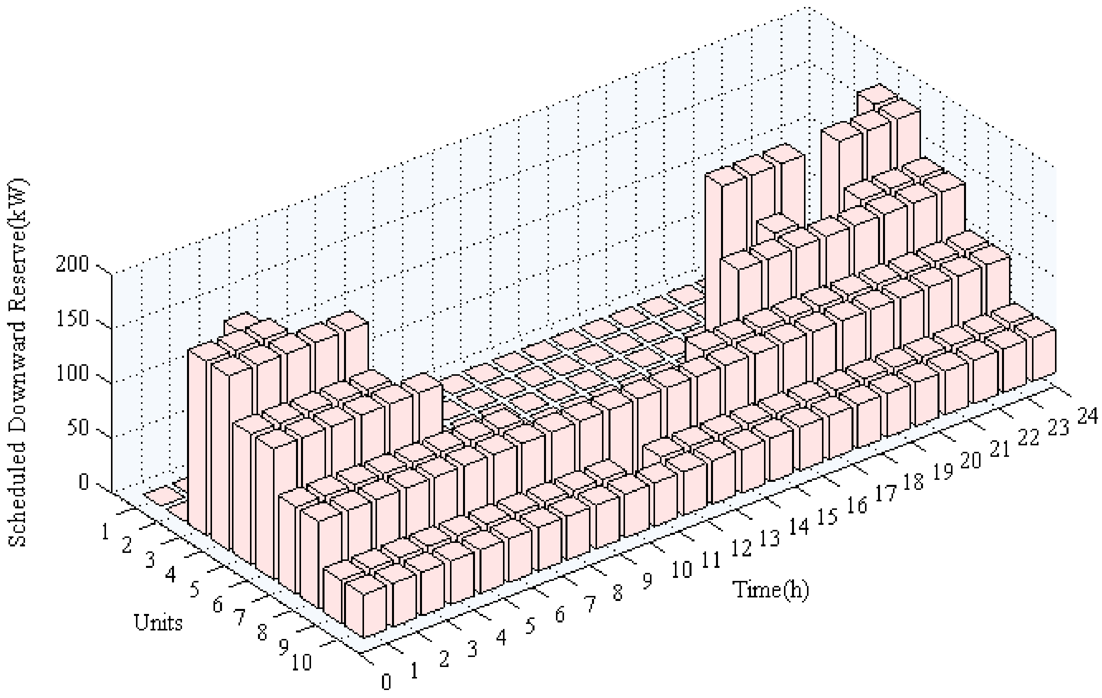

Fig. 4.7 Scheduled downward reserve in Case I

Fig. 4.8 shows power exchange between the main grid and the MG in Case I.

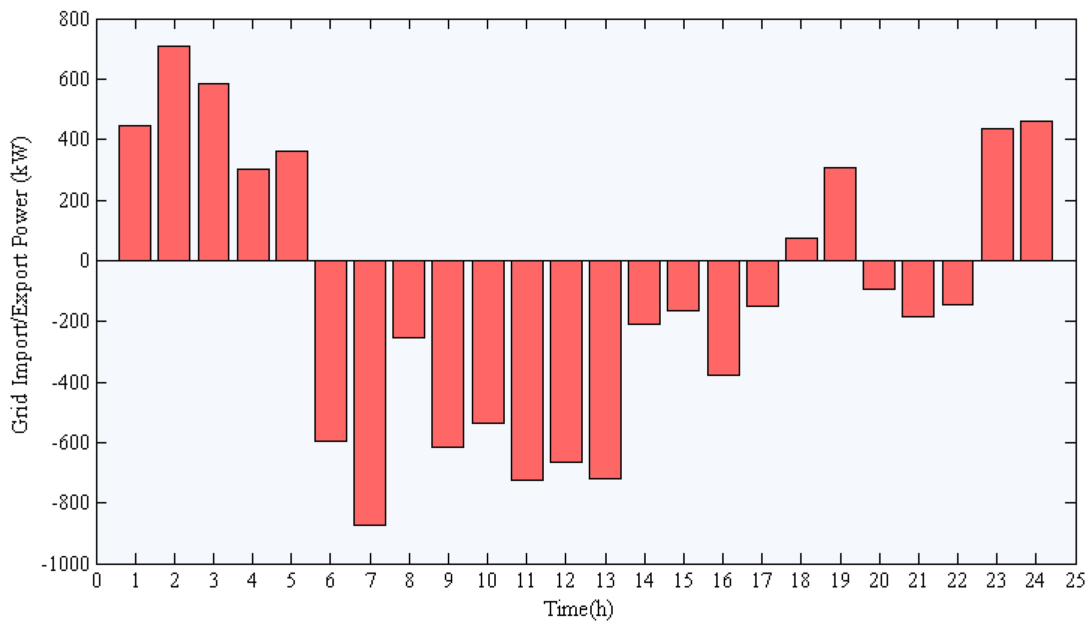

Fig. 4.8 Power imported/exported to/from grid in Case I

From the Fig. 4.8, it can be observed that from Hour 6 to 17 and 20 to 22, power is being exported to the grid and in remaining hours, power is being imported from the grid. It can be concluded that, when grid price is higher, MG can export their reserve capacity to grid and vice-versa to reduce its operating cost. By comparing Fig. 4.4 and 4.8, it can be seen that, in the above mention time interval the available wind power is lower, leading to import of power from the grid.

Case II : Microgrid Operation in Grid Isolated Mode

Similarly, in this case, MG operation in grid-isolated mode is considered using proposed robust optimization method. The cost of demand shedding is considered as \$3.5/kWh according to Federal Energy Regulation Commission (FERC), Electric Tariff [164]. Similar to the previous case, Fig. 4.9, Fig. 4.10, and Fig. 4.11 show the scheduled dispatchable unit power, upward and downward reserve capacity respectively using proposed robust optimization approach.

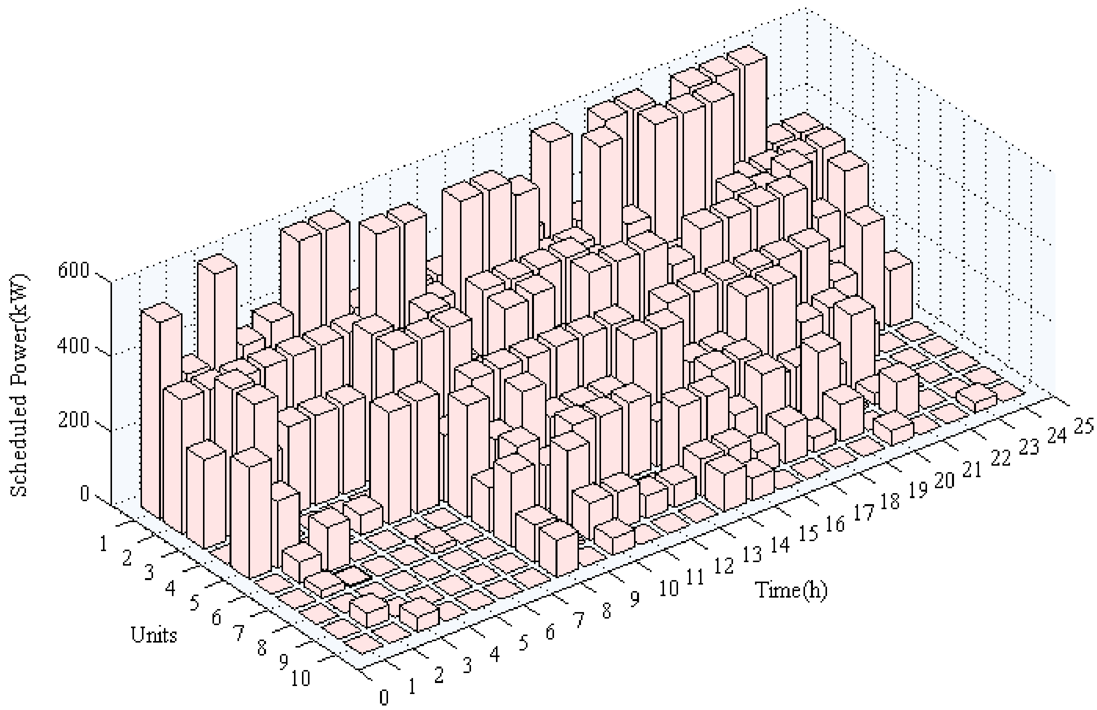

Fig. 4.9 Dispatchable unit scheduled power in Case II

The capacity of dispatchable units is fully utilized therefore leading to demand shedding. From Figs 4.10 and 4.11, it can be visualized that MG can utilize its upward reserve capacity during peak demand to reduce demand shedding events.

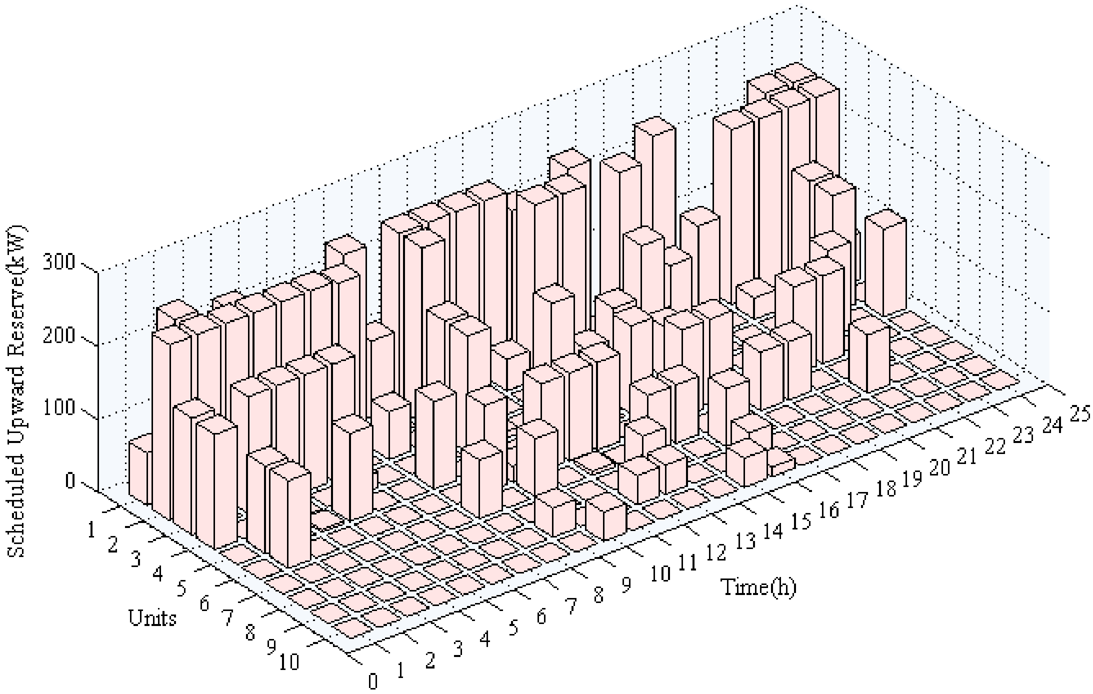

Fig. 4.10 Scheduled upward reserve in Case II

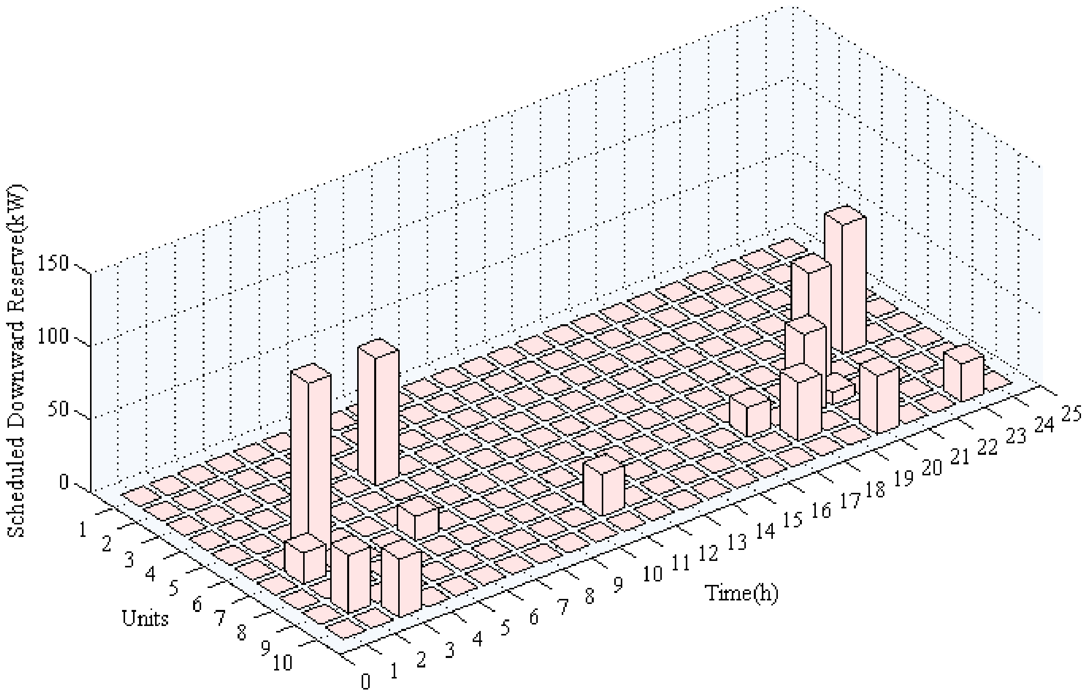

Fig. 4.11 Scheduled downward reserve in Case II

Demand shedding in Case II is shown in Fig. 4.12. From the figure, it is observed that demand shedding event occurs in Hours 8, 14 and 15. For these peak hours, the availability of wind and solar power is minimum as shown in Fig. 4.2 and Table 4.2.

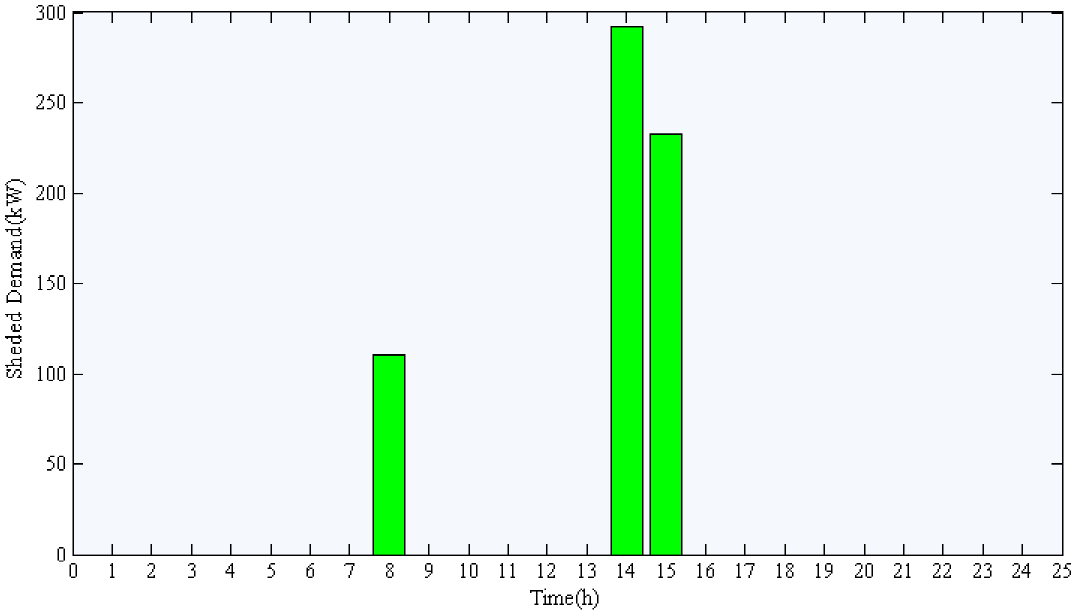

Fig. 4.12 Demand shedding in Case II

4.7.3 Discussion

A comparative analysis on MG operation is carried out. For this purpose, the same problem is simulated using deterministic and stochastic programming approach. In deterministic approach, wind power output is simply forecasted using ARIMA model and the forecasted value of wind power is considered to compute the scheduling of MG.

Table 4.3: Comaparitive Analysis of MG Daily Operation Cost

Approaches	Operation Cost ($)	
	Case I	Case II
Deterministic	857.9346	1500.230
Stochastic	830.6901 (-3.07 %)	1334.909 (-11.02 %)
Proposed	814.8662 (-5.02%)	1241.441 (-17.25 %)

In stochastic programming approach, the wind power uncertainty is modeled by generating a large number of scenarios (*i.e.* 10000) and then reducing them into a smaller number of scenarios (*i.e.*25) as in [56]. The MG operation cost obtained using proposed robust optimization approach is compared with both deterministic and stochastic approaches as shown in Table 4.3. From the Table 4.3, it is observed that in both cases (*i.e.* Grid connected operation of MG and Grid isolated operation of MG) the daily operating cost is significantly lower in the proposed approach than any other existing approach. It is also observed from Table 4.3 that, The reduction in daily cost using proposed approach, in Case II is higher than compared to Case I. This is because in Case II, small reduction in demand shedding event results in large reduction in total cost of operation. From Table 4.3 in the proposed approach the cost of MG operation is higher in grid-isolated mode than in grid-connected mode. This is due the fact that the reserves and dispatchable units are fully utilized to meet the demand.

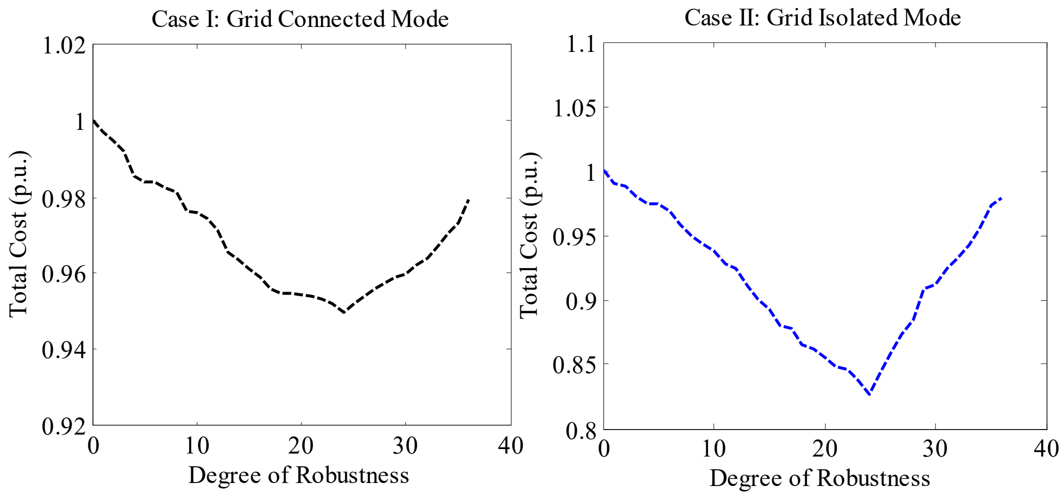

Fig. 4.13 Impact of degree of robustness on operational cost of MG

The impact of degree of robustness on operation cost, in both cases can be evaluated by varying the degree of robustness from zero to 36 during simulation. The obtained per unit cost of operation are shown in Fig. 4.13. Per unit cost of operation, at any degree of robustness is obtained by dividing its actual value by the reference value, which represents the cost of operation at zero degree of robustness. From Fig. 4.14, it can be seen that the optimal value of degree of robustness is 24, where per unit cost of operation is minimum. At this degree of robustness, optimal condition is obtained because in this problem wind is considered as an uncertain parameter and its uncertainty is considered for 24 hours. This degree of robustness takes into account all possible deviations of the uncertain parameter for whole day. Additionally, at zero degree of robustness the cost of operation obtained using proposed robust optimization based approach is equal to the cost of operation obtained using deterministic approach.

4.8 Summary

A robust optimization based approach has been proposed in this chapter for optimal generation scheduling of MG in both grid-connected and grid-isolated modes. Wind power uncertainty has been modeled through interval forecasting using ARIMA model. A comparative study on daily MG cost of operation using proposed robust optimization based approach with deterministic and stochastic approach has been performed. A significant reduction in cost of operation clearly shows strength of proposed robust optimization based approach in MG generation scheduling in the deregulated environment. The impact of degree of robustness on the cost of operation in both cases has also evaluated and compared with existing methods. The proposed approach will be more advantageous in incorporating different type of uncertainties such as Solar Power Uncertainty, Demand uncertainty and grid price uncertainty. This work may also be enhanced by incorporating multi-micro grids, different type of consumers and considering different technical constraints.

Chapter 5

Microgrid Operation Considering Solar Power Uncertainty

THIS chapter details out the stochastic and robust optimization based approaches for optimal generation scheduling of MG in both grid-connected and grid isolated modes. For stochastic and robust optimization base approach, solar power uncertainty has been modeled through scenarios and interval forecasting using ARIMA model, respectively. A comparative study on daily MG cost of operation using proposed robust optimization based approach with deterministic and stochastic approach has been performed.

CHAPTER 5

MICROGRID OPERATION CONSIDERING SOLAR POWER UNCERTAINTY

5.1 Introduction

Due to high reduction of market price of Photovoltaic (PV) panels the economics of PV based solar power generation is becoming attractive for power generating companies in present deregulated power system. Thus, the penetration of solar power is continuously increasing in the both transmission and distribution power system in the form of medium/large solar parks and small PV installations at the buildings. To integrate the solar power sources in the power system the MG is more robust and cost effective as compared to conventional centralized grid. However, several technical and regulatory challenges are created in MG operation due to random and stochastic nature of solar power. Optimal generation scheduling is a major problem for MG operator to effectively manage the balance in between the power supply and demand. The MG generation scheduling considering solar power uncertainty is the main objective of this chapter.

Solar power depends on weather conditions such as rain, dust storms and cloud covers. Due to inherent randomness of these weather conditions solar power is highly variable or random in nature. The size of solar power uncertainty can vary accoriding to size and location of solar PV array. Hence, modeling of solar power uncertainty is a challenging task for MG Operators. Modeling of solar power uncertainty affects the balancing needs and required reserve power, storage devices, with higher costs. Thus, the effective modeling of solar power uncertainty is required for cost effective energy management of MGs. Stochastic and robust optimizations are two effective approaches to model such problems considering different uncertainties. Robust optimization based approach has been proposed for optimal MG operation in deregulated environment by considering wind power uncertainty in Chapter 3.

This chapter presents stochastic and robust optimization based approach for optimal MG generation scheduling by considering solar power uncertainty. Solar power uncertainty is modelled through scenarios and interval forecasting for both stochastic and robust optimization based approaches using ARIMA model. Other uncertainties (like wind power uncertainty, demand uncertainty and grid price uncertainty) are modelled using deterministic point forecasting method. The Proposed approach is illustrated by a case study on MG having wind, PV, dispatchable generating units and loads. Obtained results show the strength of proposed approach in cost minimization over other existing approaches.

