- Optimization of Islanded Microgrid Operation -

- Dhruva Rudradev Krishnadas -

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भारतीय प्रौद्योगिकी संस्थान हैदराबाद

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Department of Electrical Engineering

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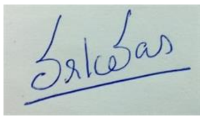

(Signature)

DHRUVA RUDRADEV KRISHNADAS

(– Student Name –)

EE12M1012

(Roll No)

Approval Sheet

This thesis entitled – Optimization of islanded microgrid operation – by – Dhruva Krishnadas – is approved for the degree of Master of Technology from IIT Hyderabad.

-Dr. Pradeep Yemula, Electrical Department -
Internal Examiner

-Dr. Phanindra Jampana, Chemical department-
External Examiner

30/6/2014

-Dr. Ketan P. Detroja-
Adviser

-Dr. Ravikumar Bhimasingu, Electrical Department-
Chairman

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Dedicated to

My family.

Abstract

Presently a lot of effort is being deployed in the area of microgrid development. In this aspect, the work presented here is in the direction of developing and coordinating various operational modules in an isolated microgrid system.

The work presented in this report looks at the prospects of incorporating a consumer side load-scheduling algorithm that works in conjunction with the unit commitment and economic load dispatch. The unit commitment and economic load dispatch are run a day in advance to determine generator outputs for the following day. From the microgrid operator point of view, the load side scheduling helps reduce the stress on the system especially during peak hours thereby ensuring system stability and security. From the consumers' point of view, the dynamic electricity prices within a day, which are a reflection of this time varying stress on the system, encourage them to endorse such a scheme and reduce their bills incurred. Owing to unpredictable weather conditions, running unit commitment and economic load dispatch in advance does not guarantee planned real-time generation in the microgrid scenario. Such variability in forecasted generation must be handled in any microgrid, while accounting for load demand uncertainties. To address this issue a load side energy management system and power balance scheme is proposed in this paper. The objective is to ascertain uninterrupted power to critical loads while managing other non-critical loads based on their priorities.

Nomenclature

MG	:	Microgrid
ESS	:	Energy storage system
DER	:	Distributed energy resources
REG	:	Renewable energy generation
DG	:	Distributed generation
PV	:	Photo-voltaic
WT	:	Wind turbine
FC	:	Fuel cell
MT	:	Micro turbine
GAMS	:	General algebraic modeling system
MIP	:	Mixed integer programming
MILP	:	Mixed integer linear programming
MINLP	:	Mixed integer non-linear programming
CAGR	:	Compound annual growth rate
MAPE	:	Mean absolute percentage error
MA_i	:	Moving average at the instant i
$\mathrm{O_i}$	:	Observation of load demand at the instant i
CMA_i	:	Centered moving average at the instant i
S_i, I_i	:	Seasonal and irregularity components at instant i
DS_i	:	Deseasonalized component at instant i
$U_{(1X2)}$	:	Coefficient matrix for linear regression

$\hat{U}_{(1X2)}$: Best obtainable coefficient matrix for linear regression

$F_{(NX1)}$: Column matrix of deseasonalized data

e : error between deseasonalized data and linear approximation

P : Projection matrix

K : Kalman matrix

t : Span over which offline optimization is performed

SL : Total number of schedulable loads

$K(j)$: Cost of unit power at time instant j

$P_{const}(sl)$: Constant power requirement of schedulable load sl

$x(sl,j)$: Status of schedulable load sl at time instant j

$d(sl,j)$: Start-up status of schedulable load sl at time instant j

$E(sl)$: Energy requirement of schedulable load sl

$T(sl)$: Time required to finish load/task sl

$T_e\ (sl)$: Earliest time limit imposed on task sl

$T_d(sl)$: Latest time limit imposed on task sl

CG : Total number of conventional generators

R : Total number of renewable sources

C : Cost function of conventional generator

C_r : Cost function of renewable generator

$u(i,j)$: Status of conventional generator i at instant j

$u_r(r,j)$: Status of renewable source r at instant j

$d(i,j)$: Start-up status of conventional generator i at instant j

$f(i,j)$: Shut-down status of conventional generator i at instant j

$S_{up}(i)$: Start-up cost of conventional generator i

$S_{dn}(i)$: Shut-down cost of conventional generator i

$P_{\min}(i)$: Minimum generation limit on conventional generator i

$P_{\max}(i)$: Maximum generation limit on conventional generator i

$P_{r,\min}(r)$: Minimum generation limit on renewable source r

$P_{r,\max}(r,j)$: Minimum generation limit on renewable source r at instant j

$P(i,j)$: Power output of conventional generator i at instant j

$P_r(i,j)$: Power output of renewable source r at instant j

$R_d(i)$: Ramp down constraint of conventional generator i

$R_u(i)$: Ramp up constraint of conventional generator i

$R_{r,d}(r)$: Ramp down constraint of renewable source r

$R_{r,u}(r)$: Ramp up constraint of renewable source r

$T_{on}(i,j)$: Up time of conventional generator i at instant j

$T_{off}(i,j)$: Down time of conventional generator i at instant j

$T_{r,on}(r,j)$: Up time of renewable source r at instant j

$T_{r,off}(r,j)$: Down time of renewable source r at instant j

$MUT(i)$: Minimum up time of conventional generator i

$MDT(i)$: Minimum down time of conventional generator i

$MUT_r(r)$: Minimum up time of renewable source r

$MDT_r(r)$: Minimum down time of renewable source r

$P_{inj}(n,j)$: Power injected at bus n at instant j

A_g : Incidence matrix of conventional generators on bus network

A_{gr} : Incidence matrix of renewable sources on bus network

A_l : Incidence matrix of loads on bus network

V : Per phase voltage of distribution network in volts

$\delta(n/k)$: Power angle at bus n or bus k

$R(n,k)$: Resistance of the line between bus n and bus k

$X(n,k)$: Reactance of line between bus n and bus k

$fl_{max}(line)$: Maximum active power transfer capability of line *line*

$P_{adj}(k)$: Adjustable load demand at instant k

$P_{curt}(i,k)$: Load demand of curtailable load i at instant k

$P_{crit}(k)$: Critical load demand at instant k

E_o : User specified battery energy state

$status(cg,k)$: Status of conventional generator cg at instant k

N : Number of curtailable loads

$P_{gen}(k)$: Power generation at instant k

α : Penalty for reducing adjustable load demand

$\beta(i)$: Penalty for disconnecting curtailable load i

γ : Penalty for using power sink

δ : Penalty for change in battery state from specified value

$\sigma(cg)$: Penalty for ramping conventional generator cg

$E_{\min}$: Minimum energy state of the battery

$\mathrm{E}_{\max}$: Maximum energy state of the battery

$P_{bat\text{-}\min}$: Minimum battery power flow limit

$P_{bat\text{-}\max}$: Maximum battery power flow limit

$P_{c\_\min}(\mathrm{cg})$: Maximum capacity of conventional generator cg

$P_{c\_\max}(\mathrm{cg})$: Minimum capacity of conventional generator cg

$P_{ramp\text{-}\min}(\mathrm{cg})$: Minimum ramping limit of unit cg in online problem

$P_{ramp\text{-}\max}(\mathrm{cg})$: Maximum ramping limit of unit cg in online problem

f : Fraction of adjustable load demand that is compromised

$u_{curt}(i,k)$: Status of curtailable load i at instant k

$P_{sink}(k)$: Power dissipated in the sink at instant k

$P_{bat}(k)$: Power output of the battery at instant k

$P_{ramp}(cg,k)$: Ramping support by unit cg at instant k

s : Sampling time of online algorithm in minutes

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Chapter 1

Introduction

The struggle between energy generation and energy demand has never been as vigorous as it is today. A large amount of energy generated today is produced from conventional energy sources. These include sources like petroleum, natural gas, coal etc. These resources are classified as extinguishable. This simply means that their availability is limited and that the regeneration of these sources is governed by very slow natural processes. The ever increasing power demand due to the boom in population and improved standard of living has further overtaxed these dwindling resources. It is also worth mentioning that the use of conventional energy sources seem even bleaker due to their effect on the environment. The environmental effect of burning of fossil fuels has been profound and nothing short of disastrous. The conventional fuels, such as coal and oil are greatly responsible for the grim state of the earth's protecting envelope-the atmosphere.