5.2 Problem Description

MG operator can solve the MG energy scheduling problem with an objective to minimize the total cost of operation considering various constraints. Parameters in both grid-connected and isolated mode are slightly different. In grid connected mode, the MG is connected to the utility grid, hence, MG can Import/Export its deficit/excess power from/to the utility grid. In the deregulated environment, MG can earn revenue by selling its excess power to the spot market. Additionally, MG can also earn revenue by selling its reserve capacity to the spot market if prices are higher than its marginal cost. On the other hand the cost of operation can be minimized by meeting its deficit power from the utility grid when grid power is cheaper than MG's reserve cost. In grid isolated mode, similar to grid connected mode, it is also required to minimize the expenses of the MG. However, more attention is given to meet the demand within technical limits of MG's parameters. The detailed basic formulation of MG energy management formulation has been described in Chapter 4, Section 4.2.

5.3 Uncertainty Modeling

Solar power is a main source of uncertainty in the operation of MG in deregulated power systems. Random nature of solar power uncertainty can be modelled by stochastic process. ARIMA model is the most popular approach for modelling any stochastic process and is widely used for forecasting of electricity price, demand and the price of commodities other than electricity. As solar power varies with atmospheric conditions, the time series of solar power is non-stationary. Since, ARIMA model is applicable for only stationary data series, solar power is converted in to stationary series by differentiation [159]. In this work, ARIMA model is considered for forecasting upper and lower limit of solar power. The typical ARIMA (p, d, q) model is expressed as

$$Y_t = \mu + \sum_{i=1}^{p} \gamma_i Y_{t-1} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-1} + \varepsilon_t \tag{5.1}$$

Where, Y_t is the forecasted limits of solar power at time t, p is the order of autoregressive coefficients, γ_i and q are the orders of moving average coefficients θ_i. The term ε_t is a normally distributed random number with mean zero and constant variance, also known as white noise or error signal. The term μ is a constant in the model. For stochastic optimization based framework, ARIMA model is used for solar power scenario generation while for robust optimization framework, it is used for solar power interval forecasting. The main objective of this chapter is to develop a stochastic and robust optimization approach for optimal generation scheduling of MG. For the sake of simplicity, modelling of seasonal impacts in the solar power uncertainty is not considered in the present work, as this thesis focuses on short term generation scheduling of MG.

5.4 Stochastic and Robust Optimization Approach

Stochastic and robust optimization approaches have been extensively used in engineering and economics field for solving different decision making problems with involvement of different uncertainties. In stochastic optimization based approach, uncertainties are modeled through a number of scenarios with known probability distributions and the expected value of the objective is optimized. In robust optimization approach uncertainties are modeled as uncertain parameters belonging to a known uncertainty set and problem is optimized for the worst case over that set.

Both Stochastic and Robust optimization are the alternative approaches to deal with uncertain data in a single period and in a multi-period decision making problems. However, the main difficulty associated with the stochastic optimization is to provide the information of probability distribution functions of the underlying stochastic parameters. This requirement creates a heavy burden on MG operator because in many real world situations, such information is unavailable or very difficult to obtain. On the other hand Robust Optimization addresses the uncertain nature of the function without making specific assumptions on probability distributions. Robust Optimization adopts a min-max approach that addresses uncertainty by guaranteeing the feasibility and optimality of the solution against all instances of the parameters within the uncertainty set. Both Stochastic and Robust Optimization approaches are widely used for modeling of decision making problems in power systems such as power trading, unit commitment and economic load dispatch etc. The details of

Stochastic and Robust optimization approaches have been provided in Chapter 3.

5.5 Proposed Problem Formulation in Stochastic Optimization Framework

This Section describes the proposed formulation of MG generation scheduling problem considering solar power uncertainty in stochastic optimization framework with an objective of total generation cost minimization for both grid connected and isolated mode. Solar power uncertainty is modeled through a number of scenarios. Scenarios are possible outcomes with occurrence probabilities. Solar power scenarios are generated using ARIMA model. A large number of scenarios are required for accurate modeling of any uncertainty. But, solving the decision making problems using such large number of scenarios is a challenging task computationally and sometime problems are also intractable. Therefore, generated scenarios are reduced in such a manner that their stochastic properties cannot be lost. Backward reduction algorithm is used for scenarios reduction in this work.

5.5.1 Grid Connected Mode

In this mode, MG is connected to the utility grid, therefore, MG can Import/Export its deficit/excess power from/to the utility grid. In the deregulated environment, MG can earn revenue by selling its excess power and reserve capacity to the spot market. On the other hand the cost of operation can be minimized by meeting its deficit power from the utility grid when grid power is cheaper than MG's reserve cost. In grid-connected mode, the problem is formulated in stochastic optimization framework as:

$$\min \sum_{t=1}^{N_t}\left[\sum_{\omega=1}^{N_\omega}\pi_\omega\left\{\sum_{j=1}^{N_j}C_j\left(P_{j,\omega,t}+r_{j,\omega,t}^{u}-r_{j,t}^{d}\right)+P_{grid,\omega,t}*\lambda_{grid,t}\right\}\right] \tag{5.2}$$

$$\sum_{j=1}^{N_j}P_{j,\omega,t}+\sum_{w=1}^{N_w}P_{w,t}^{f}+\sum_{v=1}^{N_v}PV_{v,\omega,t}=Pd_t^{f},\quad \forall\omega,\forall t \tag{5.3}$$

$$\sum_{j=1}^{N_j}\left(r_{j,\omega,t}^{u}-r_{j,\omega,t}^{d}\right)+\sum_{w=1}^{N_w}\left(\Delta P_{w,t}\right)+\sum_{v=1}^{N_v}\Delta PV_{v,\omega,t}+P_{grid,t}-\Delta Pd_t=0,\quad \forall\omega,\forall t \tag{5.4}$$

$$\Delta P_{w,t}=P_{w,t}^{a}-P_{w,t}^{f},\qquad \forall w,\forall t \tag{5.5}$$

$$\Delta PV_{v,\omega,t} = PV_{v,t}^{a} - PV_{v,\omega,t}, \qquad \forall v, \forall \omega, \forall t \tag{5.6}$$

$$\Delta P_{d,t} = P_{d,t}^{a} - P_{d,t}^{f}, \qquad \forall d, \forall t \tag{5.7}$$

$$P_{j}^{\min} \le P_{j,\omega,t} \le P_{j}^{\max}, \qquad \forall j, \forall \omega, \forall t \tag{5.8}$$

$$r_{j,\omega,t}^{u} \le R_{j,t}^{u,\max}, \qquad \forall j, \forall \omega, \forall t \tag{5.9}$$

$$r_{j,\omega,t}^{d} \le R_{j,t}^{d,\max}, \qquad \forall j, \forall \omega, \forall t \tag{5.10}$$

$$P_{j,\omega,t} + r_{j,\omega,t}^{u} - r_{j,\omega,t}^{d} \ge 0, \qquad \forall j, \forall \omega, \forall t \tag{5.11}$$

$$P_{j,\omega,t} + r_{j,\omega,t}^{u} - r_{j,\omega,t}^{d} \le P_{j,t}^{\max}, \qquad \forall j, \forall \omega, \forall t \tag{5.12}$$

$$P_{grid,\omega,t} \le P_{grid,t}^{\max}, \qquad \forall \omega, \forall t \tag{5.13}$$

In the above formulation, the objective (5.2) of scheduling problem is to minimize the total cost of operation, which includes the operating cost of dispatchable generating unit's power, reserves and cost of power imported/exported from/to grid. The objective function is subjected to different constraints expressed in (5.3) to (5.13). Constraint (5.3) defines that the total sum of scheduled power of dispatchable generating units, wind power units and PV generation must be equal to day-ahead forecasted demand for each scenario of solar power at any time t. Further, wind power, grid market price and demand can be forecasted using any existing approach.

Due to error in existing forecasting approaches, the actual values of wind power and demand may be different from their forecasted values. The system imbalance created due to the error in forecasting in real-time can be compensated with scheduling of the reserve capacity of dispatchable units or by the power from the main grid depending on the cost of compensation. In real-time, the deviation of wind power generation, PV solar power generation and MG demand from their forecasted values can be calculated by their corresponding imbalance constraints expressed in (5.5.)-(5.7). In this work, forecasting error of wind power generation, PV solar power Generation & demand is assumed as a random variable with zero mean and constant standard deviation. The Real value of wind power, PV solar power power and demand is obtained by multiplying the error coefficient to their forecasted values. Forecasted PV solar power generation is equal to reduced solar power scenarios.

Constraint (5.8) maintains scheduled power of the dispatchable generation units within predefined limits, while Constraints (5.9) and (5.10) define the scheduled upward and downward reserve of dispatchable generating units. Constraints (5.11) and (5.12) state that sum of scheduled power of dispatchable units with their respective reserves must be within their specified limits.

Due to transmission network constraints, MG cannot meet the whole demand through grid power when grid prices are lower than MG operation cost. On the other hand, the complete reserve capacity cannot be sold in the spot market during the high market price. Constraint (5.13) ensures that the power exchange between the main grid & MG is less than predefined capacity of grid connecting line. It should be noted that the network configuration of the MG is neglected in the proposed work due to following reasons: (i) Size of MG is limited to few MVA, due to this limited capacity and the proximity of load and generation network constraint are not typical constraint in MG operation, and (ii) Network model greatly complicates MG generation scheduling problem without taking any benefit.

5.5.2 Grid Isolated Mode

Similar to grid connected mode in this mode also objective is to minimize the expenses of the MG operation. However, more attention is given to meet the demand within technical limits of MG parameters. The objective function in the isolated mode can be given as follows:

$$\min \sum_{t=1}^{N_t} \left[\sum_{\omega=1}^{N_\omega} \pi_\omega \left\{ \sum_{j=1}^{N_j} C_j \left(P_{j,\omega,t} + r^u_{j,\omega,t} - r^d_{j,\omega,t} \right) + P^{shed}_{d,\omega,t} * \lambda^{shed}_d \right\} \right] \tag{5.14}$$

$$\sum_{j=1}^{N_j} \left(r^u_{j,\omega,t} - r^d_{j,\omega,t} \right) + \sum_{w=1}^{N_w} \left(\Delta P_{w,t} \right) + \sum_{v=1}^{N_v} \Delta PV_{v,\omega,t} + P^{Shed}_{d,\omega,t} - \Delta Pd_t = 0, \quad \forall \omega, \forall t \tag{5.15}$$

$$P^{shed}_{d,\omega,t} \leq P_{d,t} \qquad \forall \omega, \forall t \tag{5.16}$$

$$\sum_{j=1}^{j} P_{j,\omega,t} + \sum_{w=1}^{N_w} P^f_{w,t} + \sum_{v=1}^{N_v} PV_{v,\omega,t} = Pd^f_t, \quad \forall \omega, \forall t \tag{5.17}$$

$$\Delta P_{w,t} = P^a_{w,t} - P^f_{w,t}, \qquad \forall w, \forall t \tag{5.18}$$

$$\Delta PV_{v,\omega,t} = PV^a_{v,t} - PV_{v,\omega,t}, \qquad \forall v, \forall \omega, \forall t \tag{5.19}$$

$$\Delta P_{d,t} = P^a_{d,t} - P^f_{d,t}, \qquad \forall d, \forall t \tag{5.20}$$

$$P_j^{\min} \le P_{j,\omega,t} \le P_j^{\max}, \qquad \forall j, \forall \omega, \forall t \tag{5.21}$$

$$r_{j,\omega,t}^{u} \le R_{j,t}^{u,\max}, \qquad \forall j, \forall \omega, \forall t \tag{5.22}$$

$$r_{j,\omega,t}^{d} \le R_{j,t}^{d,\max}, \qquad \forall j, \forall \omega, \forall t \tag{5.23}$$

$$P_{j,\omega,t} + r_{j,\omega,t}^{u} - r_{j,\omega,t}^{d} \ge 0, \qquad \forall j, \forall \omega, \forall t \tag{5.24}$$

$$P_{j,\omega,t} + r_{j,\omega,t}^{u} - r_{j,\omega,t}^{d} \le P_{j,t}^{\max}, \qquad \forall j, \forall \omega, \forall t \tag{5.25}$$

In the above formulation, the objective (5.14) is to minimize net expected cost of MG including operating cost of scheduled generation and reserve capacity and cost of demand shedding for each scenario of solar power at time *t*. Constraint (5.15) ensures that the power generation is always equal to system demand for each scenario at real time. The system imbalance created due to volatile wind power generation, PV generation and demand at real-time is balanced by scheduling the reserve capacities of dispatchable generating units and shedding of demand. The demand shedding should always be less than equal to the scheduled demand in day-ahead scheduling, which is presented by (5.16). Constraint (5.17) states that the total sum of scheduled power of dispatchable generating units, wind power units and PV generation units must be equal to day-ahead forecasted demand for each solar power scenario at any time t. Imbalance constraints (5.18)-(5.20) express real-time deviation of wind power, PV generation and system demand from their forecasted values. Conventional generation unit power within predefined limits is maintained by (5.21). Constraints (5.22) and (5.23) define the scheduled upward and downward reserve of dispatchable generating units. It must be lesser than their maximum upward and downward reserve capacity respectively. Constraints (5.24) and (5.25) state that total sum of scheduled power of dispatchable units with their respective reserves must be within their specified limits.

5.6 Proposed Problem Formulation in Robust Optimization Framework

This section provides the proposed formulation of MG scheduling problem in both Grid connected and Grid isolated mode in robust optimization framework. Solar power is considered as an uncertain parameter and it is present in the constraint part of the problem, therefore, the MG generation scheduling problem is formulated as constraint robustness.

5.6.1 Grid Connected Mode

In this mode, problem described in section 4.2 is reformulated by using Robust Optimization as follows:

(i) Objective Function

$$\min \sum_{t=1}^{N_t}\left[\sum_{j=1}^{N_j} C_j\left(P_{j,t}+r_{j,t}^{u}-r_{j,t}^{d}\right)+P_{grid,t} * \lambda_{grid,t}\right] \tag{5.26}$$

The Objective function is minimization of total cost of operation is as represented as the sum of operating cost of dispatchable generating unit power, reserves and cost of power exchange between main grid & the MG.

(ii) Power Balance Equality Constraint

$$\sum_{j=1}^{j} P_{j,t}+\sum_{v=1}^{N_v}\left(\sum_{k=1}^{N_k} PV_{t,k}+z_k\Gamma_k+\sum_{k=1}^{N_k} q_k\right)+\sum_{w=1}^{N_w} W_{w,t}^{f}=Pd_t^{f}, \quad \forall t \tag{5.27}$$

Power balance constraint is shown in equation (5.27). This constraint states that the total sum of scheduled power of dispatchable generating units, wind power units and PV generation units must be equal to day-ahead forecasted demand at any time t. But irrespective of the previous formulation, here solar power is considered as an uncertain parameter and modeled in RO framework, where variables like z_k, q_k and Γ_k are introduced to solve the problem, Where, Γ_k is the degree of robustness which controls the robustness of the problem and z_k, q_k are the dual variables used to linearize the non-linearity in the problem. The wind power and demand can be forecasted using any existing approach.

$$\sum_{j=1}^{N_j}\left(r_{j,t}^{u}-r_{j,t}^{d}\right)+\sum_{w=1}^{N_w}\left(\Delta P_{w,t}\right)+\sum_{v=1}^{N_v}\Delta PV_{v,t}+P_{grid,t}-\Delta Pd_t=0, \quad \forall t \tag{5.28}$$

Due to error in existing forecasting approaches, the actual values of wind power, PV generation and demand may be different from their forecasted values. The system imbalance created due to the error in forecasting in real-time can be compensated by the reserve capacity of dispatchable units or by the power from the main grid depending on the cost of compensation.

(iii) Robust Constraints

$$z_k + q_k \geq \hat{PV}_{t,k}\, y_k, \qquad \forall k \neq 0,\ k \in N_k \tag{5.29}$$

$$q_k \geq 0, \qquad \forall k,\ k \in N_k \tag{5.30}$$

$$y_k \geq 0, \qquad \forall k \tag{5.31}$$

$$z_k \geq 0, \qquad \forall k \tag{5.32}$$

Robust constraints are represented by equations (5.29)-(5.30), Where, equation (5.29) states that dual variable z_k and q_k are taken into account as the known bounds of solar power in such a way that the sum of both variables is always greater than the solar power characterization parameter $P\hat{V}_{t,k} y_k$. y_k is an auxiliary variable, used to obtain the corresponding linear expressions. However, $P\hat{V}_{t,k}$ is obtained as the proportionate of the difference of lower and upper bounds of solar power. Further constraint (5.30), (5.31) and (5.32) show that the dual variables used in robust approach must be positive.

(iv) Imbalance Constraints

$$\Delta P_{w,t} = P_{w,t}^{a} - P_{w,t}^{f}, \qquad \forall w, \forall t \tag{5.33}$$

$$\Delta PV_{v,t} = PV_{v,t}^{a} - PV_{v,t}^{f}, \qquad \forall v, \forall t \tag{5.34}$$

$$\Delta P_{d,t} = P_{d,t}^{a} - P_{d,t}^{f}, \qquad \forall d, \forall t \tag{5.35}$$

In real-time, the deviation of wind power, PV generation and system demand from their forecasted values can be calculated by the corresponding imbalance constraints expressed in (5.33)-(5.35). In this work, forecasting error of wind power generation, PV Generation & demand is assumed as a random variable with zero mean and constant standard deviation. The Real value of wind power, PV power and demand is obtained by multiplying the error coefficient to their forecasted values.

(v) Dispatchable Units Power Constraint

$$P_j^{\min} \leq P_{j,t} \leq P_j^{\max}, \qquad \forall j, \forall t \tag{5.36}$$

$$r_{j,t}^{u} \leq R_{j,t}^{u,\max}, \qquad \forall j, \forall t \tag{5.37}$$

$$r_{j,t}^{d} \leq R_{j,t}^{d,\max}, \qquad \forall j, \forall t \tag{5.38}$$

$$P_{j,t} + r_{j,t}^{u} - r_{j,t}^{d} \geq 0, \qquad \forall j, \forall t \tag{5.39}$$

$$P_{j,t} + r_{j,t}^{u} - r_{j,t}^{d} \leq P_{j,t}^{\max}, \qquad \forall j, \forall t \tag{5.40}$$

Equation (5.36) maintains scheduled dispatchable generation unit power within predefined limits, while Constraints (5.37) and (5.38) define the scheduled upward and downward reserve of dispatchable generating units. It must be lower than their maximum upward and downward reserve capacity respectively. Constraints (5.39) and (5.40) state that sum of scheduled power of dispatchable units with their respective reserves must be within their specified limits.

(vi) Grid Power Cconstraint

$$P_{grid,t} \leq P_{grid,t}^{\max}, \qquad \forall t \tag{5.41}$$

Due to transmission network constraints, MG cannot meet the whole demand through grid power when grid prices are lower than operation cost. On the other hand, the complete reserve capacity cannot be sold in the spot market during high market prices. Constraint (5.41) ensures that the power exchange between the main grid & MG is less than predefined capacity of the grid connecting line.

5.6.2 Grid Isolated Mode

Since solar power uncertainty is involved in the constraints, the MG generation scheduling problem is formulated using Robust Optimization approach similar to Grid connected mode. Here, the objective function and supply-demand equilibrium constraint are slightly differed. Similar to previous one, in this mode also, it is required to minimize the expenses of the MG. However, more attention is given to meet the demand with stable operation. The problem in the isolated mode is formulated as:

(i) Objective Function

$$\min \sum_{t=1}^{N_t} \left[\sum_{j=1}^{N_j} C_j \left(P_{j,t} + r_{j,t}^{u} - r_{j,t}^{d} \right) + P_{d,t}^{shed} * \lambda_d^{shed} \right] \tag{5.42}$$

Similar to previously defined grid connected mode under RO Approach, the objective of MG generation scheduling problem in this mode is also the minimization of total operation cost. It states that the sum of operating cost of dispatchable generating units and cost of demand shedding should be minimized.

(ii) Power Balance Constraint

$$\sum_{j=1}^{j} P_{j,t} + \sum_{w=1}^{N_w}\left(\sum_{k=1}^{N_k} W_{t,k} + z_k \Gamma_k + \sum_{k=1}^{N_k} q_k\right) + \sum_{v=1}^{N_v} PV_{v,t}^{f} = Pd_t^{f}, \quad \forall t \tag{5.43}$$

Power balance constraint is represented in equation (5.43). This constraint states that the sum of scheduled power of dispatchable generating units, wind power units and PV generation units must be equal to day-ahead forecasted demand at any time *t*. But irrespective of the previous formulation, here solar power is considered as an uncertain parameter and modeled in RO framework, where variables like z_k, q_k and Γ_k are introduced to solve the problem, Where, Γ_k is the degree of robustness which controls the robustness of the problem and z_k, q_k are the dual variables used to linearize the non-linearity in the problem. The wind power generation and demand can be forecasted using any existing approach.

$$\sum_{j=1}^{N_j}\left(r_{j,t}^{u} - r_{j,t}^{d}\right) + \sum_{w=1}^{N_w}\left(\Delta P_{w,t}\right) + \sum_{v=1}^{N_v} \Delta PV_{v,t} + P_{d,t}^{Shed} - \Delta Pd_t = 0, \quad \forall t \tag{5.44}$$

To maintain system security and reliability, power generation is always equal to system demand at each instant. The system imbalance created due to volatile wind power, PV generation and demand at real-time is balanced by scheduling the reserve capacities of dispatchable generating units and shedding of demand.

(iii) Robust Constraints

$$z_k + q_k \geq \hat{PV}_{t,k}\, y_k, \qquad \forall k \neq 0, k \in N_k \tag{5.45}$$

$$q_k \geq 0, \qquad \forall k, k \in N_k \tag{5.46}$$

$$y_k \geq 0, \qquad \forall k \tag{5.47}$$

$$z_k \geq 0, \qquad \forall k \tag{5.48}$$

Robust constraints are represented by equations (5.45)-(5.48), Where, equation (5.45) states that dual variable z_k and q_k are taken into account as the known bounds of solar power in such a way that the sum of both variables is always greater than the solar characterization parameter $P\hat{V}_{t,k}y_k$. y_k is an auxiliary variable, used to obtain the corresponding linear expressions. However, $P\hat{V}_{t,k}$ is obtained as the proportionate of the difference of lower and upper bounds of solar power. Constraint (5.46), (5.47) and (5.48) show that the dual variables used in robust approach must be positive.

(iv) Demand Shedding Cconstraint

$$P_{d,t}^{shed} \le P_{d,t} \qquad \forall t \tag{5.49}$$

The shedding power is always less than equal to the scheduled demand in day-ahead scheduling.

(v) Imbalance Constraints

$$\Delta P_{w,t} = P_{w,t}^{a} - P_{w,t}^{f}, \qquad \forall w, \forall t \tag{5.50}$$

$$\Delta PV_{v,t} = PV_{v,t}^{a} - PV_{v,t}^{f}, \qquad \forall v, \forall t \tag{5.51}$$

$$\Delta P_{d,t} = P_{d,t}^{a} - P_{d,t}^{f}, \qquad \forall d, \forall t \tag{5.52}$$

In real-time, the deviation of wind power, PV generation and system demand from their forecasted values can be calculated by the corresponding imbalance constraints expressed in (5.50)-(5.52). In this work, forecasting error of wind power generation, PV Generation & demand is assumed as a random variable with zero mean and constant standard deviation. The Real value of wind power, PV power and demand is obtained by multiplying the error coefficient to their forecasted values.

(vi) Dispatchable Units Power Constraint

$$P_j^{\min} \le P_{j,t} \le P_j^{\max}, \qquad \forall j, \forall t \tag{5.53}$$

$$r_{j,t}^{u} \le R_{j,t}^{u,\max}, \qquad \forall j, \forall t \tag{5.54}$$

$$r_{j,t}^{d} \le R_{j,t}^{d,\max}, \qquad \forall j, \forall t \tag{5.55}$$

$$P_{j,t} + r_{j,t}^{u} - r_{j,t}^{d} \ge 0, \qquad \forall j, \forall t \tag{5.56}$$

$$P_{j,t} + r_{j,t}^{u} - r_{j,t}^{d} \le P_{j,t}^{\max}, \qquad \forall j, \forall t \tag{5.57}$$

Equation (5.53) maintains the scheduled dispatchable generation unit power within predefined limits of grid isolated mode operation, while Constraints (5.54) and (5.55) define the scheduled upward and downward reserve of dispatchable generating units, which should be lesser than their maximum upward and downward reserve capacity respectively. Constraints (5.56) and (5.57) state that sum of scheduled power of dispatchable units with their respective reserves must be within their specified limits.

5.7 Proposed Methodology

The following methodology (as shown in Fig. 5.1) is adopted to solve the formulated Stochastic and Robust Optimization based MG generation scheduling problem for both grid connected and isolated mode:

Step 1: Collect historical data: Collect the historical data of solar irradiation for a specific location where solar/PV units are located. The solar irradiation is converted in power, using power conversion formula.

Step 2: ARIMA model parameters estimation: From collected data, parameters of ARIMA model are estimated. Order of AR and MA terms are determined by the observation of Auto Correlation Function (ACF) and Partial Auto Correlation Function (PACF) plot, respectively. The coefficients of AR and MA terms and the variance of error signal are determined by Least Square method [159].

Step 3: Initialize Time Counter: Here 24 hour time period is considered to solve MG generation scheduling under solar power uncertainty. Start with time $t = 1$.

Step 4: Choose Stochastic or Robust Approach: Select an approach to solve MG generation scheduling problem. If Stochastic is selected, go to Step 5 and if Robust is selected, go to Step 8.

Step 5: Solar Power Scenario Generation: To generate solar power scenarios evaluate ARMA model Eq. (5.1).

Step 6: Solar Power Scenario Reduction: Collect generated solar power scenarios from previous step. The probability distance-based backward algorithm is used for solar power scenario reduction.

Step 7: Solve MG generation Scheduling Problem: Formulated MG scheduling problem in stochastic optimization framework in (5.2)-(5.25) is solved. Optimal results are obtained in the form of optimal scheduling of dispatchable units, optimal scheduling of upward and downward reserve, optimal Main grid to MG power exchange, optimal demand shedding.

Step 8: Interval Forecasting: To forecast upper and lower limits of wind power, ARIMA model expressed in (5.1) is simulated for each time instant.

Step 9: Robust optimization Parameter Initialization: The initial output of solar/PV unit is set to be $PV_t = PV_t^{\max}$, degree of robustness is $\Gamma_k = N_t$ with incremental factor G^k, which takes increasing values in the interval [0, 1] in steps of 0.01, denoted as δ [158].

Step 10: Iteration Counter Initialization: The total number of iterations N_k is defined and the counter is initialized with $k = 1$.

Step 11: Solar Uncertainty Characterization: The upper and lower limits of solar power are obtained from Step 3. The solar power is set in the iteration as $P\hat{V}_{t,k} = G^k \left(PV_t^{\max} - PV_t^{\min} \right)$. Value of solar power is limited in the interval $[PV_t^{\max}, PV_t^{\max} - P\hat{V}_{t,k}]$.

Step 12: Problem Solution: Formulated robust MG scheduling problem for both modes in (5-26)-(5.53) are solved and optimal results are obtained in the form of optimal scheduling of dispatchable units, optimal scheduling of upward and downward reserve, optimal power exchange between main grid to MG and optimal demand shedding etc.

Step 13: Check Iteration Counter: If iteration $k \le N_k$, update the range of incremental factor G^k by step δ and repeat Steps 11 and 12. Otherwise, go to next step.

Step 14: Check Time Counter: If the desired time period counter, i.e., 24, has achieved, go to the next step; otherwise, update *t=t+1* and go to Step 4.

Step 15: Publish results: Show obtained optimal cost of MG along with optimal value of scheduled dispatchable unit generation and reserves.

Step 16: End.

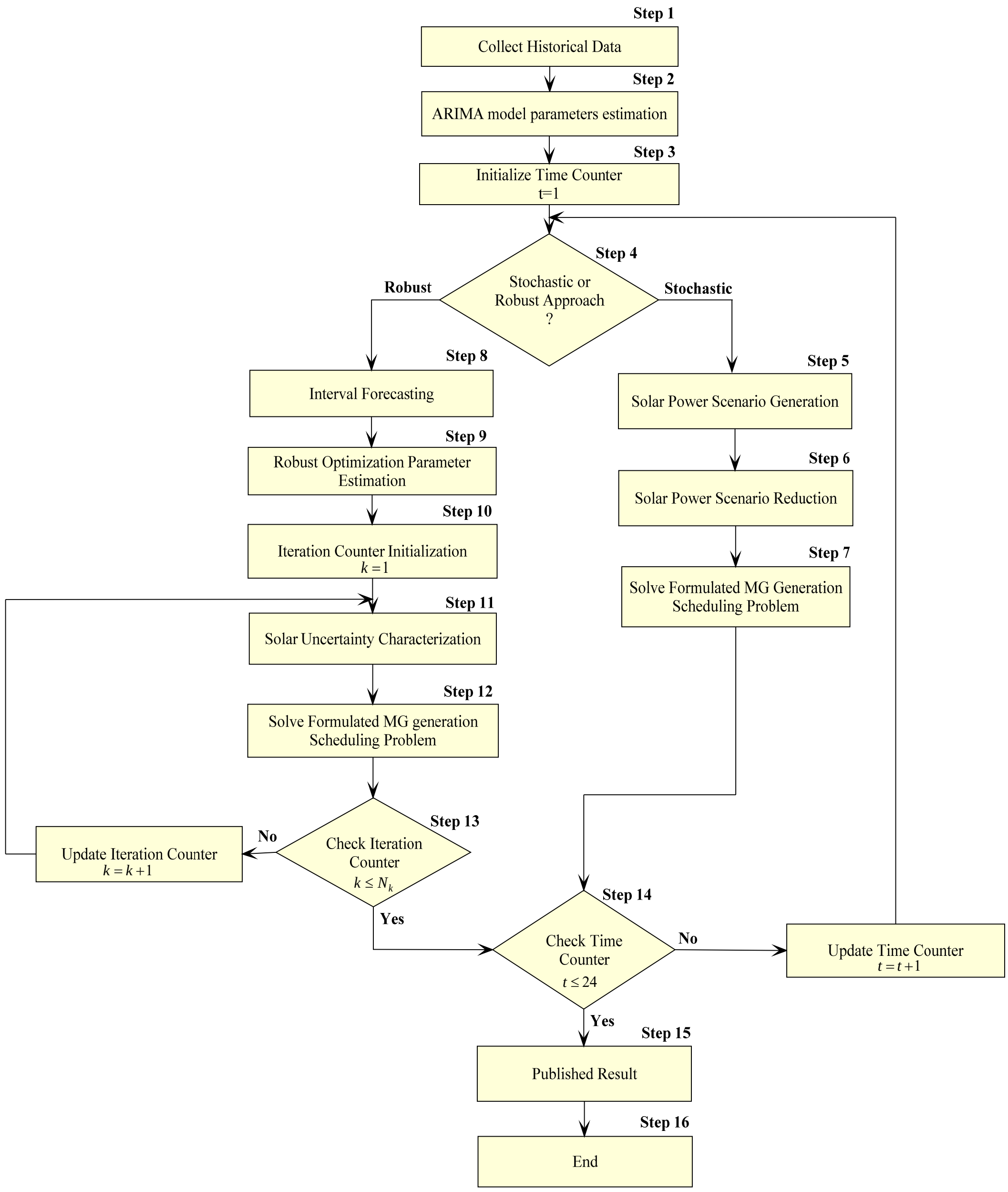

Fig. 5.1 Flow chart of proposed algorithm

5.8 Results and Discussions

In this study, installed capacity of PV unit and wind units are considered as 200 kW and 1.34 MW respectively. Wind units consists ENERCON turbine model whose parameters are given in detail in manufacturer database [160]. The historical wind speed data of the duration of 27.04.2006 to 08.06.2007, are used in this study from publically available database at Illinois Institute of Rural Affair, USA. [161]. For same site the historical solar irradiation data is obtained from NREL for same duration

[162]. Along with renewable units, 10 dispatchable units are considered, whose parameters are given in Table 5.1. Hourly grid price, demand profile and hourly forecasted wind power are shown in Fig. 5.2 and Fig. 5.3 respectively.

Table 5.1: Dispatchable Unit Parameters

Dispatchable unit	**Installed capacity (kW)**	**Upward reserve (kW)**	**Downward reserve (kW)**	**Marginal cost ($/kWh)**
1	600	240	240	0.0141
2	600	240	240	0.0222
3	400	160	160	0.02775
4	400	160	160	0.03375
5	300	120	120	0.0321
6	300	120	120	0.0384
7	200	80	80	0.04335
8	200	80	80	0.049125
9	100	40	40	0.04554
10	100	40	40	0.05154

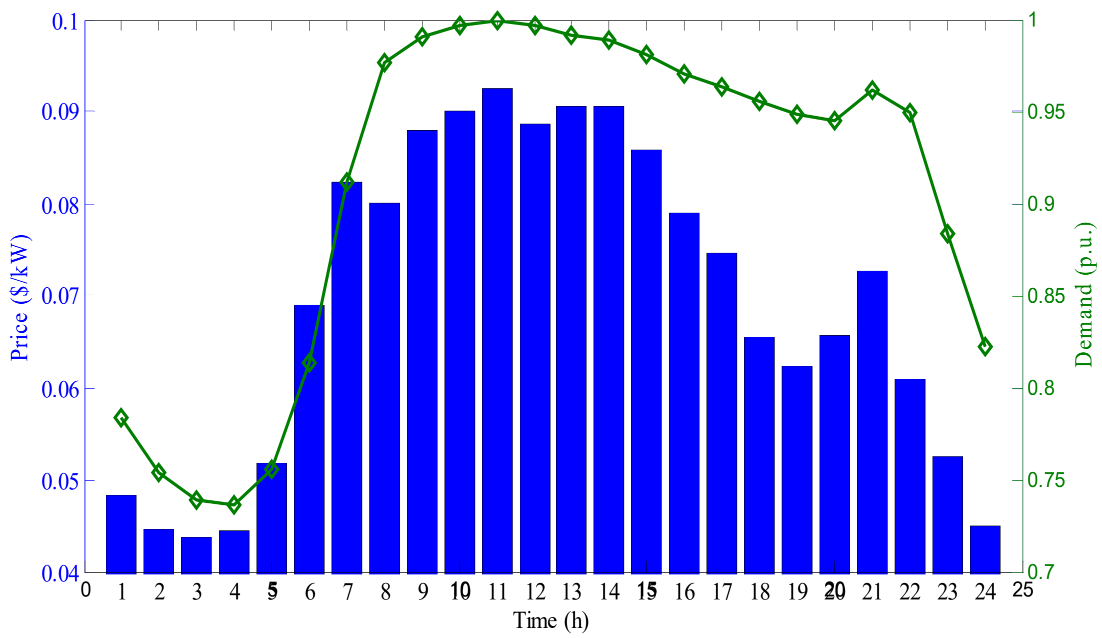

Fig. 5.2 Daily market price (bar plot) and demand profile (line plot)

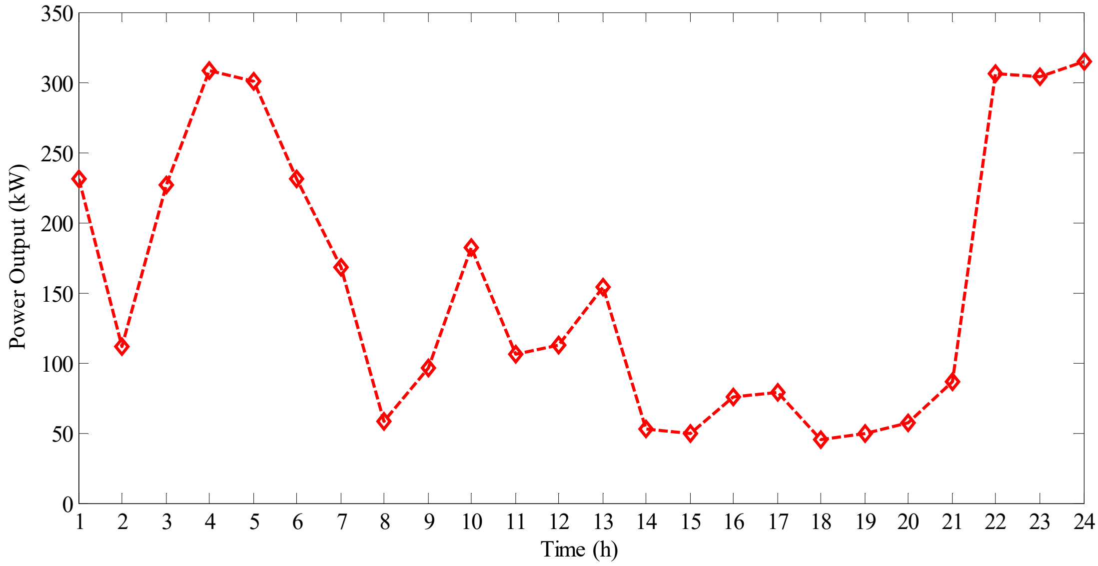

Fig. 5.3 Forecasted wind power output profile

The capacity of line linking the main grid and MG is considered as 5000 kW. Hourly grid price obtained for PJM electricity market is shown in [165]. Short-term generation scheduling on the basis of marginal generation cost is common in evolving electricity markets. The fixed cost has no role in short-term operation of electricity markets. This work focuses on short-term generation scheduling of MG in deregulated environment, considering the marginal cost of generators. Marginal cost of generators is calculated according to their cost functions.

Using the above data, proposed stochastic and robust approach is tested on a typical MG by considering both grid connected and grid isolated mode. Both modes of MG operation are coded in GAMS platform and final LP problem is solved using CPLEX solver [163].

5.8.1 Solar Power Uncertainty Modeling

For uncertainty modeling using ARIMA model, first the order of suitable ARIMA model on the basis of collected historical data is determined. Order of AR and MA terms are obtained by the observation of ACF and PACF plot. These plots are shown in Fig. 5.4 and 5.5, respectively. From these figures, it is observed that ACF plot is sinusoidal and PACF for first two legs are out of bounds. Thus, ARIMA (3,0,0) is suitable for modeling solar power uncertainty. The estimated values of AR coefficients are 1.18, -0.309, and -0.032. The value of constant term and variance of white noise are 97.86 and 0.43, respectively.

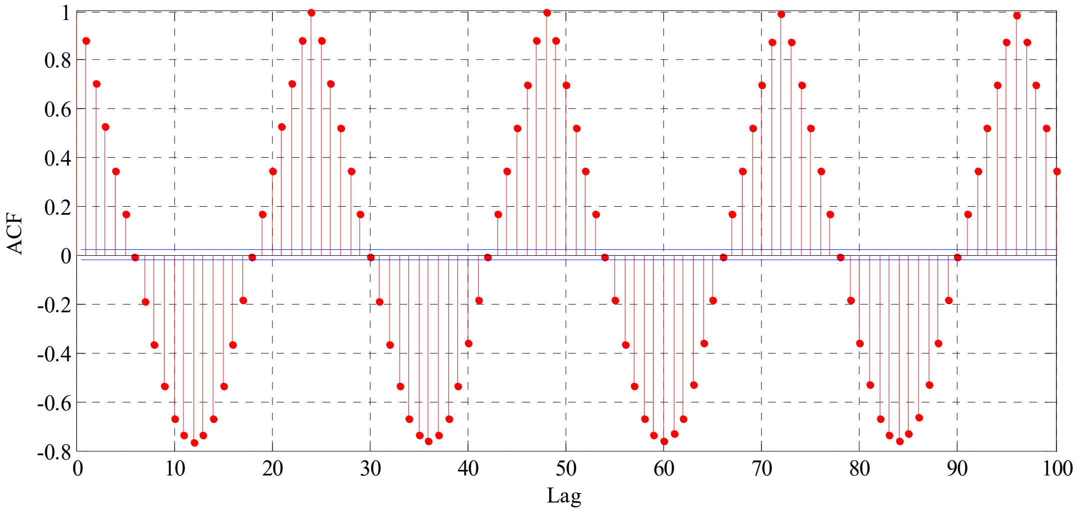

Fig. 5.4 ACF plot of sample solar power data

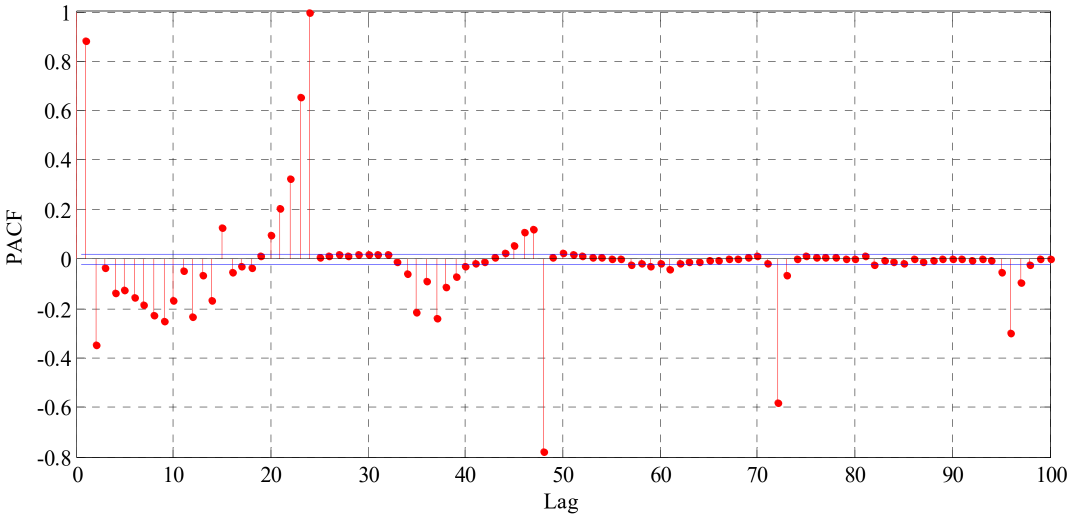

Fig. 5.5 PACF plot of sample solar power data

To solve MG generation scheduling problem using proposed stochastic optimization based methodology, 1000 solar power scenarios are generated. Generated scenarios are reduced to 25 scenarios using backward reduction algorithm. Generated 1000 solar power scenarios along with mean scenario (red) and forecasted solar power (black) is shown in Fig. 5.6. Fig. 5.7 shows the reduced 25 solar power scenarios along with mean scenario (red) and forecasted solar power (black). When spread of uncertain parameter is not very high, a mean solar power scenario can be used to solve is MG generation scheduling problem. Practically, spread is there in solar power uncertainty thus reduced solar power scenarios are used for solving MG generation scheduling problem in stochastic optimization framework. For deterministic optimization based approach, forecasted solar power is used.

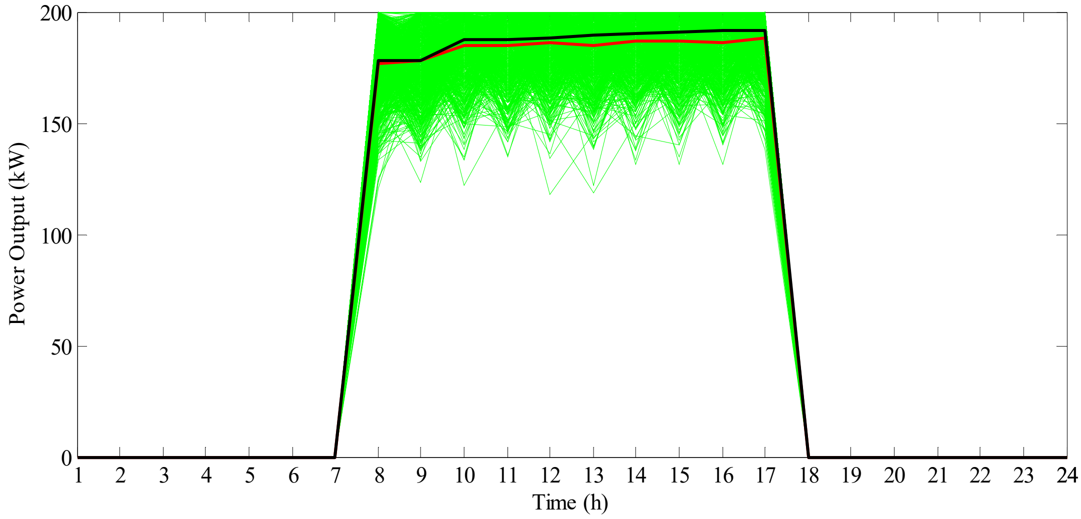

Fig. 5.6 Generated 1000 solar power scenarios (green) along with mean scenario (red) and forecasted solar power (black)

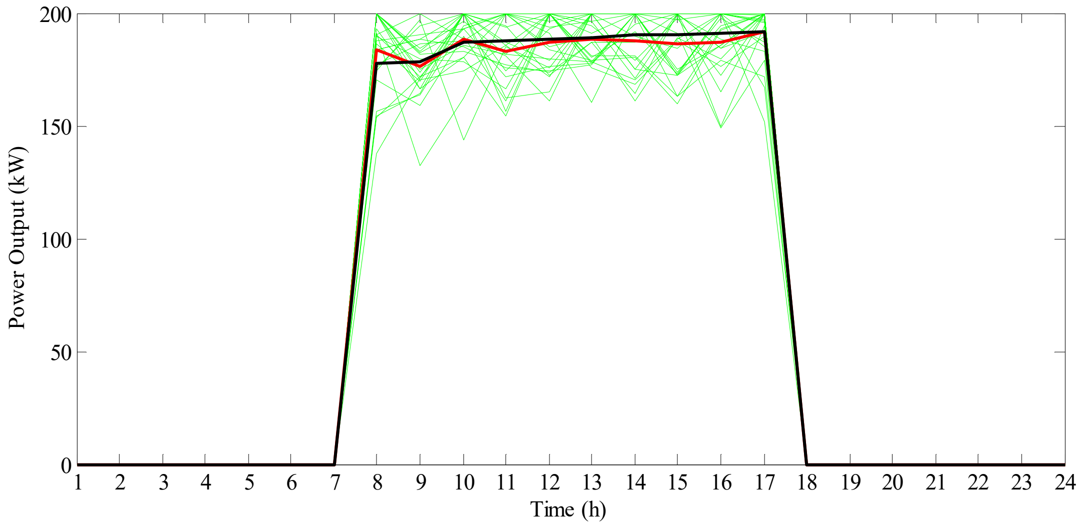

Fig. 5.7 Reduced 25 solar power scenarios (green) along with mean scenario (red) and forecasted solar power (black)

Fig. 5.8 shows the forecasted solar power for 24 hours with upper and lower bounds. On a 95% confidence interval forecasted limits are used in proposed robust optimization based MG scheduling approach.