As documented in [1], on Oct. 31, 2011, the estimated world population reached 7 billion people, and it is growing at a rate of about 215,120 people per day. Since 2005, generating capacity has increased at a 3.2% CAGR, a relatively healthy rate of growth given the poor economic conditions that have existed in many parts of the world since 2008. Of particular note, however, is the growth of generating capacity in the developing world. In these countries, the rate of growth (5.3%) is almost twice that of the whole world and almost four times that of the 30 most developed countries, where electric generation is growing slowly, at a 1.5% CAGR.

In our country power development was first started in 1897 in Darjeeling followed by the commissioning of the Hydro-power station at Sivasamudram in Karnataka during the year 1902. Since 1990, India has been one of the fastest growing markets for new electricity generation capacity. The country's annual electricity generation has increased in the past 20 years by about 120 GW, from about 66 GW in 1991 to about 100 GW in 2001 to about 185 GW in 2011. In spite of being the 4th largest consumer of electricity, of the 1.4 billion people in the world who have no access to electricity, India accounts for over 300 million. To further aggravate the situation, more than 60% of the electric power that is generated is from thermal power plants and hence there is an urgent need to consider alternatives to existing sources of power supply that are renewable and also environment friendly. The only conventional form of power that is renewable and also environment friendly is hydro-electric power. Around 30% of electric power in India is generated from hydro-electric generation units but huge river valley projects are running into problems due to the vast tracts of land that are required for them and the imbalance they create in the ecology of the region. Around the world, the conventional power systems have been facing these problems and they have led to a new trend of generating power locally at distribution level by using non-conventional/renewable energy sources like solar photovoltaic cells, wind power, biogas, and natural gas. Other generation sources like fuel cells, stirling engines and micro turbines may also be used in contiguity with the above mentioned REG sources. These generation sources are integrated into the utility distribution network and termed as DERs. This term has been introduced to distinguish this concept of generation from the conventional centralized generation scheme. The DERs are usually smaller than the conventional units used for bulk production. They are also connected to the distribution networks which usually operate at low voltage or medium voltage levels. With the integration of these generation sources the conventional distribution network becomes an active network.

1.1 Active distribution networks

Power networks around the world are undergoing a transformation like never before. There is a major transformation from stable passive distribution networks to active distribution networks with DER penetration. The need to augment the conventional generation sources has further encouraged the integration of DG systems. Stand-alone and grid connected operation of DERs help in generation augmentation, thereby improving overall power quality and reliability. Also the physical proximity of the generation sources to the load helps circumvent wasteful transmission losses. The low operational costs and reduction of environmental pollution has been a key factor in preferring renewable energy sources. In compliance with carbon-emission mitigation policies like Kyoto protocol many countries have agreed to bring down the use of fossil fuels. The present 'fit-and-forget' strategy of DG employment needs to be changed in active network management. It should not only incorporate integration of DGs in distribution networks but also explore the avenue of demand side management. Such intelligent active distribution networks are bound to gain momentum. Several factors are in favour of the evolution of active distribution networks. These factors may include rising customer expectations of power quality, a need to establish a platform to incorporate REG sources and the need to better utilize and manage assets on the operator's part. Hence, in spite of the solid establishment of the conventional power system, these technical, economic and environmental benefits have led to the gradual development and integration of DERs. To facilitate this change a strong support infrastructure is needed. Also many economical and technical challenges have to be addressed.

1.2 Microgrid

Since power is generated at low voltage, it is possible to connect a DER separately to the utility distribution network or they may be interconnected to form what is called a 'MG'. A MG is essentially an active distribution network defined as an integrated power delivery system. A MG consists of a low-voltage network composed of loads, renewable energy (RE) sources, and DG units operating as a single controllable load connected to the utility or the macrogrid. MGs are usually designed to supply loads for small communities or industries. Due to the penetration of REGs and conventional generation sources these MGs are active distribution networks. The generation sources of a MG are provided with power electronic interfaces for enhancing the flexibility of the system. The key differences between the MG and the utility grid are as follows:

- The DGs in a MG are of much smaller capacity with respect to large generators in conventional power plants.
- In MG, the power generated at distribution level can be directly fed to the distribution network.
- The DGs used in MGs are normally installed close to the customer's premises so that heat/electrical loads can be efficiently supplied with satisfactory voltage and frequency profile and negligible line losses.

Also the MGs can operate in two modes namely - grid connected mode and islanded mode. From the utility point of view the MG can be seen as an electrical load that can be controlled in magnitude. The load could be constant, or the load could increase at night when electricity is cheaper, or the load could be held at zero during times of system stress. This ascertains its easy controllability and compliance with grid rules and regulations without hampering the reliability and security of the power utility.

In grid connected mode, a MG is connected to the utility grid and can engage in bidirectional energy transportation. Since MGs are owned and managed by groups other than utility, this provides an opportunity to engage in energy business. The MG can buy power from the utility in case of any energy deficiency. The MG can also sell power to the grid at a certain profitable price during peak hours when the utility grid is under stress.

In islanded or isolated mode of operation, the MG is disconnected from the utility and operated as a stand-alone unit. Although some MGs are designed to run in islanded mode, other MGs that are usually connected in grid connected mode may transfer operation to islanded mode of operation in case of certain contingencies like the occurrence of a fault or a scheduled maintenance or when it is simply more economically convenient to operate in stand-alone mode.

As specified in [2], the various technical and economic advantages of the MG are as follows:

- It is safe to say that with large REG penetration MGs will have a much lesser environmental impact than the conventional thermal power plants. There is bound to be a reduction in emission of gaseous and particulate pollutants due to a close monitoring of the combustion process. Physical proximity of the consumers to the DGs may help increase awareness of customers towards judicious energy use.
- Reduction of physical and electrical distance between generation and demand may help reduce feeder congestion and losses.
- Power quality has also been predicted to improve with this decentralization of supply. In the MG scenario, we can achieve better supply demand matching along with a suppressed impact of large scale transmission and generation outages.
- Cost savings is also affected through integration of multiple DG sets. As they are locally placed in plug and play mode, the transmission and distribution losses are drastically reduced or eliminated. When combined in a MG, the generated power can be shared locally among the customers and this again reduces the need to import/export power from/to the utility through long feeders. Also significant cost savings can be made by utilizing the heat produced during combined heat and power mode of various DG units.

- The development of market-driven operation procedures of MGs will lead to a significant reduction of market power exerted by established generation companies. The MGs also have the scope of providing various ancillary services which can be compensated with appropriate remuneration.
- The fact that MGs can operate in complete autonomy makes it suitable for supplying power to remote areas of a country where supply from the national grid system is difficult to avail due to geographical topology or frequently disrupted due to severe climatic conditions or man-made disturbances.

However, to enjoy these benefits, the smooth operation of the MG has to be ensured and this often demands proper planning. Planning may play an important part right from the inception of the MG when technicalities such as installed capacity, distribution capacity and siting of various installments have to be decided. Planning the day to day operation of the MG is also an important issue that can prove to be highly beneficial. Proper planning can facilitate savings in operational costs and may even help prevent overloads and failures. Hence, it becomes essential to perform load and REG forecasting. The output of such operations may be used to optimally co-ordinate the generation of the various DG sets.

1.3 Load forecasting

Load forecasts have long been recognized as the initial building block for all utility planning efforts.

The forecasts for different time-horizons are implemented in different operations within a MG. For example long-term load forecasts are more relevant in the planning of the MG. Short-term load forecasting becomes a key player in deciding day-ahead operation of the MG. With supply and demand fluctuating and weather conditions ever varying, load forecasting has become vitally important for utilities. Short-term load forecasting can help estimate load flows and thus help in the economical scheduling of available resources and prevention of possible overloading. Timely implementations of such decisions lead to improved system reliability and reduced cost of operation. Short-term load forecasts can also be useful in deciding the day-ahead real-time prices that the customers are charged. .

1.4 Optimization of MG operation

Electricity demand in a power system varies throughout the day, following approximate patterns that depend on regional characteristics, temperature, time of day, day of week and season of the year among other things. Due to this reason, it is not advisable to run all available units all the time, and it is necessary to decide in advance which generators are to startup, when to connect them to the network, the sequence in which the operating units should be shut down, and for how long. Decisions to change generator output to accommodate variation on hourly time scales are usually made by processes of unit commitment and economic dispatch [3]. Unit commitment establishes generator operating schedules in advance of the operating time and takes into account generator ramping capabilities and startup and shutdown costs. Unit commitment determines when to bring generators online and offline, and so is typically run one day in advance. Economic dispatch is the process of choosing the output levels for generators that are already online, with the objective of minimizing the total cost of meeting demand. Economic dispatch tends to be quite fast, and can be run within minutes of the operating time. Solutions to unit commitment and economic load dispatch may be obtained via multi-period optimization processes such as dynamic programming, lagrange relaxation, or mixed integer programming.

A great deal of money can be saved by turning off the units when they are not needed for the time. The problem is of particular importance for scheduling thermal based generation units. As for other types of DG units like photo-voltaic panels, their aggregate costs are negligible so that their on-off statuses are not that important. The basic economics of optimal investment and available technologies need to be applied to the operation of MGs. The accumulated knowledge of power system operation in grid scale needs to be optimally applied in distribution level grid, i.e. the MG.

In addition to the above mentioned supply-side optimization, demand side optimization is also a field of immense potential for cost reduction. Load side strategies like load scheduling can go a long way in reducing the strain on the systems during peak hours. Direct load control can also help improve system reliability. The MG paradigm can help explore opportunities and challenges associated with implementing fully responsive, non-disruptive control strategies for aggregated electric loads [4].

The unique aspects of MG economics need to be utilized properly for its overall optimal operation. Unlike conventional distribution systems, MGs can provide heterogeneous levels of reliability to end-users as per necessity. The operational constraints of a conventional power system may not be similar to that of a MG. For example, in MG the stochastic nature of REGs results in time varying unit constraints. Also, due to their large space requirement sitting of these REGs cannot be close to populated areas. Another example of a constraint unique to the MG concept is the constraint on generation of noise levels. Though these are ignored in conventional power systems, they are to be considered in MG operation especially if generation sources are seated near residential areas [2].

In grid-connected mode, the MG has the flexibility of behaving as a load or a generator from the main grid point of view. It could inject energy as a generator if its own consumers are satisfied and if the main grid is in need power. Conversely, the MG can also buy energy from the grid in case of any internal energy deficiency (when MG generation falls short of MG demand). It is important to incorporate this energy trade in the optimization problem formulation.

1.5 Motivation

As mentioned above the need for incorporating REGs into the generation framework has become vital. The deregulation in the electric power industry and pressing concerns about global environmental issues as well as the increasing energy consumption have led to an increase in installation capacity of DG sources and the stress on the system. While optimal operation of DG sets is an obvious objective, there is also a need to explore the potential benefits of load management. Smart loads that may scheduled can come a long way in reducing the peak load, the need for higher installation capacity and the losses in the distribution system.

Now a days, an increasing number of MG proposals have been targeting remote communities and non-integrated areas in developing countries and geographical islands [5]. Energy sources of these islanded or isolated MGs usually include distributed generators like micro turbine, fuel cell, etc. and/or renewable energy sources like solar panel farms and wind turbines, etc. These isolated grids form autonomous MGs that supply electricity and in some cases heat and hot water to residential and commercial consumers [6]. Optimal operation of an islanded MG is more of a necessity than a technological enhancement. One of the main concerns for these MGs is the problem of power balancing.

It is clear that, in order to serve its purpose, it is important to provide a coordinated decision-making process, so as to balance demand and supply coming both from the DG sources and the distribution network. However, it is important not to forget that the primary characteristic of load control is that it must deliver a reliable resource to the power system while maintaining a level of service commensurate with customer expectations. A healthy respect to this point is essential for any demand-side management ventures.

1.6 Objectives

The scope of this work is to develop and assemble the various operational modules of a MG in order to meet certain meaningful objectives.

The objectives of the work presented here are as follows :

- To use the platform established by modern communication technologies for useful interactions between the end user and the service provider.
- To provide an opportunity for customers to participate in operational planning so as to reduce incurred bills.
- To employ demand side actions that may reduce the stress on the system.

- To schedule the production of the various generation units to meet the load demand at a minimum cost while meeting all the constraints.
- To solve the problem of power balance under conditions of uncertain REG and load demand by tactfully employing load side elements and DG units.

1.7 Outline of thesis

This section has served as an introduction to the problem at hand. It has listed the basic properties of the MG. The following section will be showcasing the literature survey that has been conducted. The literature survey will serve as a glimpse into the nature of work that is currently going on in the MG paradigm. Sections have also been dedicated to describe the layout of the MG. This will introduce the reader to the nature and specifications of the MG on which the work documented in this report is conducted. Another section has been dedicated to the elucidation of the load forecasting module. Following sections will focus on the optimization strategy for cost reduction of DG sets considering various technical constraints. It will present a form of demand-side consumer participation that becomes relevant in the overall optimization problem. A section has been reserved for the issue of power balancing. Here a real time optimization problem has been formulated to tackle power balancing problem.

To sum it up, this work provides control algorithms that may be applied to any islanded MG irrespective of spatial distribution of loads and generators, number of buses, groups of loads etc. However, to elucidate the operation of the system we will be using a specific system which has been detailed in Chapter 3.