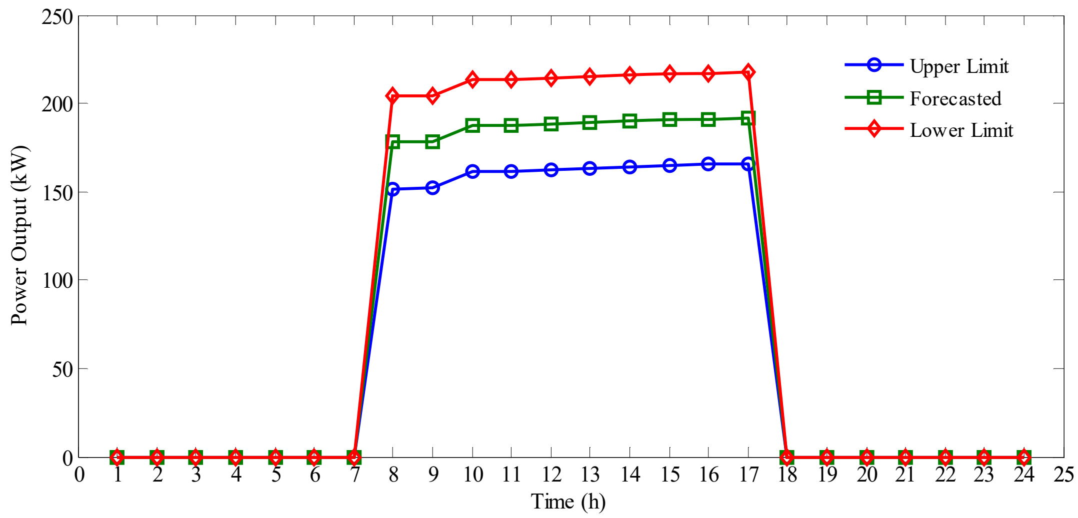

Fig. 5.8 Hourly forecasted solar power with upper and lower limits

5.8.2 Stochastic Optimization Based MG Operation in Grid Connected Mode

In this section, obtained results by solving formulated stochastic grid-connected MG operation using proposed methodology are discussed. Fig. 5.9 shows the obtained scheduled power of dispatchable units in MG during grid connected mode of operation.

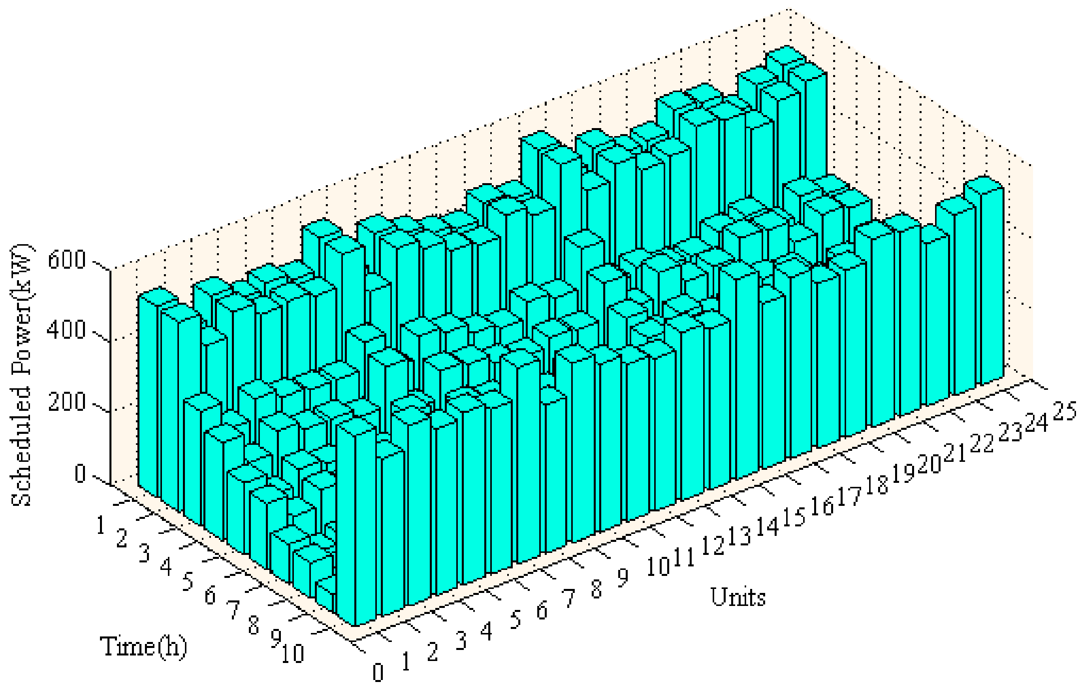

Fig. 5.9 Scheduled power of dispatchable units in grid connected mode

It can be observed from Fig. 5.9, that it will be beneficial to schedule maximum capacity from the unit with lower cost than the unit with higher cost. Further Fig. 5.10 and Fig. 5.11 show the obtained scheduled upward and downward reserves of dispatchable units respectively.

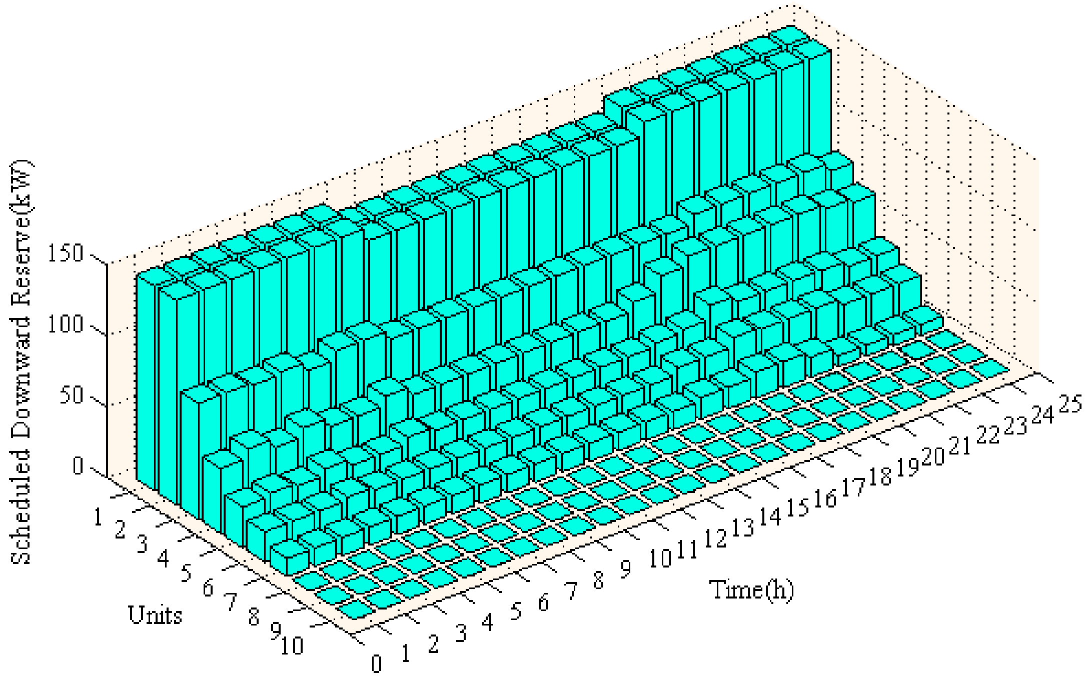

Fig. 5.10 Scheduled downward reserve in grid connected mode

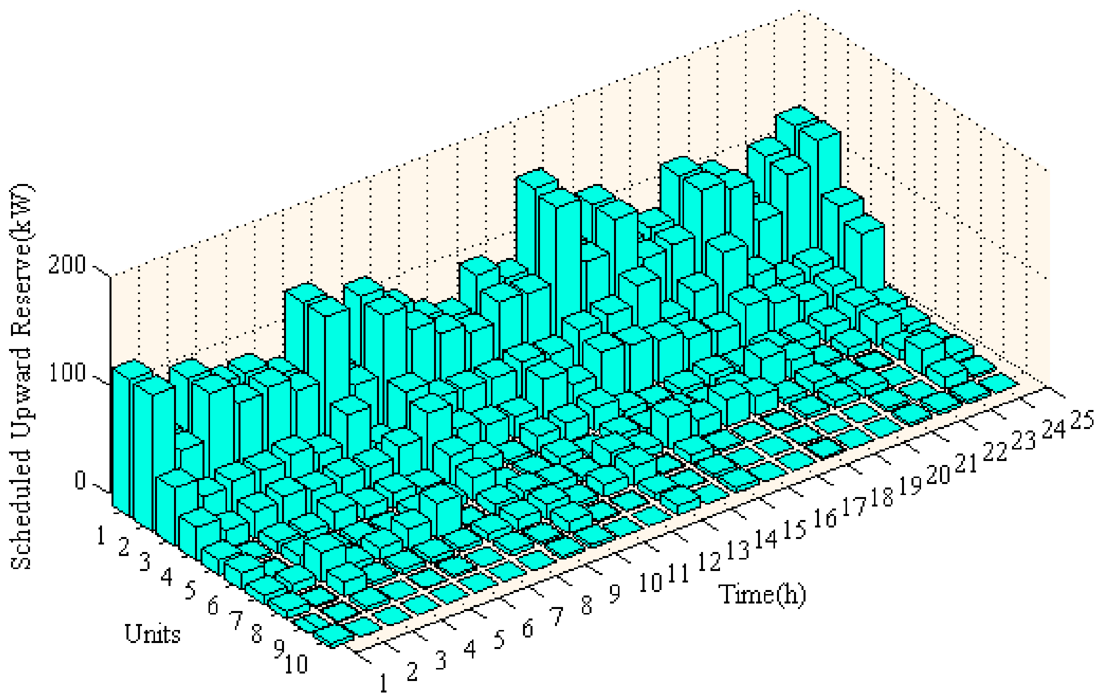

Fig. 5.11 Scheduled upward reserve in grid connected mode

It can be observed from Fig. 5.10 and Fig. 5.11, that any dispatchable unit is scheduled for one type of reserve requirement at any particular instant of time *t*. It can be observed that at the time of exporting the power the most costly dispatchable units are scheduled to their downward reserve while in case of importing the power these units are scheduled to their upward reserve. Fig. 5.12 shows power exchange between the main grid and the MG.

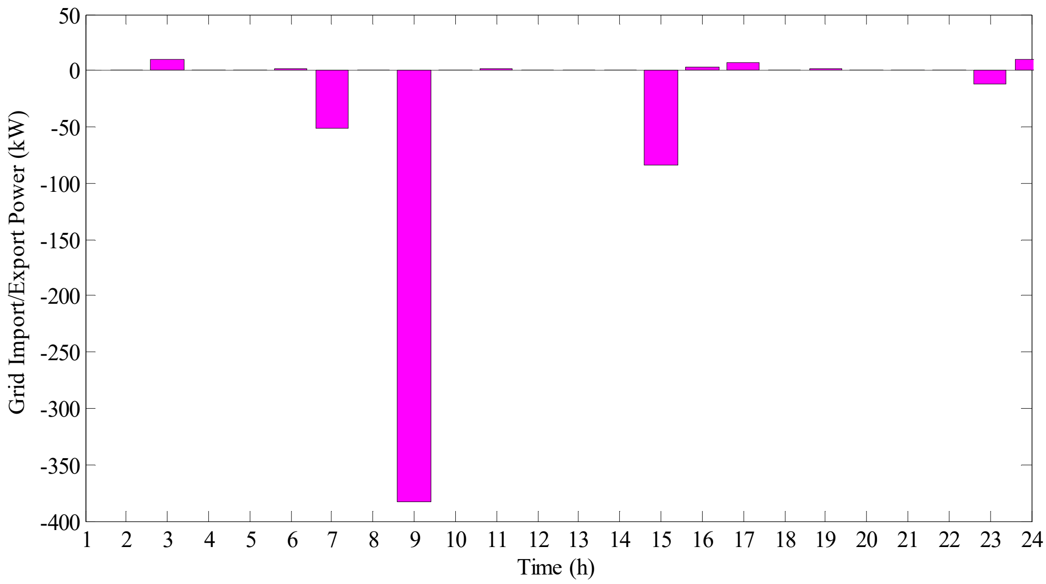

Fig. 5.12 Power imported/exported to/from grid in grid connected mode

From the Fig. 5.12, it can be observed that from hour 7, 9, 15 and 23, power is being exported to the grid and in remaining hours like as hour 1, 3, 4, 6, 11, 16, 17, 19 and 24, power is being imported from the grid. It can be concluded that, when grid price is higher, MG can export their reserve capacity to grid and vice-versa to reduce its operating cost. By comparing Fig. 5.7 and 5.8, it can be seen that, in the above mentioned time periods, the high solar and wind power is available, leading to export power to the grid.

5.8.3 Stochastic Optimization Based MG Operation in Grid Isolated Mode

Similarly, in this case, formulated stochastic MG operation in grid-isolated mode is considered using proposed methodology. The cost of demand shedding is considered as \$3.5/kWh according to Federal Energy Regulation Commission (FERC), Electric Tariff [164]. Similar to the previous case, Fig. 5.13, 5.14, and 5.15 show the scheduled dispatchable unit power, upward and downward reserve capacity respectively using proposed stochastic optimization approach. From Figs 5.14 and 5.15, it can be visualized that MG can utilize its upward reserve capacity during peak demand to reduce demand shedding events.

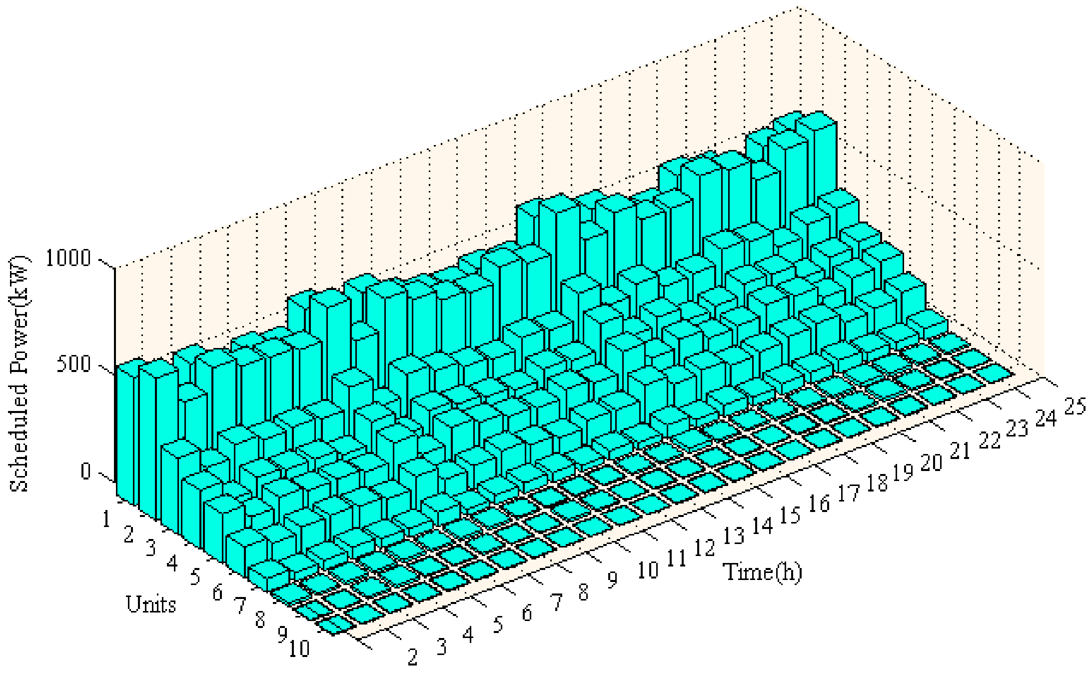

Fig. 5.13 Dispatchable unit scheduled power in grid isolated mode

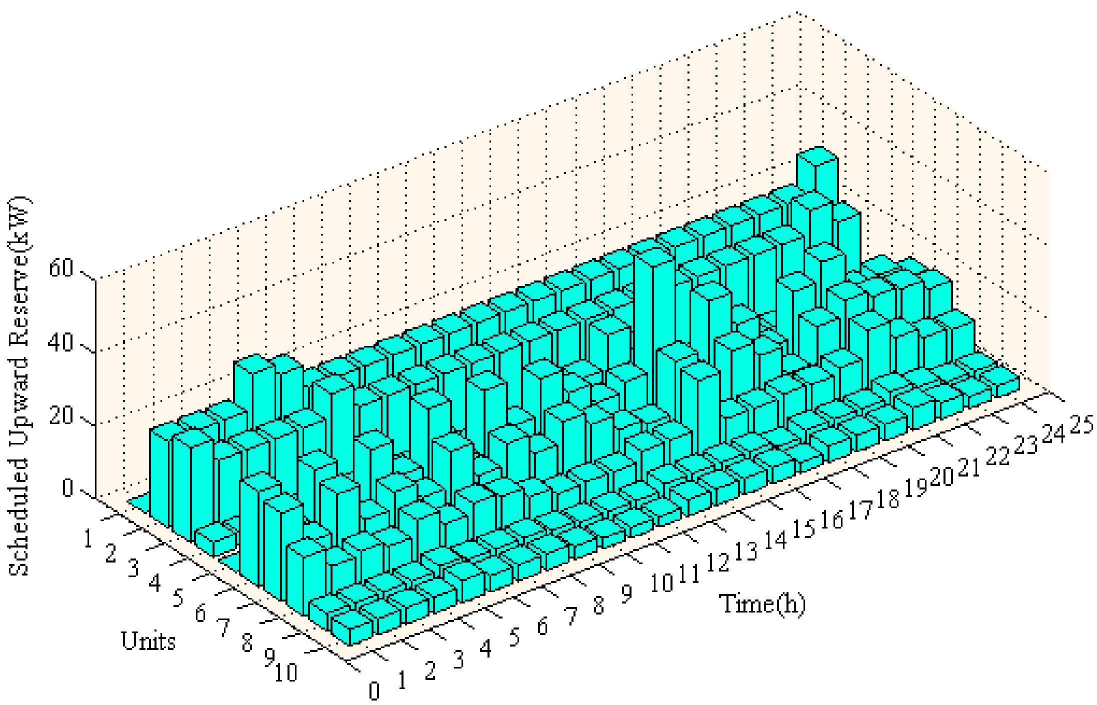

Fig. 5.14 Scheduled upward reserve in grid isolated mode.

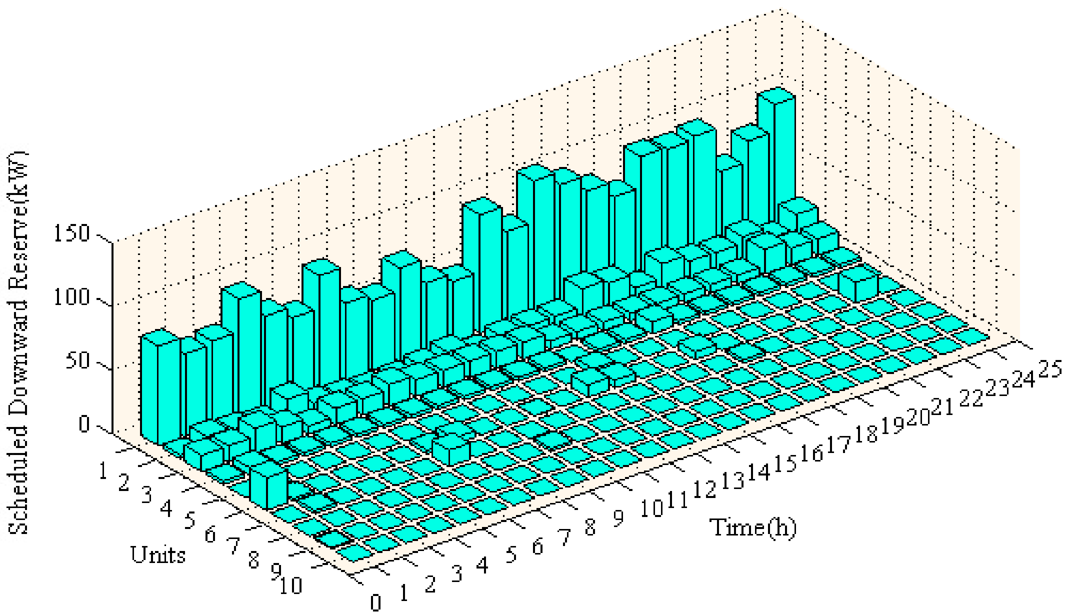

Fig. 5.15 Scheduled downward reserve in grid isolated mode

Demand shedding in stochastic optimization based grid isolated MG operation is shown in Fig. 5.16. From the figure, it is observed that demand shedding event occurs in hours 7, 14, 18 and 20. For these peak hours, availability of wind and solar power is lower as shown in Fig. 5.3 and Fig. 5.6. The capacity of dispatchable units is fully utilized therefore leading to demand shedding.

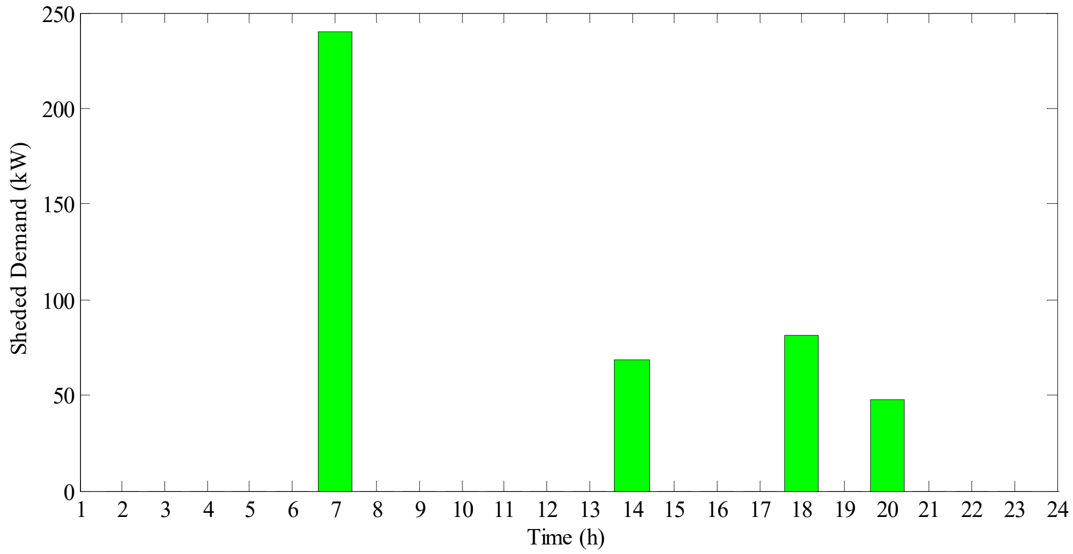

Fig. 5.16 Demand shedding in grid isolated mode

5.8.4 Robust Optimization Based MG Operation in Grid Connected Mode

In this case, MG operation in grid-connected mode is considered for simulation using proposed robust optimization method. Fig. 5.17 and 5.18 show the obtained scheduled power of dispatchable units, scheduled upward reserve and scheduled downward reserve respectively during grid connected mode of operation.