Chapter 2

Literature Survey

In the previous chapter, an introduction to the problem at hand was given. It showcased the shortcomings of the existing conventional grid. It spoke of how the existing power system is antiquated and inefficient in many ways. Furthermore, it was documented that the existing grid does not take full advantage of the advanced automations available today that could help prevent outages or help restore the system after outages. Also, the conventional grid did not speak of integrating renewable energy sources which have become an immediate necessity due to growing concerns of greenhouse gas emissions and shortage of non-renewable sources of energy. The introduction also dealt with some basic definitions and concepts unique to the MG paradigm, which has been gaining steam. This chapter consists of a brief literature survey which covers a sum-up of various research works focused on MGs, load forecasting, unit commitment and economic load dispatch and optimal demand-side management.

2.1 The institution of Microgrids

Ref. [7] served to provide an overview of the existing MG architecture and control mechanism. It also highlighted the importance of power and management strategies and described the potential approaches for market participation of the MG. As illustrated in Fig 2.1, the MG encompasses a portion of an electric power distribution network that is located downstream of the distribution substation, and it includes a variety of DG units and a host of electricity/heat consumers. Although the MG in the figure usually operates in grid-connected mode, it has sufficient capacity, controls and operational strategies to at least provide power to a certain fraction of the load when it is disconnected from the grid. The MG that shall be introduced in our study is one that is almost incessantly working in such an islanded mode of operation.

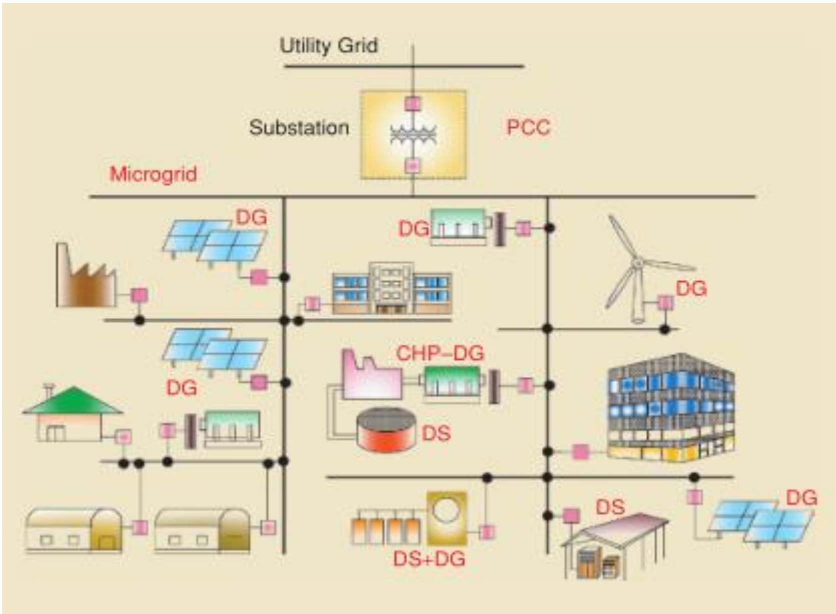

Figure 2.1: Typical MG layout including DGs and loads [7]

In [8], the ongoing research, development and demonstration currently in progress in the European Union, United States, Canada and Japan have been documented. The article follows a series of symposiums started in Berkeley, California on June 17, 2005, followed by a second in Montreal, Canada, on June 23, 2006 and by a third in Nagoya, Japan, on April 6, 2007. Presentations and other materials from these events are available online [9]. A particularly interesting example in Canada is the Ramea wind-diesel generator system in Canada. Traditionally, the remote and/or inaccessible parts of the Canadian landscape have been almost exclusively supplied by diesel generators. The Ramea project shown in Fig 2.2 is an example of islanded operation of the MG. It is an autonomous diesel-based system with medium wind penetration. While diesel remains ultimately responsible for supplying the load, the system can absorb the total wind power generated as long as the diesel generator are loaded to at least 30% of its rated capacity. Another magazine article that looks into design and testing work conducted on MGs around the world is the Ref. [10]. A trend has clearly begun to appear in the area of power delivery. Around the world several such active experiments are being conducted covering an array of technologies. As is evident from the ongoing research, MG topologies and operational configurations are being defined and design criteria established for all possible MG applications.

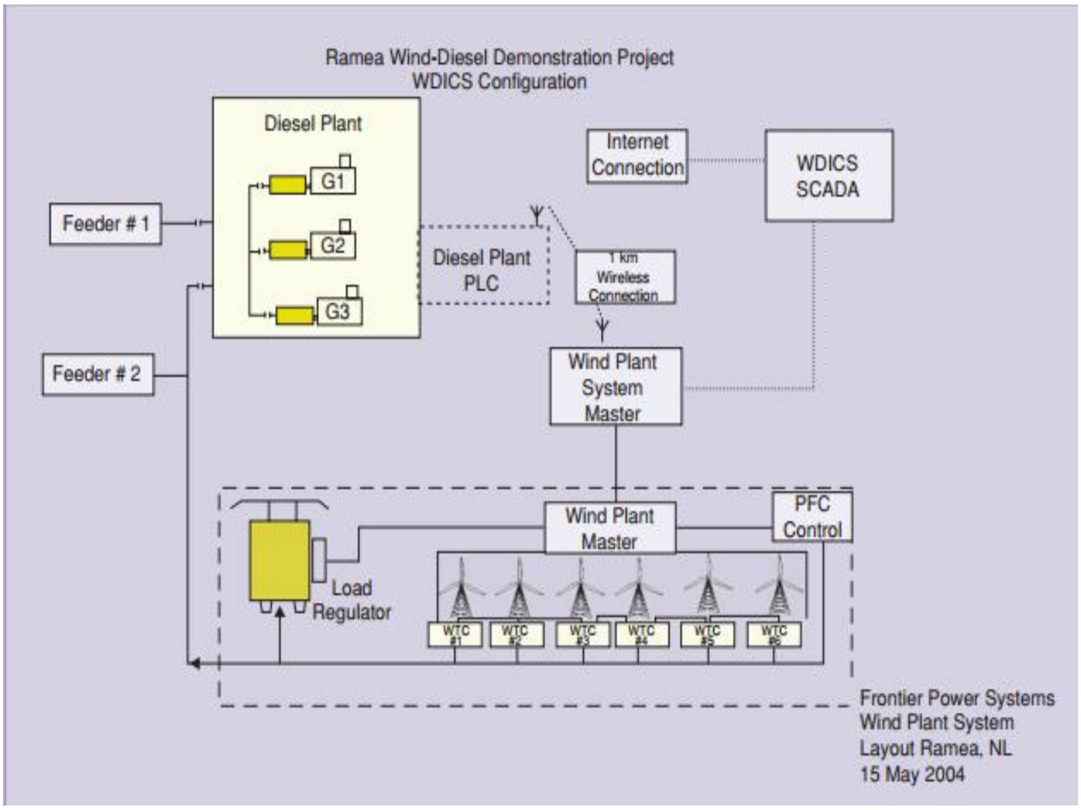

Figure 2.2: Ramea integrated wind-diesel project [8]

An established reference for the MG paradigm that has served as a benchmark in system-architecture is the IEEE Smart Grid conceptual model.

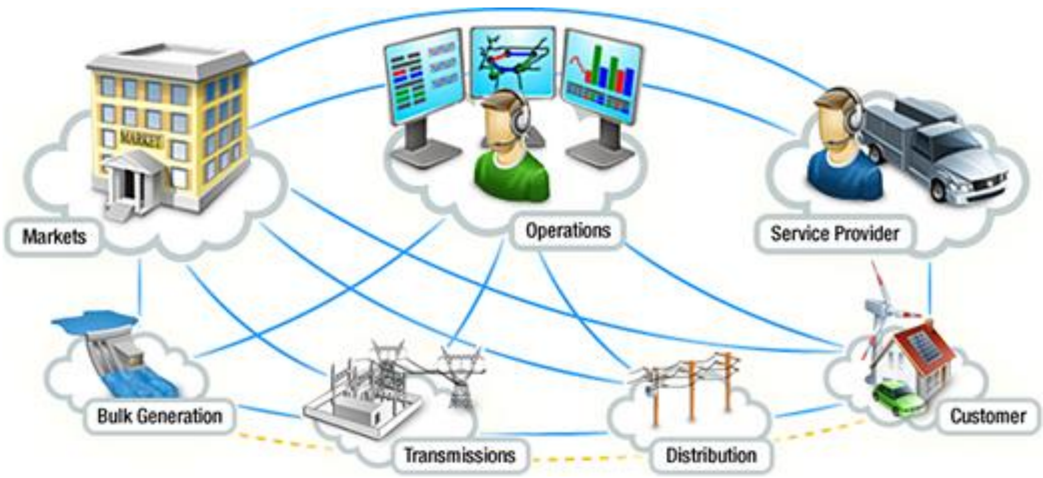

Figure 2.3: Smart grid conceptual framework [11]

The National Institute of Standards and Technology (NIST) smart grid conceptual model shown in Fig 2.3 provides a high-level framework for the smart grid that defines seven important domains: bulk generation, transmission, distribution, customers, operations, markets and service providers. It shows all the communications and energy/electricity flows connecting each domain and how they are interrelated. Each individual domain is itself comprised of important smart grid elements that are connected to each other through two-way communications and energy/electricity paths. These connections are the basis of the future, intelligent and dynamic power electricity grid.

2.2 Short term load forecasting

Short-term load forecasting has been useful in safe and economic planning operation of an electrical power system. It has been also used in start-up and shut-down schedules of generating units, overhaul planning and load management. One of the characteristics of electric power is that it cannot be stockpiled, that is, the power energy is generated, transmitted, distributed and consumed at the same time. In normal working condition, system generating capacity should meet load requirement anytime. If the system generating capacity is not enough, essential measures should be taken, such as adding generating units or importing some power from the neighboring network. On the other hand, if the system generating capacity is of surplus, essential measure should be taken too, such as shutting-down some generating units, or outputting some power to neighboring network. Load variation trend and feature forecasting are essential for power dispatch, layout and design department of power system. So it is no wonder that a lot of work has been conducted in the area of load forecasting.

Regression being one of the most popular statistical tools has been extensively used in this area. For electric load forecasting, regression has been used to model relationship of load consumption and other factors, such as weather, day type and customer class. Several research papers presented different regression models for next day peak forecasting. The model incorporated deterministic influences, such as holidays, stochastic influences such as average loads and exogenous influences such as weather conditions. Such an innovative use of linear regression based forecasting was used in Ref. [12].

Another popular technique used is the Time series model of load demand. Time series methods are based on the assumption that load data have an internal structure, such as auto-correlation or trend or seasonal variation. Time series models detect and explore such a structure. A host of time series models have been developed and used for the purpose of load forecasting; these include autoregressive moving average, autoregressive integrated moving average, autoregressive moving average with exogenous variables and autoregressive integrated moving average with exogenous variables. Ref. [13] describes a model based on autoregressive integrated moving average with exogenous variables for the implementation of short-term load forecasting in distributed power systems.

In [14], the group proposes an artificial neural network based short-term load forecasting scheme that considers electricity price as one of the main characteristics of the system load, demonstrating the importance of considering pricing when predicting loading in today's electricity markets. Historical load data from the Ontario hydro system as well as pricing information from the neighboring system were used for testing, showing the good performance of the proposed method. The traditional model in [14], which was altered to accommodate the effect of prices was an additive load demand model. This model was assumed to be combination of four components. The four components were as follows:

- Normal part of the load which is a set of standardized load shapes for each type of day that has been identified throughout the year.
- Weather-sensitive part of the load which has been coupled to the season of the year.
- Special-event part of the load which is associated with the occurrence of a special event leading to a significant deviation from the typical load demand.
- Random part of the load which is represented by a zero-mean white noise.

Another versatile load forecasting method was showcased in [15]. Here a set of rules have been formulated to serve as correction factors which help improve the accuracy of the base load prediction model. This was essentially framed as a multiplicative model. In some cases additive correction factors were also accommodated. The rules accounted for various weather non-sensitive parameters like season of the year, day of the week etc. It also considered a host of weather sensitive parameters like temperature, humidity, wind speed, solar insolation, cloud coverage etc. Rules were framed for selection of reference days. This detailed piece of research work showed results for both day-ahead predictions and week-ahead predictions.

Ref. [16] relied on the use of artificial neural networks for time-series prediction. Artificial neural network is a network, in which a large number of processing units make extensive exchanges, and is the abstract, simplified simulation of the human brain. The nature of the neural network used to predict is related to the size of the network parameters. Network structure includes the number of neurons, the number of hidden layers and connection methods. For a given structure, the training process is to adjust the parameters to obtain the basic contact approximation. The error is defined as the root mean square error, and the training process can be regarded as an optimization problem to minimize this error. Usually the available time-series data is divided into two parts: training data and test data. Training data is more than twice as much as test data in general. The most popular neural network model, the back propagation model was used for time-series prediction. Steps to implement the model were also explained in the paper.

In the analysis of predicting power load forecasting based on least squares neural network, the instability of the time series could lead to decrease of prediction accuracy. On the other hand, neural network and chaos theories parameters must be carefully predetermined in establishing an efficient model. In order to solve the problems mentioned above, the work in Ref [17] established the neural network and chaos theory was established. Chaotic time Series method was used to find the optimal time lag. Then the time series is decomposed by wavelet transform to eliminate the instability. Chaotic time Series method is adopted to determine the parameters of neural network. The authors took the multilayer back propagation neural network, widely applied for short-term load forecasting combined with one tool of soft theory – rough set to reduce the influence due to drawbacks of the back propagation method such as low training speed and susceptibility to noise and weak interdependency data through attribution reduction with rough set. The rough set had a number of advantages which included the fact that it could deal with incomplete, uncertain and ambiguous data and complex data containing a large number of variables. Moreover, it could abstract knowledge or patterns from data – to draw rules from the load index system composed of maximum and minimum of load as goal attributes and temperature, humidity and sunlight time as condition attributes by calculating the former to each latter and the significance of each condition attributes in the condition set so as to reduce condition attributes which contain bad data. After attribute reduction, the noise data and weak interdependency data were eliminated, so the influences they have on back propagation during the initialization, study and training process could be avoided.

Fuzzy set theory was introduced by Zadeh 1956. He demonstrated the application of the theory of fuzzy sets and fuzzy logic for control theory, treating input and signals as fuzzy instead of crisp values. Measured data and input signals are inevitably loaded with errors due to measuring instrument and human collection errors. The theory of fuzzy sets describes variables in a range of values rather than a single crisp value, thus enabling efficient description of unreliable and inaccurate data. However, fuzzy logic theory describes the relation between fuzzy data governed by imprecise propositions which were referred to as approximate reasoning by Zadeh. Electric load demand depends on a collection of seasonal, weekly, and daily factors of weather, as well as human habits and social behavior. Any parametric load model that strives to depict the dependence of the load on these factors is subject to inaccurate and imprecise representation, partly due to measuring instrument and human collection errors in the data involved.