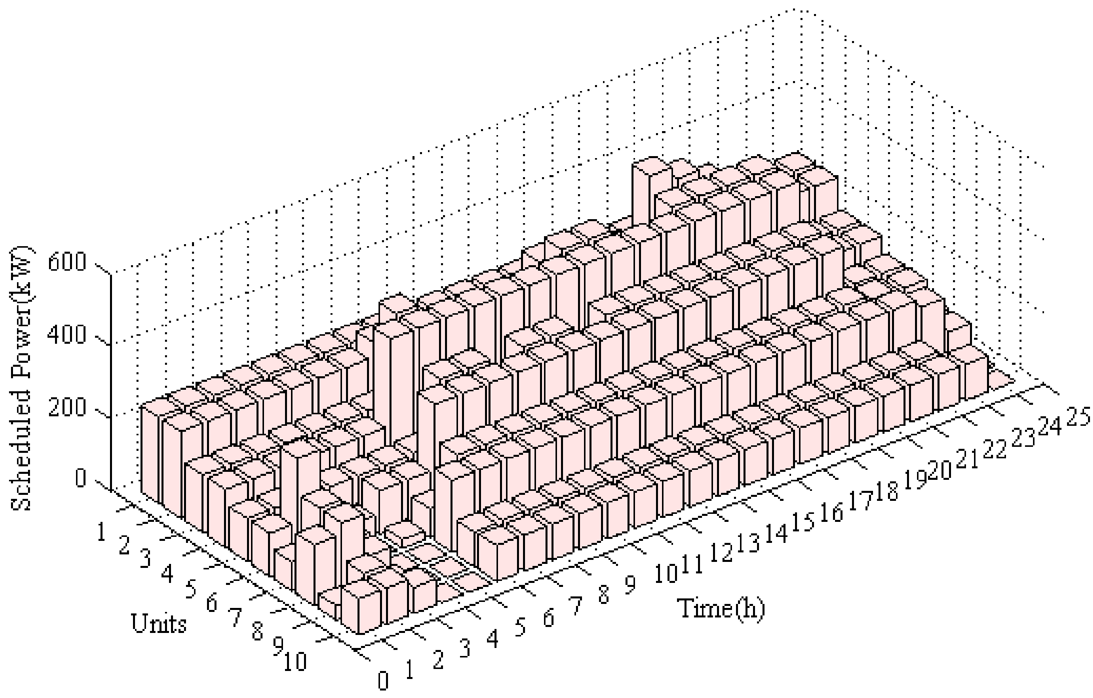

Fig. 5.17 Scheduled power of dispatchable units in grid connected mode

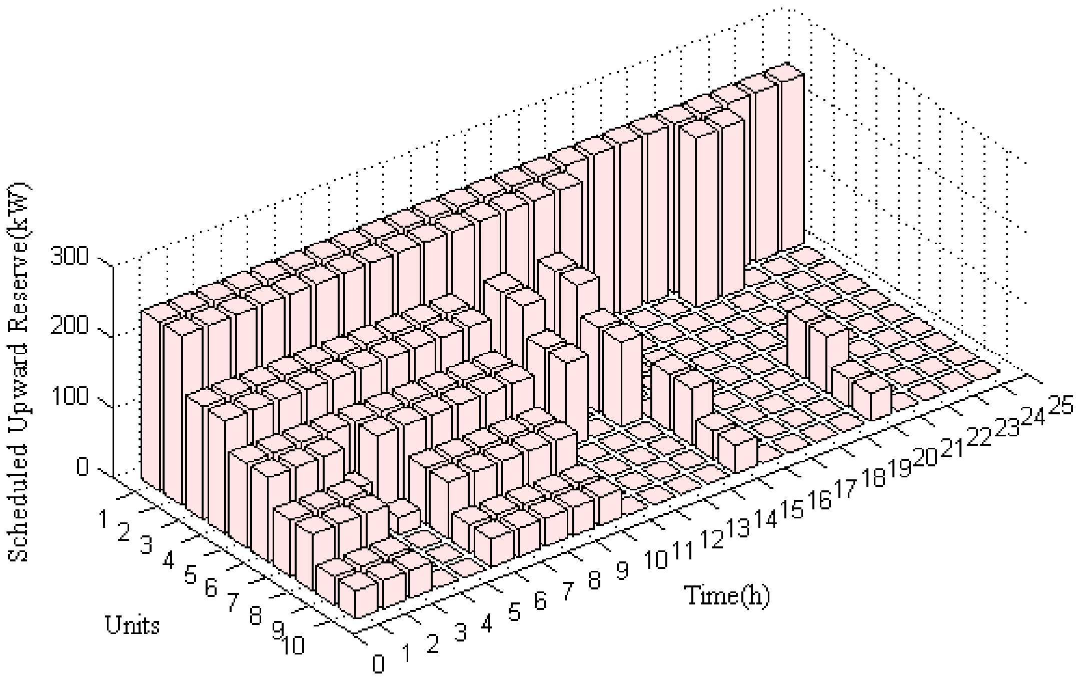

Fig. 5.18 Scheduled upward reserve in grid connected mode

From the Fig. 5.17, it can be observed that it will be beneficial to schedule maximum capacity from the unit with lower cost than the unit with higher cost. From the Fig. 5.18 and Fig. 5.19, it can be observed that any dispatchable unit is scheduled for one type of reserve requirement at any particular instant of time *t*. It can be observed that at the time of exporting the power the most costly dispatchable units are scheduled to their downward reserve while in case of importing the power these units are scheduled to their upward reserve. Fig. 5.20 shows power exchange between the main grid and the MG in Case I.

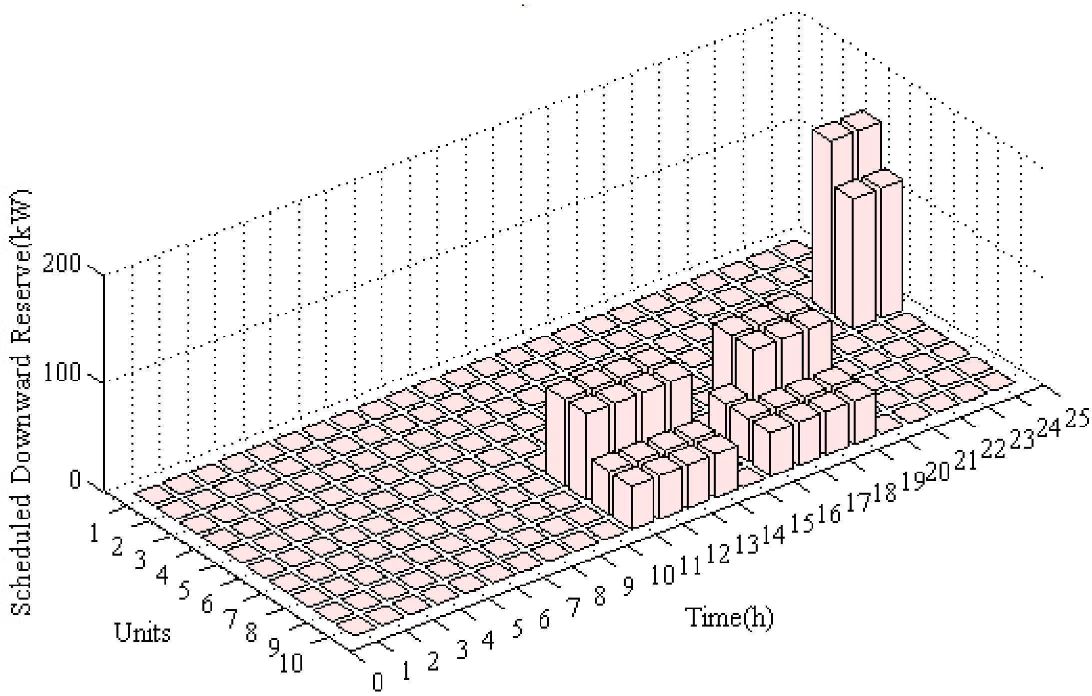

Fig. 5.19 Scheduled downward reserve in grid connected mode

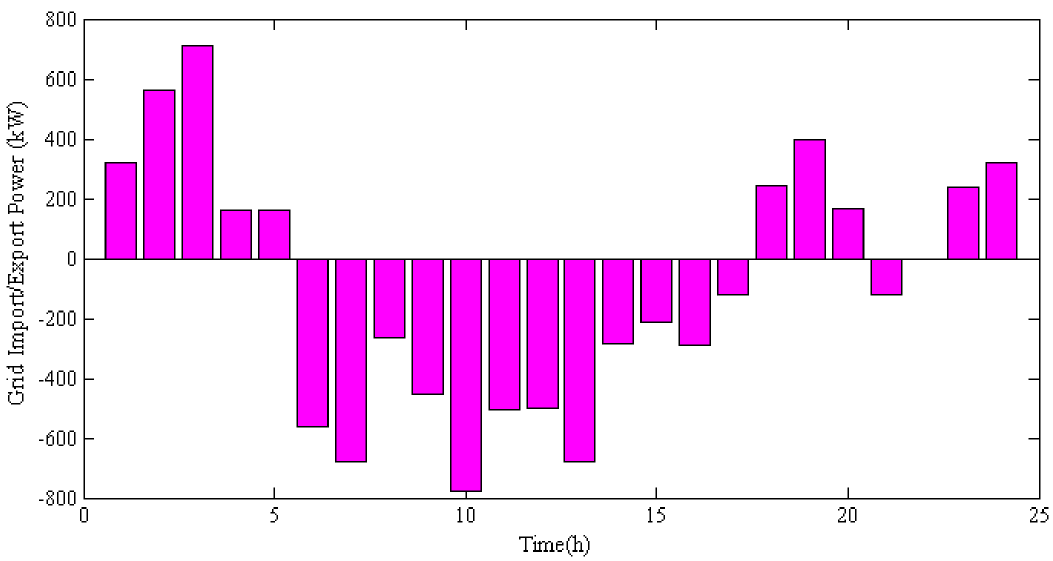

Fig. 5.20 Power imported/exported to/from grid in grid connected mode

From the Fig. 5.20, it can be observed that from hour 6 to 17 and 21, power is exported to the grid and in remaining hours, power is being imported from the grid. It can be concluded that, when grid price is higher, MG can export their reserve capacity to grid and vice-versa to reduce its operating cost.

5.8.5 Robust Optimization Based MG operation in grid isolated mode

Similarly, in this case, MG operation in grid-isolated mode is considered using proposed robust optimization method. The cost of demand shedding is considered as \$3.5/kWh according to Federal Energy Regulation Commission (FERC), Electric Tariff [164]. Similar to the previous case, Fig. 5.21, Fig. 5.22, and Fig. 5.23 show the scheduled dispatchable unit power, upward and downward reserve capacity respectively using proposed robust optimization approach. The capacity of dispatchable units is fully utilized, therefore, leading to demand shedding. From Figs 5.22 and 5.23, it can be visualized that MG can utilize its upward reserve capacity during peak demand to reduce demand shedding events.

Demand shedding in grid isolated mode is shown in Fig. 5.24. From the figure, it is observed that demand shedding event occurs in hours 16, 19 and 24.

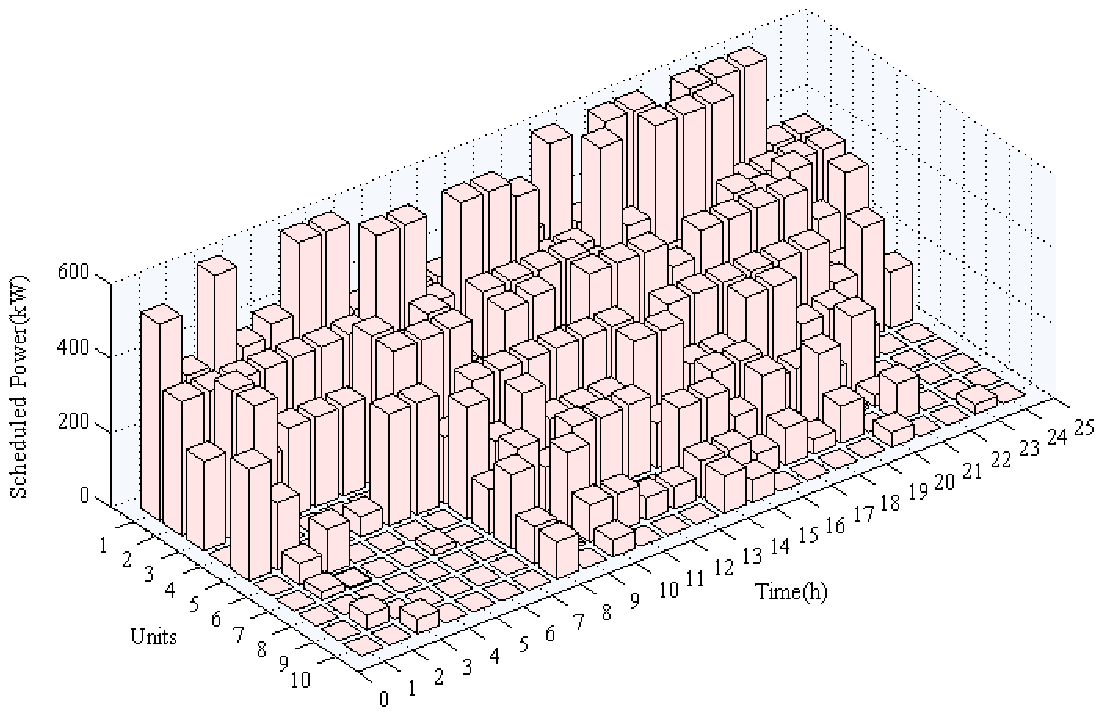

Fig. 5.21 Dispatchable unit scheduled power in grid isolated mode

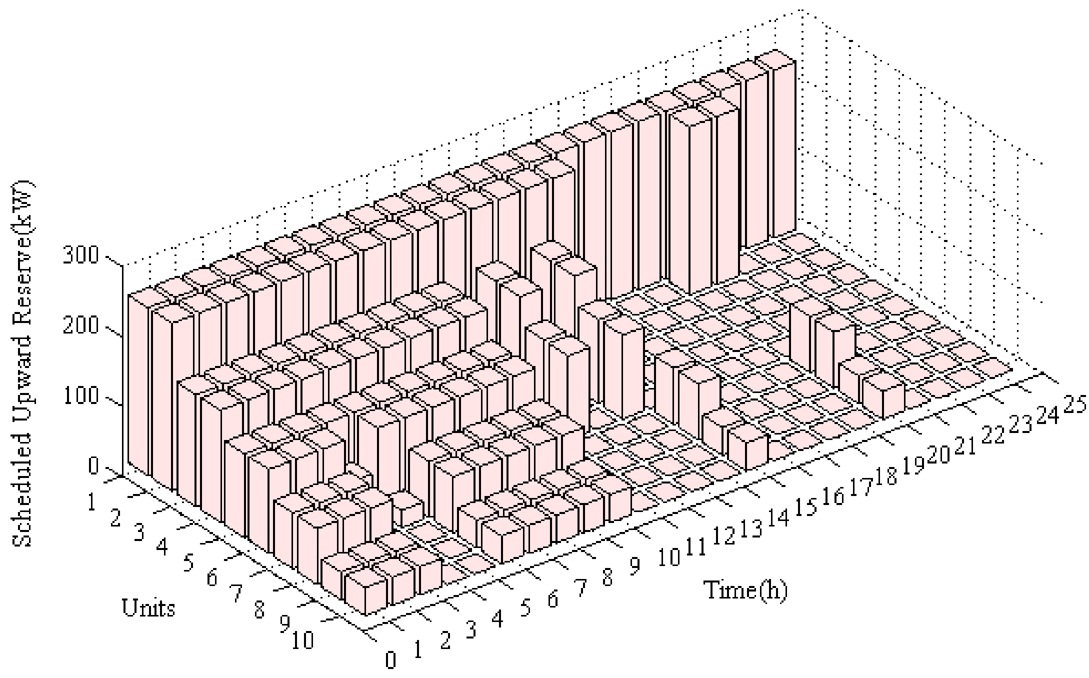

Fig. 5.22 Scheduled upward reserve in grid isolated mode

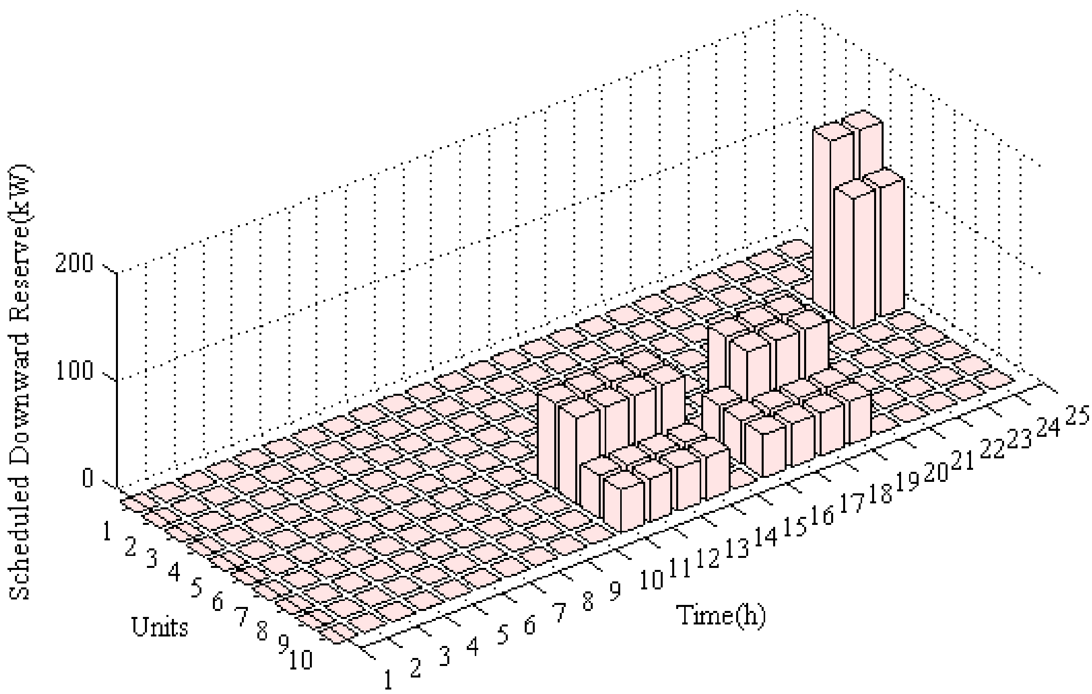

Fig. 5.23 Scheduled downward reserve in grid isolated mode

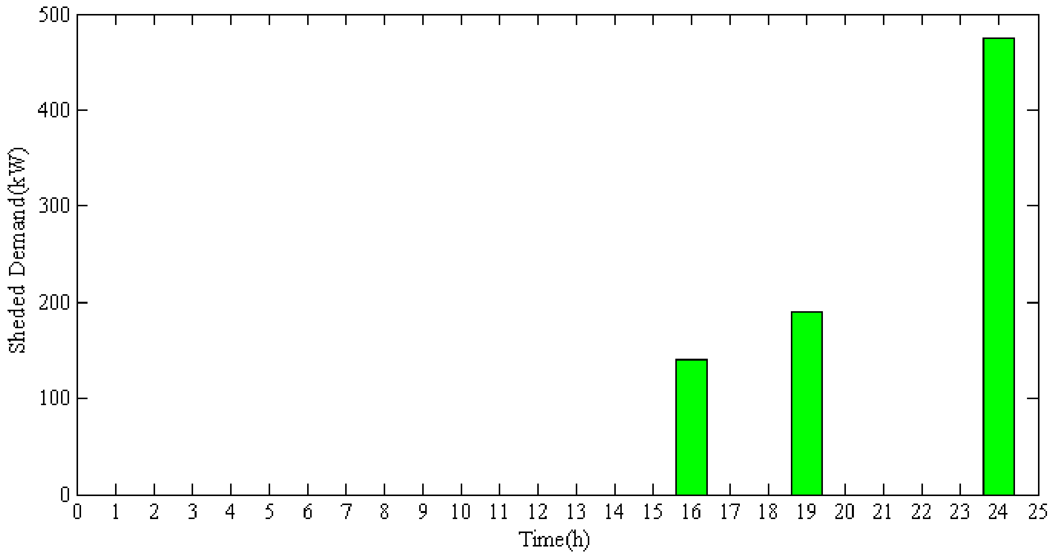

Fig. 5.24 Demand shedding in grid isolated mode

5.8.6 Comparative Analysis

A comparative analysis on MG operation is carried out. For this purpose, the same problem is simulated using deterministic, stochastic and robust optimization programming approach. In deterministic approach, solar/PV power output is simply forecasted using ARIMA model and the forecasted value of solar/PV power is considered to compute the scheduling of MG.

Table 5.2: Comaparitive Analysis of MG Daily Operation Cost

Approaches	Operation Cost ($)	
	Grid Connected Mode	Grid Isolated Mode
Deterministic	857.9346	1500.230
Stochastic	820.59 (-4.35 %)	1334.909 (-11.02 %)
Proposed	794.3616 (-7.49%)	1275.1955 (-15.00 %)

In stochastic programming approach, the solar power uncertainty is modeled by generating a large number of scenarios (*i.e.* 10000) and then reducing them into a smaller number of scenarios (*i.e.* 25). The MG operation cost obtained using proposed robust optimization approach is compared with both deterministic and stochastic approaches as shown in Table 5.2. From the Table 5.2, it is observed that in both modes (*i.e.* Grid connected operation of MG and Grid isolated operation of MG) the daily operating cost is significantly lower in the proposed approach than any other existing approach. It is also observed from Table 5.2, that the reduction in daily cost using proposed approach, in grid isolated mode is higher than compared to grid connected mode. This is because in grid isolated mode, small reduction in demand shedding event results in large reduction in total cost of operation. From Table 5.2, in the proposed approach the cost of MG operation is higher in grid-isolated mode than in grid-connected mode. This is due the fact that the reserves and dispatchable units are fully utilized to meet the demand.

5.8.7 Impact of Degree of Robustness

The impact of degree of robustness on operation cost, in both cases can be evaluated by varying the degree of robustness from zero to 24 during simulation. The obtained per unit cost of operation are shown in Fig. 5.25. Per unit cost of operation, at any degree of robustness is obtained by dividing its actual value by the reference value, which represents the cost of operation at zero degree of robustness. From Fig. 5.25, it can be seen that the optimal value of degree of robustness is 12; where per unit cost of operation is minimum. At this degree of robustness, optimal condition is obtained because in this problem solar power is considered as an uncertain parameter and solar power is available for ten hours only in a day, but as seasonal impact on uncertainty is not considered, so its uncertainty can be considered for 12 hours. This degree of robustness takes into account all possible deviations of the uncertain parameter for whole day. Additionally, at zero degree of robustness the cost of operation obtained using proposed robust optimization based approach is equal to the cost of operation obtained using deterministic approach.