In [18], the forecasting module was formed by combining the powers of neural network and fuzzy logic. Expert knowledge represented by fuzzy rules is used for preprocessing input data fed to a neural network. For training the neural network for day-ahead load forecasting, fuzzy if-then rules are used, in addition to historical load and weather data that are usually employed in conventional supervised learning methods. The fuzzy-neural network was trained on real data from a power system and evaluated for forecasting day-ahead load profiles based on forecast weather data and other parameters.

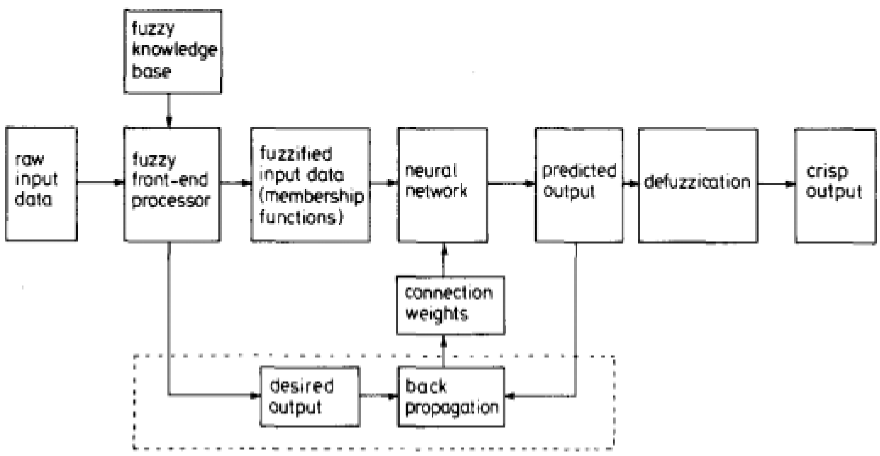

Figure 2.4: Overall fuzzy-neural architecture documented in [18]

Fuzzy sets and fuzzy-rule based inference combined with statistical methods like regression have also been used for solving the load forecasting model [19].

2.3 The need for optimization in MG

Optimization is all about maximizing or minimizing a cost function. When it comes to the system operator this translates into either maximizing profit or minimizing cost of production. Most of the power systems start off as monopoly. The monopoly provided the secure and relative cheap energy along with an uncontrollable bureaucratic organization. The deregulation philosophy broke the monolithic power sector into distinct parts, as generators, transmission, distribution, trader, etc. After the liberalization problems emerged in the supply, investment and price side. The state stepped back to control the uncontrolled free market. In the monopolistic case the organization prospers, the energy is supplied. If the company makes a loss, it will be covered by the state/owner. Normally the prices contain the reserves for long-term investment, some profit and the cost of the huge organization. In the deregulated environment the profit is the only driver. There is no investment without the hope of return and there is no energy supply if it is not profitable.

In [20], a comparison was performed on various load sharing techniques, which include linear, non-linear and dynamic power sharing techniques.

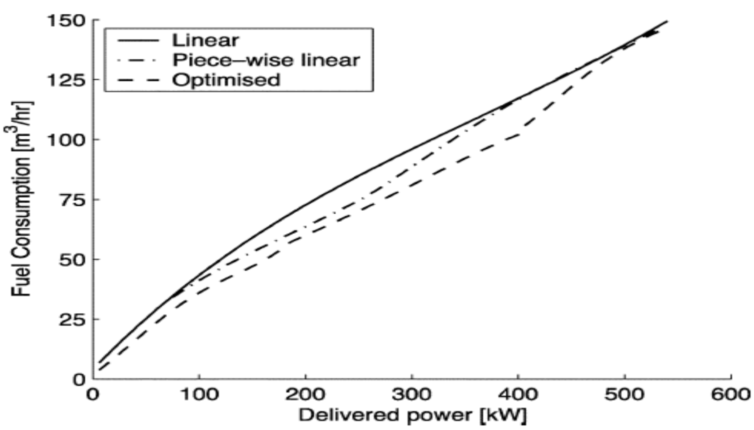

Figure 2.5: Fuel consumption comparison [20]

The linear power sharing technique was based on frequency droop scheme. In broad terms, this scheme uses a (small) change in the power bus frequency to determine the amount of power that each generator should put into the power bus. Also explained in the research article was the non-linear power sharing scheme. A nonlinear power-sharing scheme may be created by specifying a set of nonlinear power-deployment curves. However, they may be simplified to form piece-wise linear curves. The characteristics of each of these linear sections may be set according to a higher level regulating policy. For example, the policy could be to improve the efficiency of the system or to improve the dynamic response or to allow a particular reserve power within an operating range. The dynamic power sharing policy described in [20], allowed for the independent movement of the frequency intercept (y-axis intercept) of the different generators ergo facilitating a means to modify the amount of power each source contributes to the overall demand. The optimal power sharing scheme referred to in this paper points to a highly non-linear power sharing scheme which may be optimized for a specific purpose. Figure 2.5 shows a comparison of the fuel consumption of the generating units under these schemes.

In today's scenario of dwindling conventional resources and deteriorating environmental conditions, the need to conduct system operation with not just minimal fuel consumption but also with a minimum impact on the environment has become very important.

In case of optimization some parameters are set between predefined limits. Typically we look for the minimum or the maximum of the objective (or cost) function. In a simple case we have only one cost function; we call it single objective optimization, in other cases we look for the optimum of more values. This is the multi objective optimization. Such problems are dealt with when we are trying to minimize or maximize two or more quantities by performing optimization. Such is the case when the optimization module strives to reduce both the cost of production and the effect of generation on the environment.

2.4 Optimization for cost reduction of generator operation

A lot of work has been conducted on optimization in the MG paradigm. This work is not restricted to the operation of the MG. Although the work presented in this paper focuses on optimization of operation of the MG, Ref. [20] presented a dynamic programming approach for multi-objective planning of electrical distribution systems. In this planning, the optimal feeder routes and branch conductor sizes of a distribution system are determined by simultaneous optimization of cost and reliability. The multiple planning objectives are minimization of installation and operational cost, and also interruption cost. The first objective function consists of the installation cost of new feeder branches and substations, maintenance cost of the existing and new feeder branches, and the cost of energy losses. The second objective function measures the reliability of the distribution network in terms of the associated interruption costs for all the branches, which includes the cost of non-delivered energy, cost of repair, and the customer damage cost due to interruptions. In [21], the focus was directed on formulation of installation capacity optimization for determining the optimum capacity of a stand-alone hybrid generation system. The capacity determination of a hybrid generation system becomes complicated as a result of the uncertainty in the renewable energy together with load demand and the nonlinearity of system components.

The following paragraphs will brief the reader on research studies performed on the optimization of MG optimization specifically. The optimization of operation of a MG is posed as a MILP problem in [22]. The system setup explained there included small DG sets, storage devices and controllable loads. The MG considered there was not an isolated one and avenues were made to enable energy trading with the upstream utility. The significance of this work lies in the simple co-ordination of generator operational costs, grid-trading costs and demand side management costs in the objective function. In this work no complex heuristics or decompositions were used and the full model was formulated and solved in an efficient way using

CPLEX solver. The advantage of this commercially available solver is that it is based on a branch and bound algorithm and hence when it terminates, the solution is known to be globally optimal.