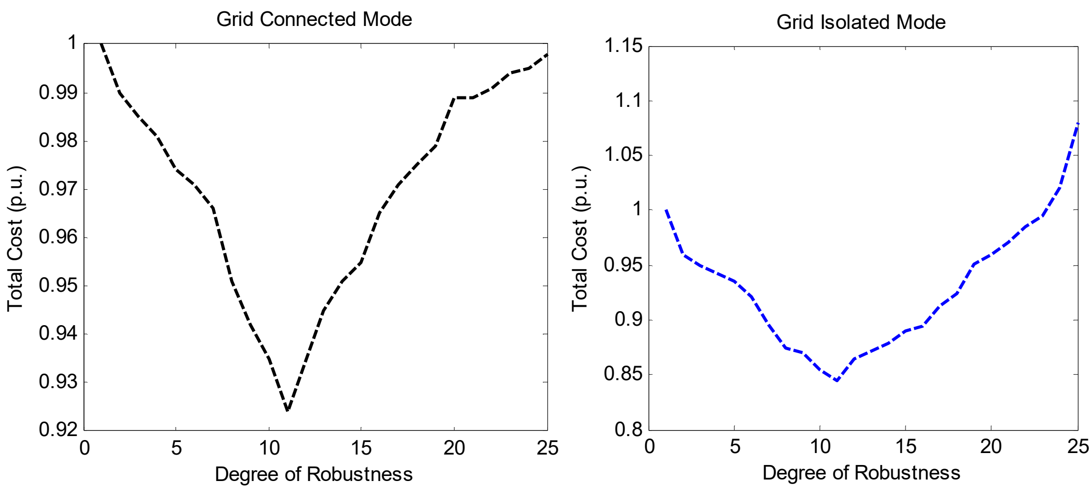

Fig. 5.25 Impact of degree of robustness on operational cost of MG

5.9 Summary

Stochastic and robust optimization based approaches have been proposed in this chapter for optimal generation scheduling of MG in both grid-connected and grid-isolated modes. For stochastic and robust optimization base approach, solar power uncertainty has been modeled through scenarios and interval forecasting using ARIMA model, respectively. A comparative study on daily MG cost of operation using proposed robust optimization based approach with deterministic and stochastic approach has been performed. A significant reduction in cost of operation clearly shows strength of proposed robust optimization based approach over stochastic and deterministic approach in MG generation scheduling in the deregulated environment. The impact of degree of robustness on the cost of operation in both cases has also been evaluated and compared with existing methods. The proposed approach will be more advantageous in incorporating different type of uncertainties such as Demand uncertainty and grid price uncertainty. This work may also be enhanced by incorporating multi-micro grids, different type of consumers and considering different technical constraints.

Chapter 6

Robust Microgrid Operation Considering Wind and Solar Power Uncertainty

THIS chapter enhances the proposed robust optimization based approach for optimal generation scheduling of MG in both grid-connected and grid-isolated modes by considering both wind and solar power uncertainty. Both wind power and solar power uncertainty have been modeled through interval forecasting using ARIMA model. A comparative study on daily MG cost of operation using proposed robust optimization based approach with deterministic and stochastic approach has been performed.

CHAPTER 6

ROBUST MICROGRID OPERATION CONSIDERING WIND AND SOLAR POWER UNCERTAINTY

6.1 Introduction

Micro Grid (MG) is commonly referred as an efficient way for integration of DG in the distribution system. In general, DG is a small scale generating unit, installed near the consumers in the distribution system to mitigate transmission losses and network congestion. DG can have a conventional or renewable energy sources. However, DG with renewable energy sources is widely utilized due to their peculiar characteristics such as pollution free, sustainable and freely available energy resources. Among the available renewable energy sources, wind power and solar power would be the most promising renewable sources throughout the world. Although, wind power and solar power generation are stochastic in nature, high penetration of wind and solar DGs in the distribution system leads considerable technical and economical challenges for MG operators in satisfying load demand and maintaining the stable and reliable operation of MGs. Due to wind power and solar power uncertainty, the reserve power requirement in MG management is increased that leads towards increased total MG operating cost.

Uncertainty presents in wind and solar power generation due to forecasting deviation results a great impact on the generation scheduling both in grid connected and grid isolated MG. In Chapter 3, uncertainty modeling approaches are discussed in detail. The impact of wind power uncertainty on the operation of grid connected and grid isolated MG has been investigated using robust optimization approach in Chapter 4. In chapter 5, solar power uncertainty in generation scheduling problem of both grid connected and grid isolated MG has been considered using stochastic and robust optimization approach. However, the impact of one uncertainty to another uncertainty has not been considered, therefore, MG operation considering both wind power and solar power uncertainty is needed to be modeled because both wind power and solar power are common energy sources in the MGs.

This chapter presents robust optimization based approach for optimal MG operation in deregulated environment considering both wind power and solar power uncertainties. Proposed approach is formulated for generation scheduling problem of MG in both grid-connected and grid-isolated mode. Wind power and solar power uncertainties can be modelled through interval forecasting using time series based ARIMA model. Other uncertainties present in demand profile and grid price has been modelled using deterministic point forecasting method. The Proposed approach is illustrated by a realistic case study on MG having wind power, solar/PV power, dispatchable generating units and loads. Obtained results show the strength of proposed approach in cost minimization over the other existing approaches.

This chapter is organized as follows: Section 6.2 describes the generation scheduling problem of grid connected and isolated MG. Modeling of both wind power and solar power uncertainty is described in Section 6.3. Section 6.4 highlights the Robust Optimization approach. Section 6.5, proposes the formulation of the robust MG energy-scheduling model considering both wind power and solar power generation uncertainties. Section 6.6 introduces the test platform and provides a detailed case study of the proposed algorithm and compares the simulation results obtained using proposed robust optimization based approach and other existing approaches under various operational conditions. Section 6.7 concludes the Chapter.

6.2 Problem Description

MG generation scheduling problem can be modeled with an objective of total cost of operation minimization. The basic architecture of MG generation scheduling problem considering multiple uncertainties (like wind power and solar power uncertainty) has been shown in Fig. 6.1. It is clear from Fig. 6.1 that constraint parameters are slightly different in both grid-connected and grid isolated mode. The dispatchable unit parameters, forecasted demand, uncertain wind and solar power are common input for both grid-connected and isolated MG. Forecasted market price is an input parameter for only grid connected MG. Day ahead and real time power balance, dispatchable unit’s generation, upward and downward reserves, power imbalance are common constraints in both mode of operation of MG. In grid-connected mode MG can Import/Export its deficit/excess power from/to the utility grid. While grid isolated mode demand shedding events are occurred when all existing power of MG is utilized to meet the required demand. The detailed basic formulation of MG energy management formulation is described in Section 4.2.

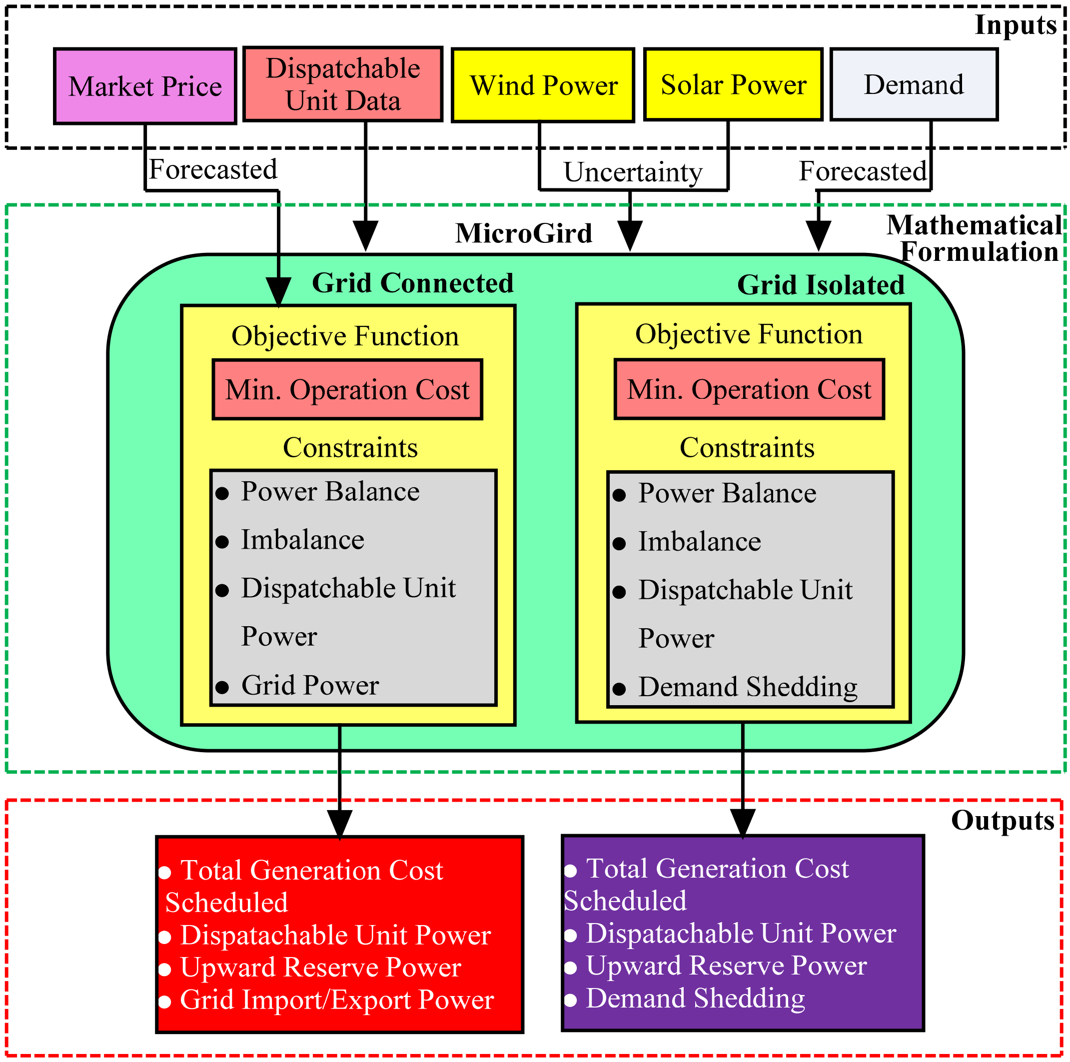

Fig. 6.1 Generation scheduling problem of grid connected and isolated MG

6.3 Uncertainty Modeling

Wind and solar are main source of uncertainty in the operation of grid connected and isolated MG in deregulated power systems. Similar to earlier chapter, random nature of such sources is modelled by stochastic process using ARIMA model. As both wind and solar power are vary with atmospheric conditions, the time series of wind and solar power are non-stationary. Since, ARIMA model is applicable for only stationary data series, so wind and solar power time series models are converted in to stationary series by differentiation [159]. The typical ARIMA (p, d, q) model is expressed as equation (6.1)

$$Y_t = \mu + \sum_{i=1}^{p} \gamma_i Y_{t-1} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-1} + \varepsilon_t \tag{6.1}$$

Where, Y_t is the forecasted wind and solar power along with upper and lower limits at time t, p is the order of autoregressive coefficients, γ_i and q are the orders of moving average coefficients θ_i. The term ε_t is a normally distributed random number with mean zero and constant variance, also known as white noise or error signal. The term μ is a constant in the model.

6.4 Robust Optimization Approach

Robust optimization is nothing but it addresses those uncertain parameters in optimization problems with uncertain parameters which are not described by using probability distributions but uncertainty sets [84]. An uncertainty set has set structure which is used to characterize the uncertain parameter's possible outcomes. In a robust optimization the aim is to determine a solution to an optimization problem in such a way that the obtained solution is feasible for any realization of the uncertain parameters within the uncertainty set and for the worst-case realization of these uncertain parameters, solution is optimal. In any decision making problem there are three types of robustness (i) constraint robustness (ii) objective robustness (iii) combinational robustness. If uncertainty is present in only constraint parameter, then the problem is defined as constraint robustness problem. If uncertainty is present in only objective function parameter, then the problem is classified as objective robustness problem. If uncertainty is present in both constraint parameter and objective function parameter then it is defined as combinational robustness. Due to effective modeling of uncertain parameters the problem formulated by the robust optimization is tractable and has low computational burden [84].

When degree of robustness is zero, the problem reduces to a deterministic case which solves the problem using the nominal values *i.e.,* expected values of the uncertain coefficients. Degree of robustness can be adjusted according to the trade-off between decision maker's risk preference and the conservatism of the solution [85].

6.5 Proposed Problem Formulation

This section provides the proposed formulation of MG scheduling problem in both Grid connected and Grid isolated mode using robust optimization approach. In this problem, wind and solar power is considered as uncertain parameter that is present in the constraints, therefore the formulated problem has constraint robustness.

6.5.1 Grid Connected Mode

In this mode, problem described in section 4.2 is reformulated by using Robust Optimization as follows:

(i) Objective Function

$$\min \sum_{t=1}^{N_t}\left[\sum_{j=1}^{N_j} C_j\left(P_{j,t}+r_{j,t}^{u}-r_{j,t}^{d}\right)+P_{grid,t}*\lambda_{grid,t}\right] \tag{6.2}$$

Since uncertainty is present in the constraint only, the Objective function is given in equation (6.2), in which minimization of total cost of operation is represented as the sum of operating cost of dispatchable generating unit's power, reserves and cost of power exchange between main grid & the MG.

(ii) Power Balance Constraint

$$\sum_{j=1}^{j} P_{j,t}+\sum_{w=1}^{N_w}\left(\sum_{k=1}^{N_k} W_{t,k}+z_k\Gamma_k+\sum_{k=1}^{N_k} q_k\right)+\sum_{v=1}^{N_v}\left(\sum_{k`=1}^{N_{k`}} PV_{t,k`}+z_{k`}\Gamma_{k`}+\sum_{k`=1}^{N_{k`}} q_{k`}\right)=Pd_t^{f},\forall t \tag{6.3}$$

Power balance constraint is represented in equation (6.3). This constraint states that the sum of scheduled power of dispatchable generating units, wind power units and PV generation must be equal to day-ahead forecasted demand at any time t. But irrespective of the previous formulation, both wind power and solar power are considered as uncertain parameter and modeled in RO framework, where variables like z_k, q_k, Γ_k and $z_{k'}, q_{k'}, \Gamma_{k'}$ are introduced to solve the problem, Where, $\Gamma_k, \Gamma_{k'}$ represent the degree of robustness which controls the robustness of the problem in case of wind power uncertainty and solar power uncertainty respectively and $z_k, z_{k'}$ and $q_k, q_{k'}$ are the dual variables to linearize the non-linearity in the problem for both wind power and solar power uncertainty respectively.

(iii) Robust Constraints

$$z_k+q_k \ge \hat{W}_{t,k}y_k, \qquad \forall k\neq 0,\ k\in N_k \tag{6.4}$$

$$z_{k'}+q_{k'} \ge P\hat{V}_{t,k'}y_{k'}, \quad \forall k'\neq 0,\ k'\in N_{k'} \tag{6.5}$$

$$q_k, q_{k'} \ge 0 \qquad \forall k,\forall k',\ k\in N_k, k'\in N_{k'} \tag{6.6}$$

$$y_k, y_{k'} \geq 0 \qquad \forall k, \forall k' \tag{6.7}$$

$$z_k, z_{k'} \geq 0 \qquad \forall k, \forall k' \tag{6.8}$$

Robust constraints are represented by equations (6.4)-(6.8), Where, equation (6.4) and (6.5) states that dual variable $z_k, z_{k'}$ and $q_k, q_{k'}$ are taken into account as the known bounds of wind and solar power in such a way that the sum of both variables is always greater than the wind and solar characterization parameters $\hat{W}_{t,k} y_k$ and $P\hat{V}_{t,k'} y_{k'}$. y_k and $y_{k'}$ are represent the auxiliary variable in case of wind power and solar power uncertainty respectively, used to obtain the corresponding linear expressions. However, $\hat{W}_{t,k}$ and $P\hat{V}_{t,k'} y_{k'}$ are obtained as the proportionate of the difference of lower and upper bounds of wind and solar power, respectively. Constraint (6.6), (6.7) and (6.8) show that the dual variables used in robust approach must be positive.

(iv) Real time Power Balance Constraint

$$\sum_{j=1}^{N_j} \left(r_{j,t}^{u} - r_{j,t}^{d} \right) + \sum_{w=1}^{N_w} \left(\Delta P_{w,t} \right) + \sum_{v=1}^{N_v} \Delta PV_{v,t} + P_{grid,t} - \Delta Pd_t = 0, \quad \forall t \tag{6.9}$$

Due to error in existing forecasting approaches, the actual values of wind power, PV generation and demand may be different from their forecasted values. The system imbalance created due to the error in forecasting in real-time can be compensated by the reserve capacity of dispatchable units or by the power from the main grid depending on the cost of compensation.

(v) Imbalance Constraints

$$\Delta P_{w,t} = P_{w,t}^{a} - P_{w,t}^{f} \qquad \forall w, \forall t \tag{6.10}$$

$$\Delta PV_{v,t} = PV_{v,t}^{a} - PV_{v,t}^{f}, \quad \forall v, \forall t \tag{6.11}$$

$$\Delta P_{d,t} = P_{d,t}^{a} - P_{d,t}^{f} \qquad \forall d, \forall t \tag{6.12}$$

In real-time, the deviation of wind power, PV solar power generation and system demand from their forecasted values can be calculated by the corresponding imbalance constraints expressed in (6.10) - (6.12). In this work, forecasting error of wind power generation, PV Generation & demand is assumed as a random variable with zero mean and constant standard deviation. The Real value of wind power, solar/PV power and demand is obtained by multiplying the error coefficient to their forecasted values.

(vi) Dispatchable Units Power Constraint

$$P_j^{\min} \le P_{j,t} \le P_j^{\max} \qquad \forall j, \forall t \tag{6.13}$$

$$r_{j,t}^{u} \le R_{j,t}^{u,\max} \qquad \forall j, \forall t \tag{6.14}$$

$$r_{j,t}^{d} \le R_{j,t}^{d,\max} \qquad \forall j, \forall t \tag{6.15}$$

$$P_{j,t} + r_{j,t}^{u} - r_{j,t}^{d} \ge 0 \qquad \forall j, \forall t \tag{6.16}$$

$$P_{j,t} + r_{j,t}^{u} - r_{j,t}^{d} \le P_{j,t}^{\max} \qquad \forall j, \forall t \tag{6.17}$$

Equation (6.13) maintains scheduled dispatchable generation unit power within predefined limits, while Constraints equation (6.14) and (6.15) define the scheduled upward and downward reserve of dispatchable generating units. It must be lesser than their maximum upward and downward reserve capacity respectively. Constraints equation (6.16) and (6.17) state that sum of scheduled power of dispatchable units with their respective reserves must be within their specified limits.

(vii) Grid Power Cconstraint

$$P_{grid,t} \le P_{grid,t}^{\max}, \quad \forall t \tag{6.18}$$

Due to transmission network constraints, MG cannot meet the whole demand through grid power when grid prices are lower than operation cost. On the other hand, the complete reserve capacity cannot be sold in the spot market during high market prices. Constraint equation (6.18) ensures that the power exchange between the main grid & MG is less than predefined capacity of the connecting.

6.5.2 Grid Isolated Mode

Since wind and solar power uncertainty is involved in the constraints, the MG generation scheduling problem in this mode is formulated using Robust Optimization approach similar to Grid connected mode differing in the objective function and supply-demand equilibrium constraint. Similar to previous one, in this mode also, it is required to minimize the expenses of the MG. However, more attention is given to meet the demand with stable operation. The problem in the isolated mode is formulated as:

(i) Objective Function

Similar to previously defined grid connected mode under RO Approach, the objective of MO in this mode is also the minimization of total operation cost. It states that the sum of operating cost of dispatchable generating units and cost of demand shedding should be minimized.

$$\min \sum_{t=1}^{N_t}\left[\sum_{j=1}^{N_j} C_j\left(P_{j,t}+r_{j,t}^{u}-r_{j,t}^{d}\right)+P_{d,t}^{shed} * \lambda_d^{shed}\right] \tag{6.19}$$

(ii) Power Balance Constraint

Power balance constraint is same as grid connected mode formulation in RO framework by equation (6.2).

$$\sum_{j=1}^{j} P_{j,t}+\sum_{w=1}^{N_w}\left(\sum_{k=1}^{N_k} W_{t,k}+z_k\Gamma_k+\sum_{k=1}^{N_k} q_k\right)+\sum_{v=1}^{N_v}\left(\sum_{k`=1}^{N_{k`}} PV_{t,k`}+z_{k`}\Gamma_{k`}+\sum_{k`=1}^{N_{k`}} q_{k`}\right)=Pd_t^f,\forall t \tag{6.20}$$

Power balance constraint is represented in equation (6.20). This constraint states that the sum of scheduled power of dispatchable generating units, wind power units and PV generation must be equal to day-ahead forecasted demand at any time t. But irrespective of the previous formulation, both wind power and solar power are considered as uncertain parameter and modeled in RO framework, where variables like z_k, q_k, Γ_k and $z_{k'}, q_{k'}, \Gamma_{k'}$ are introduced to solve the problem, Where, $\Gamma_k, \Gamma_{k'}$ represent the degree of robustness which controls the robustness of the problem in case of wind power uncertainty and solar power uncertainty respectively and $z_k, z_{k'}$ and $q_k, q_{k'}$ are the dual variables to linearize the non-linearity in the problem for both wind power and solar power uncertainty respectively.

(iii) Robust Constraints

$$z_k + q_k \geq \hat{W}_{t,k} y_k, \qquad \forall k \neq 0,\ k \in N_k \tag{6.21}$$

$$z_{k'} + q_{k'} \geq P\hat{V}_{t,k'} y_{k'}, \quad \forall k' \neq 0,\ k' \in N_{k'} \tag{6.22}$$

$$q_k, q_{k'} \geq 0, \quad \forall k, k',\ k \in N_k, k' \in N_{k'} \tag{6.23}$$

$$y_k, y_{k'} \geq 0, \quad \forall k, k' \tag{6.24}$$

$$z_k, z_{k'} \geq 0, \quad \forall k, k' \tag{6.25}$$

Robust constraints are represented by equations (6.21)-(6.25), Where, equation (6.21) and (6.22) states that dual variable $z_k, z_{k'}$ and $q_k, q_{k'}$ are taken into account as the known bounds of wind and solar power in such a way that the sum of both variables is always greater than the wind and solar characterization parameters $\hat{W}_{t,k} y_k$ and $P\hat{V}_{t,k'} y_{k'}$. y_k and $y_{k'}$ are represent the auxiliary variable in case of wind power and solar power uncertainty respectively, used to obtain the corresponding linear expressions. However, $\hat{W}_{t,k}$ and $P\hat{V}_{t,k'}$ are obtained as the proportionate of the difference of lower and upper bounds of wind and solar power, respectively. Constraint (6.23), (6.24) and (6.25) show that the dual variables used in robust approach must be positive.