Ref. [23] deals with an optimization problem where the objective function is to maximize the expected profit enjoyed by the DG set owners over a period of time by coordinating the use of heuristic methods and dynamic programming. In [24], the objective is again to reduce the operational cost of a hybrid energy system. An economic index named levelised unit cost of electricity has been identified here. This is a function of the installation cost and the capital recovery factor. The operational cost of a unit is the product of this index and the real power output of the unit.

In [25] a multi agent system was introduced for controlling the MG along with a classical distributed algorithm based on the symmetrical assignment problem for achieving the optimal energy exchange between the production units of the MG and the local loads, as well the main grid. Distributed algorithm based on the symmetrical assignment problem for the optimal energy exchange between the production units of the MG and the local loads, as well the main grid.

In [26] the optimization problem involves minimization of a multi-objective cost function, which involves minimization of operational cost of the MG along with reduction of environmental effects. Although, they seem to be conflicting objective functions, in most conditions the operational costs of eco-friendly REGs are less. However, weight coefficient N is proposed to coordinate the proportion of generating cost objective and environmental cost objective. Ref. [27] also addresses a similar multi-objective optimization problem. A fuzzy system was used to choose one solution from the set of pareto optimal solutions obtained by solving the problem, that will satisfy all the objectives to some extent. Ref. [28] is yet another optimization problem where the objectives are to reduce operational cost and NO_x emission levels. Weightings were tested to develop the trade off relations between the two objective functions. A fuzzy set was used to make the final decision.

In [29], the concept of optimization was extended to reactive power as well. The control variables in the real power optimization scheme continued to be the power outputs of the various generation units with the objective of minimizing the cost while that for the reactive power bus voltages, shunt capacitance/reactance and transformer tap positions were taken as the control variables with the objective of minimizing cost/losses. These two sub problems were solved simultaneously using particle swarm optimization.

Ref. [30] also deals with two sub problems, one dealing with minimizing the overload and the other dealing with minimization of generation cost. Ref. [31], serves as a review paper on the various multi-objective optimization problems formulated and solved in this area with focus on various objective functions (conflicting and otherwise) and constraints.

The Smart energy management system proposed in [32] includes power forecasting module, ESS and optimization module. The smart management of storage system and economic dispatch of the DG sets are bundled up into a single object optimization problem. The entire problem is solved using a derivative of the genetic algorithm.

In [33] a hierarchical control strategy with three distinct levels has been proposed. As seen in Figure 2.6, the three levels are as follows

- local micro source controllers and load controllers
- MG system central controller
- Distribution management system

Here the distribution management system may control the operation of multiple MG establishments.

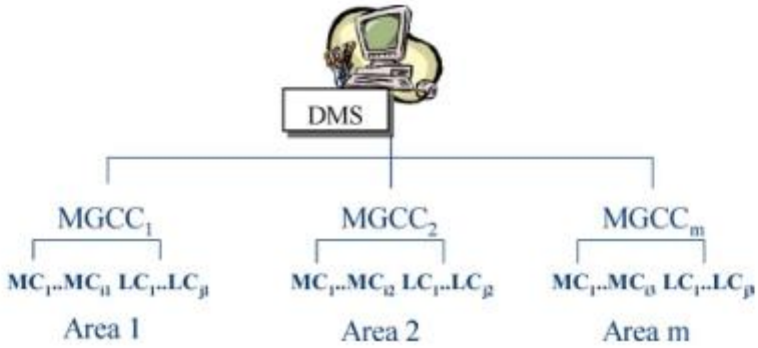

Figure 2.6: Hierarchical control strategy [33]

In [34], local measurement of the MG load demand, wind power Generation and Solar Power generation as well as weather conditions serve as prerequisites to forecast the RE power generation and MG load demand. An artificial neural network ensemble is developed to predict 24-h-ahead photovoltaic generation and 1-h-ahead wind power generation and load demand. Here, a fuzzy logic expert system is used for battery scheduling. The proposed approach can handle uncertainties regarding the fuzzy environment of the overall MG operation and the uncertainty related to the forecasted parameters.

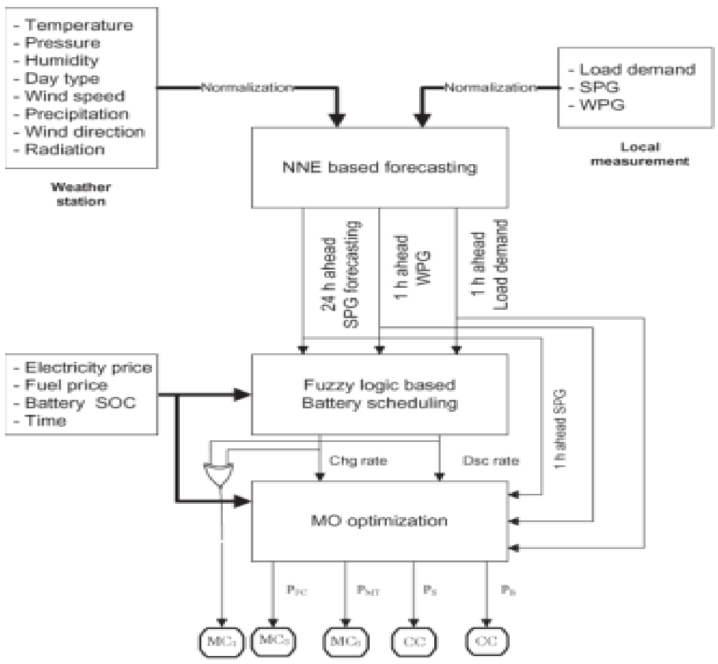

Figure 2.7: MIEM control structure based on fuzzy battery scheduling [27]

Due to stochastic nature of REG sources and invariable variations in forecasted and actual Load demand values, MG optimization will be incomplete without addressing the issues of inherent uncertainty. In [35], spinning reserve constraints have been formulated to address the issues due to uncertainty in forecast of load demand and prediction of wind velocity and irradiance. The spinning reserve is the extra generating capacity that is available by increasing the power output of generators that are already connected to the power system. For most generators, this increase in power output is achieved by increasing the torque applied to the turbine's rotor. It should also be noted that spinning reserve may positive or negative, i.e. the output of an online generator may be increased or decreased. In [28], it is assumed that variations in predicted load and output of REGs are within certain limits. Another interesting feature in [35], are the flow limit constraints. These additional constraints further limit the inter-area power flow. Another paper which has addressed the security constraints associated with line overloads is Ref. [36]. Here the operational optimization with security constraints is performed with minimum deviation from the operational schedule without security constraints.

In [37], the stochastic loads, probabilistic WT models and probabilistic PV models have been modeled. The spinning reserve amount is determined by maximizing the total profit while considering the unreliability of units and uncertainties caused by non-dispatchable units and loads. In order to reduce the computational burden, various uncertainties are aggregated and rounded to an equivalent distribution. The optimization is solved by MILP. The optimizer minimizes the total operational cost along with expected energy not served.

An optimization algorithm was proposed in [38], which provided generation economic dispatch minimizing simultaneously the cost of primary reserve services, while ensuring the secure operation of the power system in the presence of disturbances. The primary reserves included security margins as constraints and these were extracted from decision trees developed for a number of pre-specified contingencies. The decision tree creates a chain rule path, which leads to secure or insecure state of the system, following the pre-specified disturbance. Each set of rules that leads to a secure state is recorded as constraints set. The economic dispatch algorithm is executed for each pre-specified disturbance and each constraint set leading to a secure operating state of the system.