(iv) Real time Power Balance Constraint

$$\sum_{j=1}^{N_j}\left(r_{j,t}^{u} - r_{j,t}^{d}\right) + \sum_{w=1}^{N_w}\left(\Delta P_{w,t}\right) + \sum_{v=1}^{N_v} \Delta PV_{v,t} + P_{d,t}^{Shed} - \Delta Pd_t = 0, \quad \forall t \tag{6.26}$$

To maintain system security and reliability, the generation is always equal to system demand at each instant. The system imbalance created due to volatile wind power, PV generation and demand at real-time is balanced by scheduling the reserve capacities of dispatchable generating units and shedding of demand.

(v) Demand Shedding Cconstraint

$$P_{d,t}^{shed} \leq P_{d,t} \quad \forall t \tag{6.27}$$

The shedding power is always less than equal to the scheduled demand in day-ahead scheduling.

(vi) Imbalance Constraints

$$\Delta P_{w,t} = P_{w,t}^{a} - P_{w,t}^{f}, \qquad \forall w, \forall t \tag{6.28}$$

$$\Delta PV_{v,t} = PV_{v,t}^{a} - PV_{v,t}^{f}, \quad \forall v, \forall t \tag{6.29}$$

$$\Delta P_{d,t} = P_{d,t}^{a} - P_{d,t}^{f}, \qquad \forall d, \forall t \tag{6.30}$$

In real-time, the deviation of wind power, PV generation and system demand from their forecasted values can be calculated by the corresponding imbalance constraints expressed in (6.28)-(6.30). In this work, forecasting error of wind power generation, PV Generation & demand is assumed as a random variable with zero mean and constant standard deviation. The Real value of wind power, PV power and demand is obtained by multiplying the error coefficient to their forecasted values.

(vii) Dispatchable Units Power Constraint

$$P_j^{\min} \le P_{j,t} \le P_j^{\max}, \qquad \forall j, \forall t \tag{6.31}$$

$$r_{j,t}^{u} \le R_{j,t}^{u,\max}, \qquad \forall j, \forall t \tag{6.32}$$

$$r_{j,t}^{d} \le R_{j,t}^{d,\max}, \qquad \forall j, \forall t \tag{6.33}$$

$$P_{j,t} + r_{j,t}^{u} - r_{j,t}^{d} \ge 0, \qquad \forall j, \forall t \tag{6.34}$$

$$P_{j,t} + r_{j,t}^{u} - r_{j,t}^{d} \le P_{j,t}^{\max}, \qquad \forall j, \forall t \tag{6.35}$$

Equation (6.31) maintains scheduled dispatchable generation unit power within predefined limits, while Constraints (6.32) and (6.33) define the scheduled upward and downward reserve of dispatchable generating units. It must be lesser than their maximum upward and downward reserve capacity respectively. Constraints (6.34) and (6.35) state that sum of scheduled power of dispatchable units with their respective reserves must be within their specified limits.

6.6 Proposed Simulation Procedure

The following simulation procedure (as shown in Fig. 6.2) is adopted to solve the formulated Robust Optimization based MG generation scheduling problem for both grid connected and isolated mode:

Step 1: Collect historical data: Collect the historical data of wind speed and PV solar power generation for a specific location where wind and solar units are located. The wind speed is converted in power using power curve of standard turbine models.

Step 2: ARIMA model parameters estimation: From collected data, parameters of ARIMA model are estimated. Order of AR and MA terms are determined by the observation of Auto Correlation Function (ACF) and Partial Auto

Correlation Function (PACF) plot, respectively. The coefficients of AR and MA terms and the variance of error signal are determined by Least Square method [159].

Step 3: Load Dispatchable Units and Demand Data: Collect specification data of dispatchable generation units including their cost parameters, minimum and maximum generation capacities, and upward and downward reserve capacities. Hourly forecasted demand profile is uploaded for one day generation scheduling of MG.

Step 4: Initialize Time Counter: Here 24 time periods are considered to solve MG generation scheduling under both solar and wind power uncertainty. Start with time $t = 1$.

Step 5: Forecast Wind and Solar Power Interval: To forecast upper and lower limits of wind and solar power, ARIMA model expressed in (6.1) is simulated for each time instant.

Step 6: Select Mode of Operation of MG: Select either grid connected or isolated mode for generation scheduling of MG. If grid connected mode is selected, go to next step. Otherwise, grid isolated mode is selected, go to Step 13.

Step 7: Load Market Prices: Load forecasted electricity market price for optimal generation scheduling of MG according to grid prices.

Step 8: Robust optimization Parameter Initialization: For grid connected MG' generation scheduling , the initial output of wind and PV solar power unit is set to be $W_t = W_t^{\max}$ and $PV_t = PV_t^{\max}$, degree of robustness is $\Gamma_k = N_t$ with incremental factor G^k, which takes increasing values in the interval [0, 1] in steps of 0.01, denoted as δ [158].

Step 9: Iteration Counter Initialization: The total number of iterations N_k is defined and the counter is initialized with $k = 1$.

Step 10: Uncertainty Characterization: The upper and lower limits of wind and solar power are obtained from Step 5 for grid connected MG generation scheduling. The wind and solar power are set in the iteration as $\hat{W}_{t,k} = G^k\left(W_t^{\max} - W_t^{\min}\right)$ and $P\hat{V}_{t,k'} = G^{k'}\left(PV_t^{\max} - PV_t^{\min}\right)$, respectively. Value of wind and solar power is limited in the interval $[W_t^{\max}, W_t^{\max} - \hat{W}_{t,k}]$ and $[PV_t^{\max}, PV_t^{\max} - P\hat{V}_{t,k'}]$.

Step 11: Solve Grid Connected MG Generation Scheduling Problem: Formulated MG scheduling problem for grid connected mode in Section 6.5.1 is solved and optimal results are obtained in the form of optimal scheduling of dispatchable units, optimal scheduling of upward and downward reserve, optimal Main grid to MG power exchange..

Step 12: Check Iteration Counter: If iteration $k \le N_k$, update the range of incremental factor G^k by step δ and repeat Steps 10 and 11. Otherwise, go to step 18.

Step 13: Robust optimization Parameter Initialization: For solving grid isolated MG generation scheduling problem using robust optimization based approach the initial outputs of wind and solar power unit are set to be $W_t = W_t^{\max}$ and $PV_t = PV_t^{\max}$, degree of robustness is $\Gamma_k = N_t$ with incremental factor G^k, which takes increasing values in the interval [0, 1] in steps of 0.01, denoted as δ [158].

Step 14: Iteration Counter Initialization: The total number of iterations N_k is defined and the counter is initialized with $k = 1$.

Step 15: Uncertainty Characterization: The upper and lower limits of wind and solar power are obtained from Step 5. The wind power and solar power are set in the iteration as $\hat{W}_{t,k} = G^k\left(W_t^{\max} - W_t^{\min}\right)$ and $P\hat{V}_{t,k} = G^k\left(PV_t^{\max} - PV_t^{\min}\right)$. Value of wind and solar power are limited in the interval $[W_t^{\max}, W_t^{\max} - \hat{W}_{t,k}]$ and $[PV_t^{\max}, PV_t^{\max} - P\hat{V}_{t,k}]$, respectively.

Step 16: Solve Grid Isolated MG Generation Scheduling Problem: Formulated MG scheduling problem for grid isolated mode is solved and optimal results are obtained in the form of optimal scheduling of dispatchable units, optimal scheduling of upward and downward reserve, optimal demand shedding.

Step 17: Check Iteration Counter: If iteration $k \le N_k$, update the range of incremental factor G^k by step δ and repeat Steps 15 and 16. Otherwise, go to next step.

Step 18: Check Time Counter: If the desired time period counter, i.e., 24, is achieved, go to the next step; otherwise, update *t=t+1* and go to Step 4.

Step 19: Published results: Show obtained optimal cost of MG along with optimal value of scheduled dispatch-able unit generation and reserves.

Step 20: End.

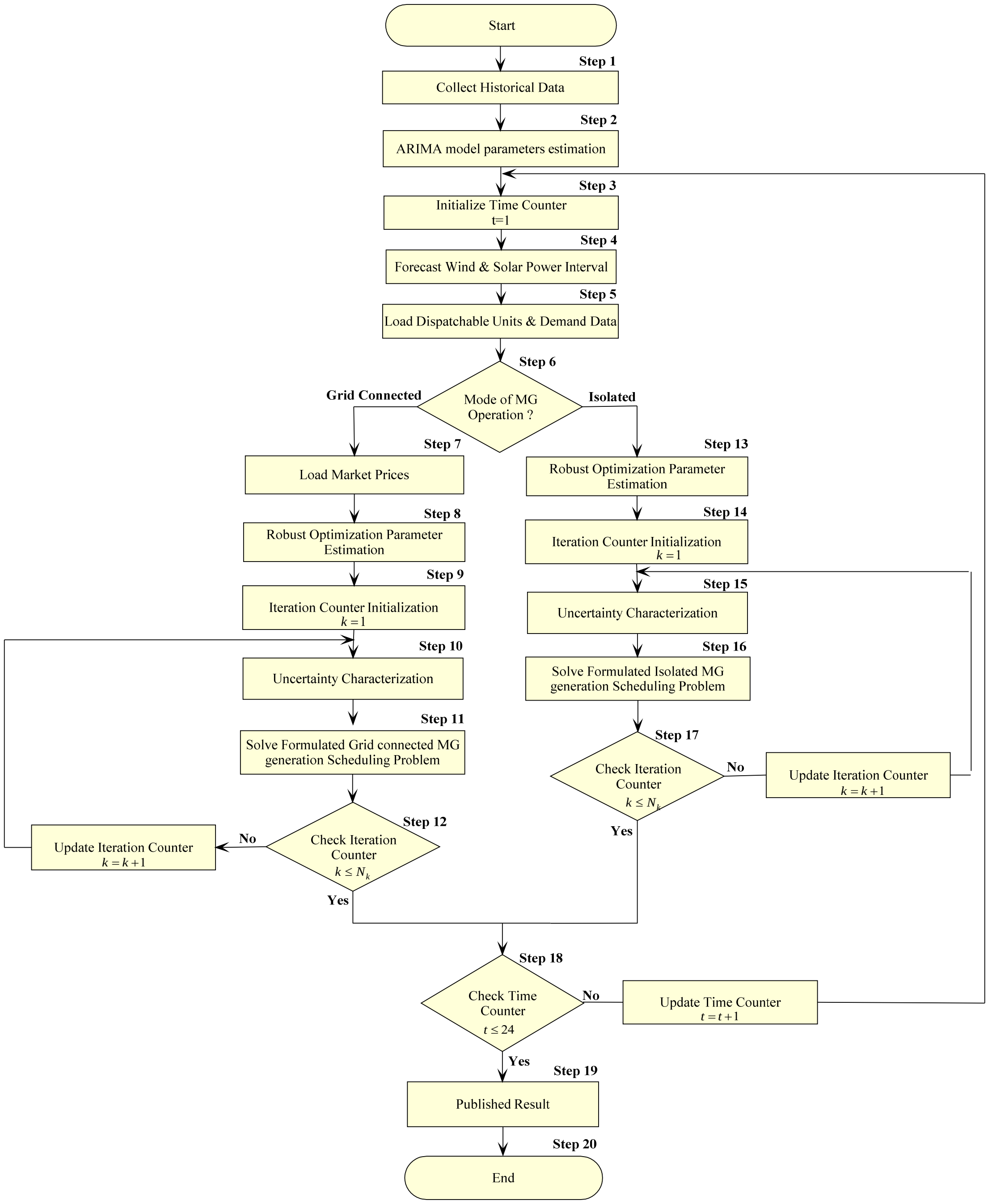

Fig. 6.2 Flow chart of proposed algorithm

6.7 Result and Discussions

6.7.1 Data

In this study, installed capacity of PV unit and wind units are considered as 200 kW and 1.34 MW respectively similar to previous chapters. Wind units consists of ENERCON turbine model whose parameters are given in detail in manufacturer database [160]. The historical wind speed data of the duration of 27.04.2006 to 08.06.2007, are used in this study from publically available database at Illinois Institute of Rural Affair, USA. [161]. For same site the historical solar irradiation data is obtained from NREL for same duration [162]. Along with renewable units, 10 dispatchable units are considered whose parameters are discussed in Table 4.1 (chapter 4). Hourly grid prices and demand profile are considered as Table 6.1.

Table 6.1: Daily Market Price and Demand Profile

Time (h)	**Price ($/kw)**	**Demand (pu)**
1	0.04836	0.784
2	0.04461	0.754
3	0.043695	0.739
4	0.044535	0.736
5	0.051765	0.756
6	0.069	0.814
7	0.08238	0.912
8	0.080115	0.977
9	0.08802	0.991
10	0.090045	0.997
11	0.09258	1
12	0.088725	0.997
13	0.0906	0.992
14	0.09054	0.989
15	0.08595	0.981
16	0.07908	0.971
17	0.07461	0.964
18	0.06552	0.956
19	0.062415	0.949
20	0.065775	0.945
21	0.07266	0.962
22	0.0609	0.950
23	0.05253	0.884
24	0.044925	0.822

Similar to earlier chapters, ARIMA model is used for modeling wind and solar power uncertainty. For uncertainty modeling using ARIMA model first the order of suitable ARIMA model on the basis of collected historical data is determined. Order of AR and MA terms are obtained by the observation of ACF and PACF plot. Forecasted limits of both wind power and solar power for 24 hours with upper and lower bounds are similar to previous figures discussed in Fig. 4.4 (Chapter 4) and Fig. 5.8 (Chapter 5). On a 95% confidence interval forecasted limits are used in proposed robust optimization based MG scheduling approach.

6.7.2 Case I: Microgrid Operation in Grid Connected Mode

In this case, MG operation in grid-connected mode is considered for simulation using proposed robust optimization method. Fig. 6.3 shows the scheduled power of dispatchable units in MG during grid connected mode of operation. From the figure, it can be observed that it will be beneficial to schedule maximum capacity from the unit with lower cost than the unit with higher cost.

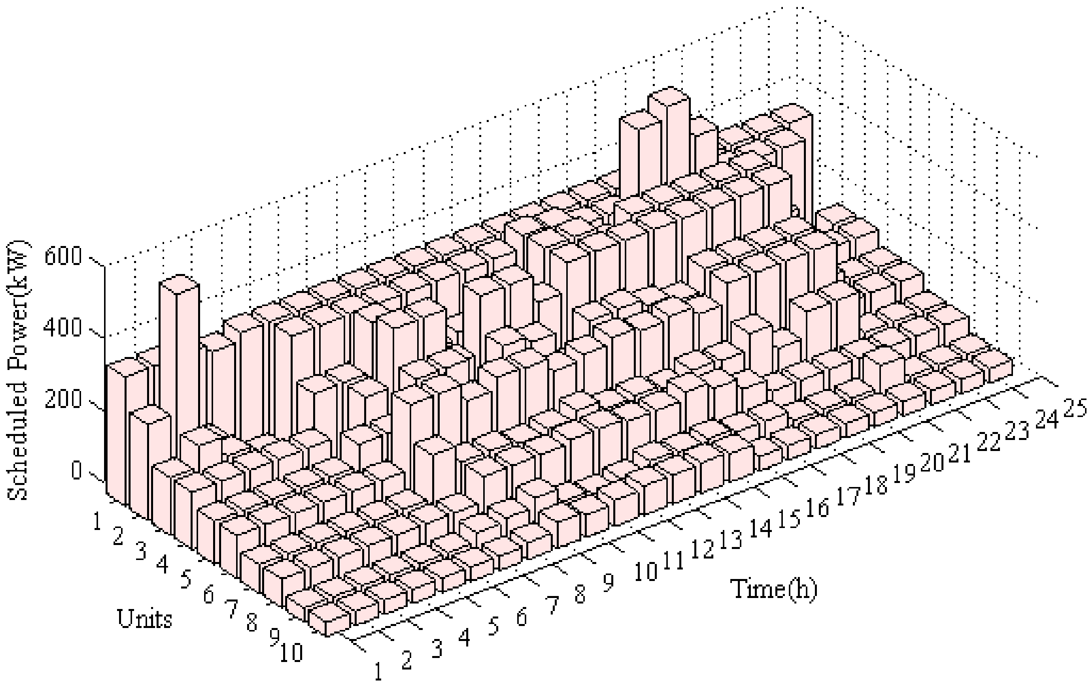

Fig. 6.3 Scheduled power of dispatchable units

Fig. 6.4 and Fig. 6.5 show the obtained scheduled upward and downward reserves of dispatchable units respectively. From the figures, it can be observed that any dispatchable unit is scheduled for one type of reserve requirement at any particular instant of time *t*. It can be observed that at the time of exporting the power the most costly dispatchable units are scheduled to their downward reserve while in case of importing the power these units are scheduled to their upward reserve.

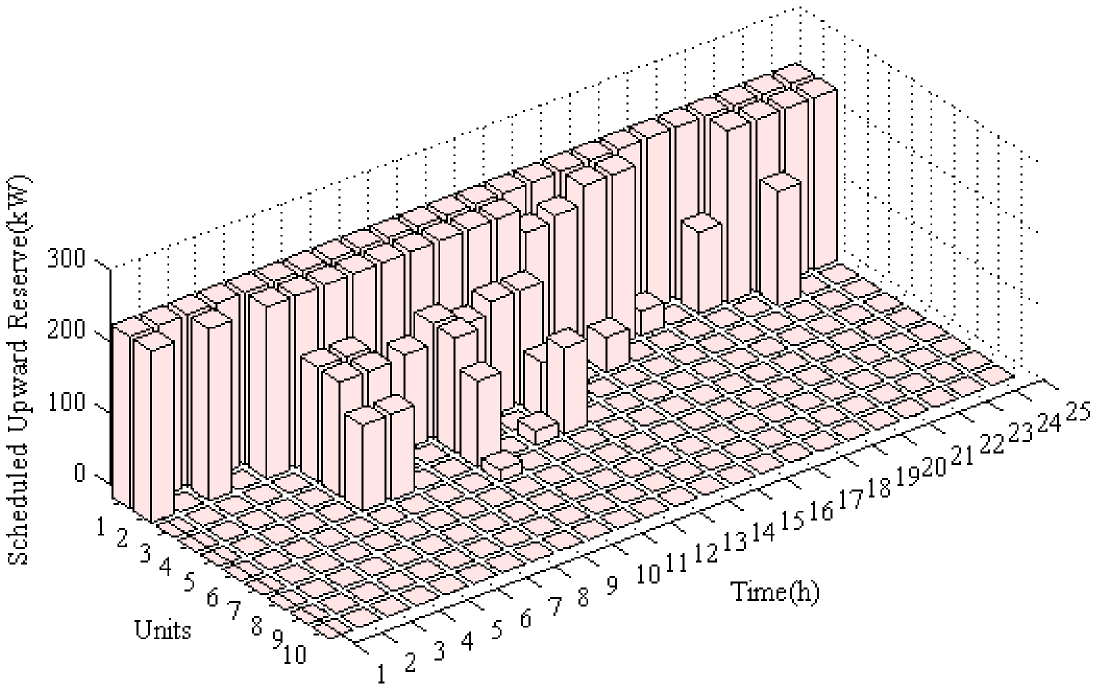

Fig. 6.4 Scheduled upward reserve

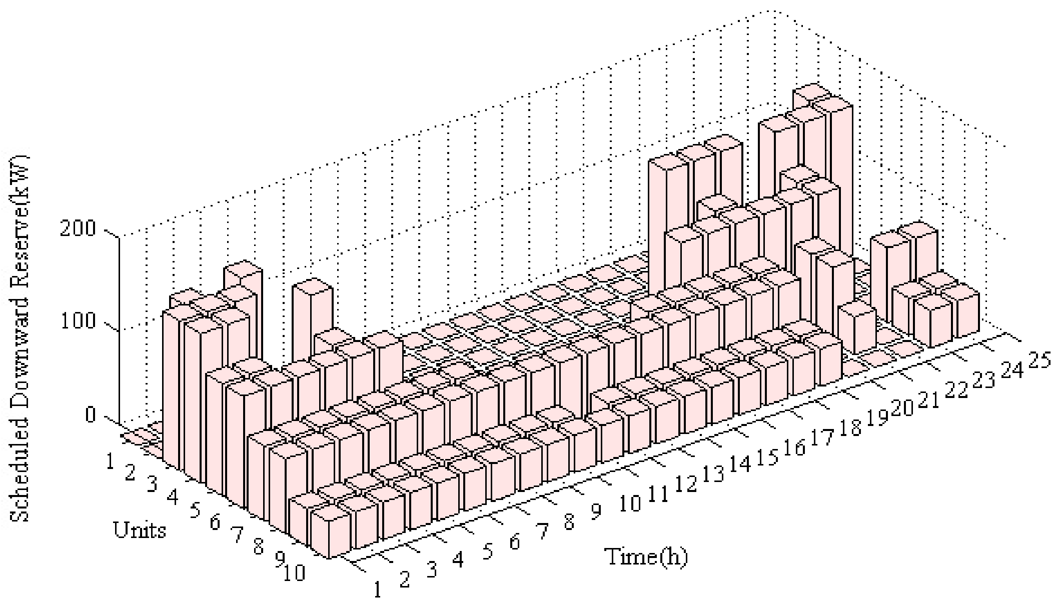

Fig. 6.5 Scheduled downward reserve

Fig. 6.6 shows power exchange between the main grid and the MG in grid connected mode. From the figure, it can be observed that from Hour 6 to 17 and 21, power is being exported to the grid and in remaining hours, power is being imported from the grid.

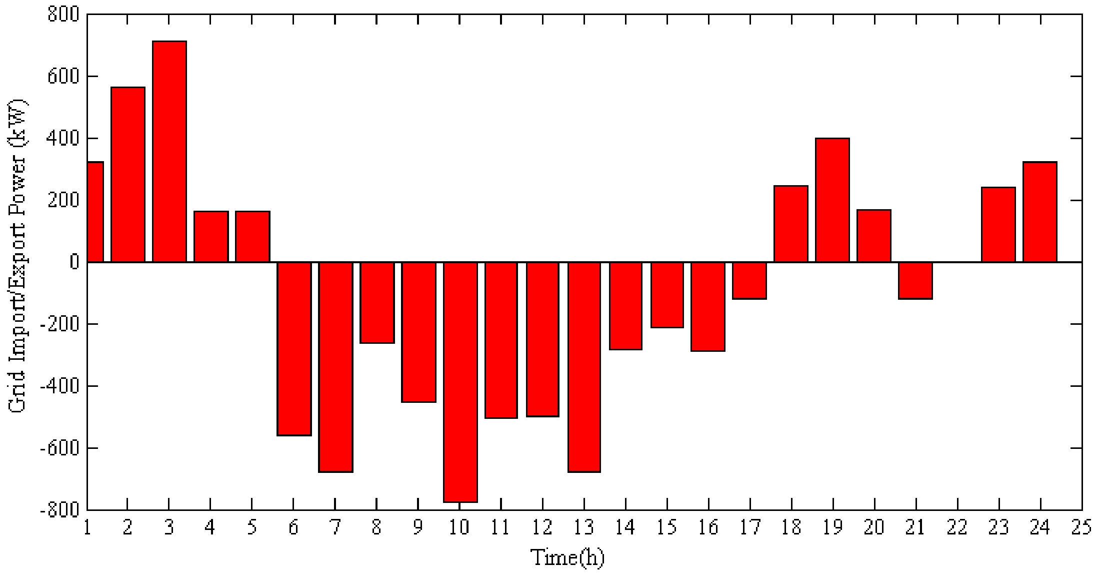

Fig. 6.6 Power imported/exported to/from grid

It can be concluded that, when grid price is higher, MG can export their reserve capacity to grid and vice-versa to reduce its operating cost.

6.7.3 Case II: Microgrid Operation in Grid Isolated Mode

Similarly, in this case, MG operation in grid-isolated mode is considered using proposed robust optimization method. The cost of demand shedding is considered as \$3.5/kWh according to Federal Energy Regulation Commission (FERC), Electric Tariff [164]. Similar to the previous case, Figs 6.7, 6.8, and 6.9 show the scheduled dispatchable unit power, upward and downward reserve capacity respectively using proposed robust optimization approach. Demand shedding in Case II is shown in Fig. 6.10. From the figure, it is observed that demand shedding event occurs in Hours 10, 16 and 24. The capacity of dispatchable units is fully utilized therefore leading to demand shedding. From Fig. 6.8 and 6.9, it can be visualized that MG can utilize its upward reserve capacity during peak demand to reduce demand shedding events.

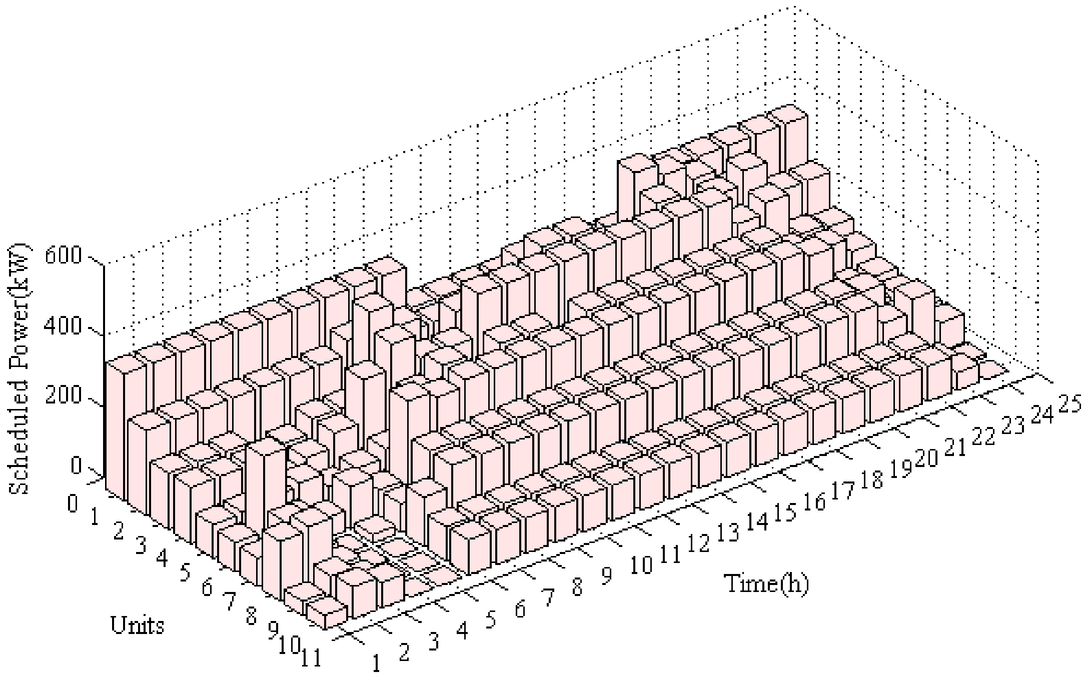

Fig. 6.7 Dispatchable unit scheduled power

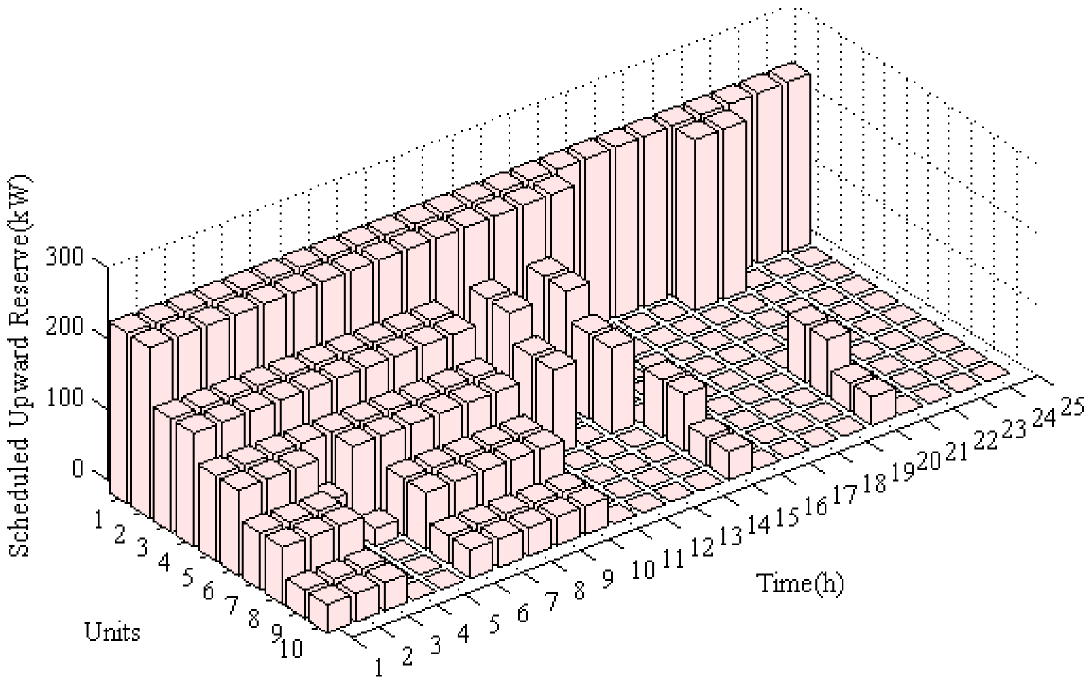

Fig. 6.8 Scheduled upward reserve

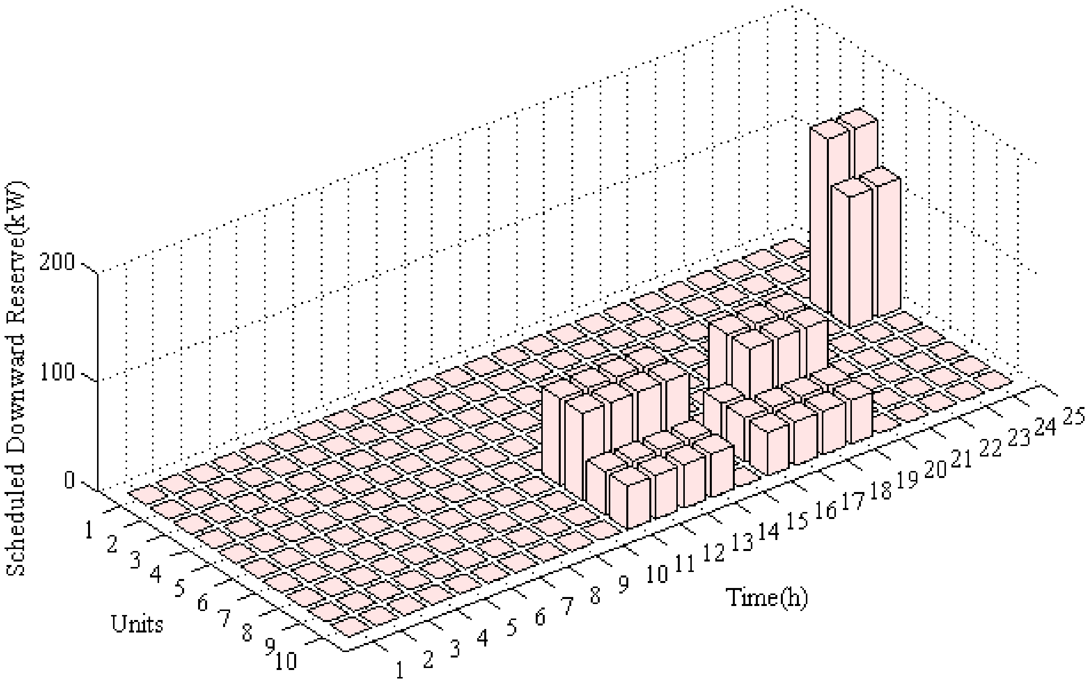

Fig. 6.9 Scheduled downward reserve

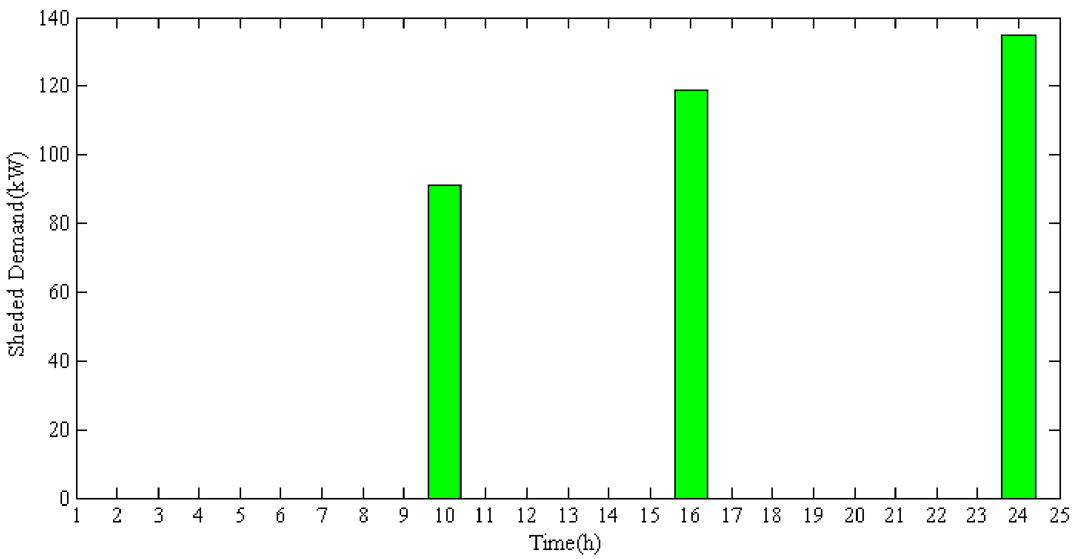

Fig. 6.10 Demand shedding

6.7.4 Discussion

A comparative analysis on MG operation is carried out. For this purpose, the same problem is simulated using deterministic and stochastic programming approach. In deterministic approach, wind power output is simply forecasted using ARIMA model and the forecasted value of wind power is considered to compute the scheduling of MG.

Table 6.2: Comparative Analysis of MG Daily Operation Cost

Approaches	Daily MG Operation Cost ($)	
	Case I	Case II
Deterministic	857.9346	1500.230
Stochastic	814.2935 (-5.08 %)	1284.09 (-14.40 %)
Proposed	747.7512 (-12.84%)	1195.191 (-20.33 %)

In stochastic programming approach, the wind power and solar power uncertainty is modeled by generating a large number of scenarios (i.e. 1000) and then reducing them into a smaller number of scenarios (i.e.25) as in [56]. The MG operation cost obtained using proposed robust optimization approach is compared with both deterministic and stochastic approaches as shown in Table 6.2. From the Table 6.2, it is observed that in both cases (i.e. Grid connected operation of MG and Grid isolated operation of MG) the daily operating cost is significantly lower in the proposed approach than any other existing approach. It is also observed from Table 6.2 that, The reduction in daily cost using proposed approach, in Case II (grid isolated mode) is higher than compared to Case I (grid connected mode). This is because in Case II, small reduction in demand shedding event results in large reduction in total cost of operation. From Table 6.2 in the proposed approach the cost of MG operation is higher in grid-isolated mode than in grid-connected mode. This is due the fact that the reserves and dispatchable units are fully utilized to meet the demand.

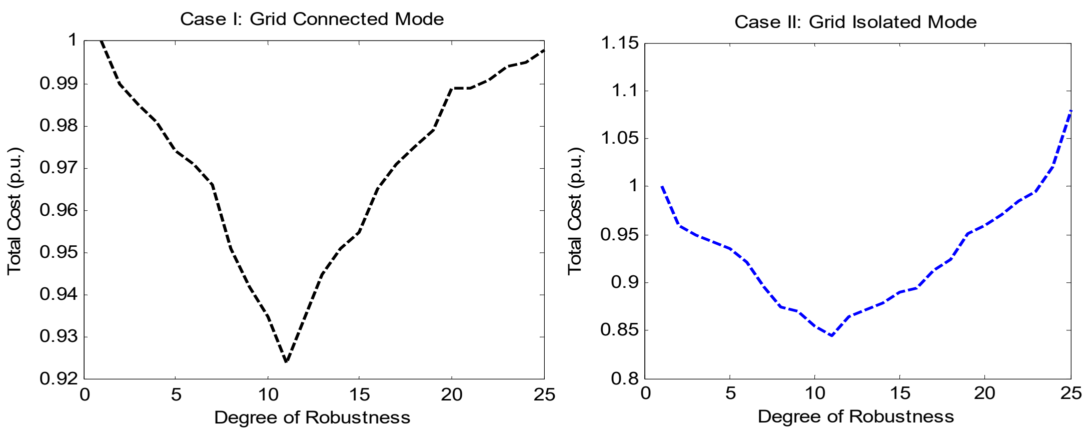

Fig. 6.11 Impact of degree of robustness on operational cost of MG.

The impact of degree of robustness on operation cost, in both cases can be evaluated by varying the degree of robustness from zero to 25 during simulation. The obtained per unit cost of operation are shown in Fig. 6.11. Per unit cost of operation, at any degree of robustness is obtained by dividing its actual value by the reference value, which represents the cost of operation at zero degree of robustness. From Fig. 6.11, it can be seen that the optimal value of degree of robustness is 12, where per unit cost of operation is minimum. At this degree of robustness, optimal condition is obtained because in this problem both wind power and solar power are considered as an uncertain parameter and its uncertainty is considered for 24 hours in case of wind power and 12 hours for the case of solar/PV power. This degree of robustness takes into account all possible deviations of the uncertain parameter for whole day. Additionally, at zero degree of robustness the cost of operation obtained using proposed robust optimization based approach is equal to the cost of operation obtained using deterministic approach.

6.8 Summary

A robust optimization based approach has been proposed in this chapter for optimal generation scheduling of MG in both grid-connected and grid-isolated modes. Both wind power and solar power uncertainty have been modeled through interval forecasting using ARIMA model. A comparative study on daily MG cost of operation using proposed robust optimization based approach with deterministic and stochastic approach has been performed. A significant reduction in cost of operation clearly shows strength of proposed robust optimization based approach in MG generation scheduling in the deregulated environment. The impact of degree of robustness on the cost of operation in both cases has also evaluated and compared with existing methods. The proposed approach will be more advantageous in incorporating different type of uncertainties such as demand uncertainty and grid price uncertainty. This work may also be enhanced by incorporating multi-micro grids, different type of consumers and considering different technical constraints.

Chapter 7

Conclusions and Suggestions for Further Work

T HIS chapter summarizes the thesis by outlining the major contributions and findings from the research. It further proposes some future works that can be done to improve MG generation scheduling problem.

CHAPTER 7

CONCLUSIONS AND SUGGESTIONS FOR FURTHER WORK

7.1 General

Penetration of renewable energy resources to the transmission and distribution power systems is continuously increasing throughout the world for mitigation of the present energy and environmental challenges in cost effective and sustainable manner. Among the renewable energy sources, penetration of the wind and solar power is increasing rapidly due to their widespread availability and mature technology. MGs are efficient way to integrate such renewable sources as Distributed Energy Resources (DERs) into the distribution grids. However, integration of such energy sources causes various technical and economic challenges in the operation of MGs, due to random nature of wind and solar power. Thus, energy management of MGs is complex decision making problem that is main focus of presented thesis. Complexity of MGs Energy Management System (EMS) is further increased due to restructuring of power system and market price volatility due to MG based EMS throughout the world. Therefore, development of efficient approaches for MG management under different uncertainties is required.

This research work attempts to develop efficient approaches for MG management with an objective to minimize the total cost of operation subject to different constraint parameters considering renewable power uncertainties. This addresses multiple concerns associated with generation scheduling problem of MG in both grid connected and grid isolated mode in the robust optimization framework. Effectiveness of proposed robust optimization based approach over stochastic and deterministic approach has been evaluated through comparative analysis.

A summary of main findings of the research work carried out in this thesis and future scope in this area are presented in subsequent sections.

7.2 Summary of Significant Findings

The research work undertaken in this thesis is initiated by developing an understanding of MG generation scheduling problem in both grid connected and grid isolated mode considering wind power uncertainty. A robust optimization based approach has been proposed for optimal generation scheduling of MG in both grid-connected and grid-isolated modes. Wind power uncertainty has been modeled through interval forecasting using ARIMA model. Further a comparative study on daily MG cost of operation using proposed robust optimization based approach with deterministic and stochastic approach has been performed. For this purpose, the same problem is simulated using deterministic and stochastic programming approach. In deterministic approach, wind power output is forecasted using ARIMA model and the forecasted value of wind power is considered to compute the scheduling of MG. The impact of degree of robustness on total operation cost of MG in both cases has also been evaluated by varying the degree of robustness. Per unit cost of operation, at any degree of robustness is obtained by dividing its actual value by the reference value, which represents the cost of operation at zero degree of robustness.

Obtained results, thus show a significant reduction in total operating cost, which clearly highlights the strength of proposed robust optimization based approach in MG generation scheduling problem in the deregulated environment. From the analysis based on impact of degree of robustness on the MG operating cost, it was observed that the optimal value of degree of robustness is 24, where per unit cost of MG operation is minimum. At this degree of robustness, optimal condition is obtained because the uncertainty of wind power is considered for 24 hours. This degree of robustness takes into account all possible deviations of the uncertain parameter for whole day. Additionally, at zero degree of robustness the cost of operation obtained using proposed robust optimization based approach is equal to the cost of operation obtained using deterministic approach.

This thesis further contributes by the enhancement of the earlier proposed robust optimization based approach for optimal generation scheduling of MG in both grid-connected and grid-isolated modes considering solar power uncertainty. A stochastic optimization based approach has also been proposed for optimal generation scheduling of both grid connected and isolated MG considering solar power uncertainty. For both stochastic and robust optimization based approaches, solar power uncertainty has been modeled through a number of scenarios and interval forecasting using ARIMA model, respectively. Further this research work contributes by presenting a comparative study on daily MG cost of operation using proposed robust optimization based approach with deterministic and stochastic approach has been performed. Obtained results show a significant reduction in cost of operation, which clearly highlights the strength of proposed robust optimization based approach over stochastic and deterministic approaches in MG generation scheduling in the deregulated environment. The impact of degree of robustness on the cost of operation in both cases has also been evaluated and compared with existing methods.

Finally, this thesis contributes by proposing a robust optimization based approach for optimal generation scheduling of MG in both grid-connected and grid-isolated modes considering wind and solar power uncertainties. Wind power and solar power uncertainties have been modeled through interval forecasting using ARIMA model. A comparative analysis on daily cost of operation of MG using proposed robust optimization based approach with deterministic and stochastic approach has been performed. A significant reduction in cost of operation in the proposed approach shows the strength of proposed robust optimization based approach in MG generation scheduling in the deregulated environment. The impact of degree of robustness on the cost of operation in both cases has also evaluated and compared with existing methods.

MG operation under renewable power uncertainties is a recent relevant and attractive area of research. The area lies at the confluence of multiple streams of knowledge, where electrical engineering, economics and regulation are merged. Such studies help to develop an understanding of inter-relation between issues arising from different fields of knowledge. The present work provides an understanding of MGs generation scheduling for both grid connected and isolated modes under renewable power uncertainties. MG generation scheduling problem considering wind and solar power uncertainties has been modeled in robust and stochastic optimization framework. Proposed work handles the multiple issues of MG generation scheduling problem that would continue to attract research interest.

7.3 Suggestions for Further Work

Research and development is a continuous process. Each step of research work opens many avenues for future research. As a consequence of the investigations carried out, a variety of issues pertaining to MG’s generation scheduling under renewable power uncertainties has been handled. Though, there are several inter-related issues to be resolved, some of them require urgent attention due to their wide implications. Following are some of the aspects, identified as promising area for future research work in the realm of study:

i. ARIMA model is used to model wind and solar power uncertainty through interval forecasting. Modelling of such uncertainties could be further improved by using advanced forecasting models and incorporating information about numerical weather prediction and seasonal variations.
ii. Demand and grid price uncertainty are modelled deterministically in the present work. Such uncertainties could be modelled similar to wind and solar power uncertainties.
iii. The presented robust optimization based formulation of MGs' generation scheduling problem can be enhanced by considering network constraints, transmission losses and security constraints in both DC and AC power flow framework.
iv. Energy storage is an important component of MGs operation particularly in grid isolated MG. Further MG generation scheduling problem could be modeled considering energy storage.
v. Proposed models and solution algorithms could be further illustrated by practical case studies based on large MGs in Indian power system.
vi. Consideration of multi-micro grids and different type of consumers could be considered as an extension to the work. This would be another important extension of proposed work.

Apart from these issues for future research, MG's generation scheduling problem under renewable power uncertainty poses several unique operation and planning challenges for MG operators as well as for system operators. These challenges create ample opportunities for researchers in this area.

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Publications from the Work

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Published Work

SCI Journal

1. R. A. Gupta and Nandkishor Gupta "A Robust Optimization Based Approach for Microgrid Operation in Deregulated Environment" in Energy Conversion and Management, Elsevier vol.93, pp 121-131,2015.

IEEE International Conferences:

2. R. A. Gupta and Nandkishor Gupta "Generation Scheduling at PCC in Grid Connected Microgrid" *IEEE* International Conference on Recent Advances and Innovations in Engineering (ICRAIE-2014), pp. 1-5, 2014.
3. R. A. Gupta and Nandkishor Gupta "Robust Microgrid Operation Considering Renewable Power Uncertainties" in *IEEE* National Power System Conference (NPSC-2014), IIT, Guwahati, India pp. 1-5, 2014.

Communicated (Under Review) Work

4. R. A. Gupta and Nandkishor Gupta "A Robust Approach for Microgrid Operation considering Solar Power Uncertainty" under review for Electric Power System Research, Elsevier.
5. R. A. Gupta and Nandkishor Gupta "Microgrid Operation Management considering Solar and Wind power Uncertainties" under review for Energy Conversion and Management, Elsevier.