As seen in Ref. [32], an ESS can also enter the unit commitment and economic load dispatch optimization problem. There the main objective of the storage module was to maximize the net present value. The net present value is determined through an economic analysis, over the storage module lifespan, considering its capital, operating and maintenance costs and parameters on which they depend, and energy purchase and sales costs. An equality constraint of the ESS periodical behavior was formulated to ensure that it does not dry up or overcharge. In fact the constraint dictates that it returns to its initial state of charge condition at the end of the day.

Ref. [39] is yet another siting of the ESS in the cost minimization optimization problem. Here a knowledge based energy system is proposed for the scheduling of an ESS installed in a wind-diesel isolated power system. The main aim of this controller is to minimize the cost of operation of the system over a given period of time. The wind and load data are independent and considered as uncontrollable inputs. The controller must then schedule the diesel generation as well as the charging and discharging of the ESS in order to minimize the cost of operation, hour by hour, based on rules implemented in its knowledge base. Here the controller is tested and validated for both conditions, specifically when the diesel generator is in continuous and discontinuous operation.

2.5 Demand side management strategies

Traditional demand-management programs use direct load control, where portions of system load are under control of the utility. Electricity loads are well suited to providing reserves because they can respond very quickly (in many cases the ramp rate is constrained only by the speed of the communications network). For some time, system operators have used nonselective load shedding (i.e., disconnecting entire regions from the grid) as a measure of last resort to avoid system collapse.

Selective load shedding (i.e., disconnecting customers or specific customer loads based on prearranged agreements), on the other hand, has much more potential from the perspective of customer acceptance because noncritical loads can be targeted for shedding. Loads with significant energy storage capacity (thermal or electrical) are especially well suited for providing spinning reserve. This is because the time required to restore the system, and allow loads to return to normal, is often short enough that the end-use function may not suffer [40].

Ref. [41] presents a scenario in which a large number of end users possess controllable loads. Specifically speaking, the controllable loads used in their work were thermostatically controllable loads. Control strategies employed here may involve complete disconnection of the load for a particular period of time or a change in the thermostat settings. It was also assumed that only one control strategy can be applied to a particular load in a particular control window. The strategies introduced here involve reduction of load over a specified time via direct control of these controllable loads. This is done so by the formulation of an optimization problem.

In Ref. [42], the controllable load is modeled in such a way that they can be scheduled to meet the REG. Here causal scheduling schemes are explored. Loads such as electric vehicles and thermostatic loads require a certain amount of energy over time. Here electric vehicles and thermostatic loads are clubbed together as their flexibility can absorb variability in REG. Both [43] and [44] also deal with load scheduling. In the former, the objective is to better utilize REG by shifting part of the load to periods with higher renewable generation. The electricity consumption of aggregated smaller loads which were referred to as deferrable loads, were shifted over time, and used (in aggregate) to compensate the random fluctuations in renewable generation. A real-time distributed deferrable load control algorithm was introduced to reduce the variance of aggregate load (load minus renewable generation) by shifting the power consumption of deferrable loads to periods with high renewable generation. At every time step, the algorithm minimizes the expected variance to go with updated predictions. In the latter the scheduling scheme is designed to follow a load curve while reducing the peak to average ratio. Here the objective was to reduce the sum of squared errors between the aggregate scheduled load and a specified target load profile.

A lot of work has also been performed on rescheduling loads so that the stress on the system during peak hours may be reduced. This is sometimes termed as peak shaving. However, at first glance this might appear as a bleak plan formulated by the system operators to get their way around to enhance the reliability of their infrastructure. Hence, such rescheduling plans are laden with incentives to endorse customer participation. Efforts have even been made to better understand customer reaction to such rescheduling schemes. Ref. [45] investigates load-shifting behavior in response to dynamic pricing among both customers experienced with and new to demand response.

The smart grid opens the possibility for demand-response programs. In order for end-users to obtain the maximal benefit from DR programs, low priority load should be shifted from the high energy price periods or should be operated at reduced power levels. To that end, Ref. [46] proposed a linear programming model, which reschedules the household appliances at relatively lower energy price periods to minimize the total energy cost in a day. Since this kind of rescheduling of a task creates inconvenience to the users, their model considered this inconvenience as disutility and modeled it as a function of delay. A disutility factor is defined which is a user defined adjustable parameter. Its value depends on the user's tolerance of delay per appliance. It plays the same role as assigning weights to the disutility function. The constraints related to different power consumption patterns of different loads and the constraints imposed by the utility were considered to effectively model the appliance power consumption.

A lot of work on energy demand rescheduling to reap financial benefits in the MG/ smart-grid paradigm was adopted from smart homes. Ref. [47] is one such example where an event driven smart home controller is used to facilitate automated demand side management while enabling consumer economic savings. Here the optimization problem formulated is a binary linear programming problem, the output of which specifies the best time to run appliances in the smart household, under a virtual power threshold constraint, taking into account real power threshold and the forecast of consumption from non-schedulable loads. The optimization is performed each time the system is triggered by proper events, in order to tailor the controller action to the real-time dynamics of a household. Here different scenarios of controller operation have been analyzed. These include cases of home domain overload management, scheduling under a time of use tariff and demand side management. Fortunately, with the advent of the MG concept, projection of these strategies into a distribution level system has become simpler in comparison to the proposition of employing these strategies meaningfully in the conventional power grid.

The changes in ways to control loads, coupled with increased penetration of renewable energy sources, offer a new set of challenges in balancing consumption and generation. Increased deployment of energy storage devices in the distribution grid will help make this process happen more effectively and improve system performance. Various applications of energy storage devices have been looked into in references [48, 49]. As seen in [50, 51] energy storage acts an energy buffer by ensuring that inherent variations in REG are compensated; thereby reducing voltage fluctuations and improving power quality. The planning, sizing and sitting of energy storage devices are also looked into as an optimization problem. In the above mentioned references batteries have been presented to have a good market potential in peak-load deduction (peak shaving) at substations, storage of off-peak wind energy, power smoothing for large solar arrays and in providing ancillary services (frequency regulation, black start capability). Ref. [52] also shows the automatic power balancing by the use of an energy storage operating in DC voltage control mode. This DC voltage controller was designed using a typical PI regulator. Also separate load curtailment policies were discussed in case the power balancing was not achieved due to insufficient power rating or energy rating of the energy storage. In AC systems as well ESS are used to mitigate power fluctuation and assist in voltage and frequency regulation.

Demand side management techniques are becoming increasingly popular in tackling the issue of power balancing particularly when there is a large penetration of renewable DG sets, whose output levels are uncertain. In Ref. [53], the responsive loads have been centered as the potential solution to the reliable integration of wind generation into the power system. Loads can often respond to operator request almost instantaneously unlike DG units which may require time to produce a significant change in output. Also, since these loads are spatially distributed throughout the grid they provide the opportunity to devise spatially precise responses to contingencies. The level of spatial and temporal flexibility that comes with considering loads as a means of providing a certain kind of spinning reserve especially to support the growing penetration of REG units has been the crux of this work. Here the issue of uncertainty in a REG penetrated environment has been addressed by real time management of generator output along with the smart control of load values. Here the amount of reserves to be dispatched and/or the amount of load to be reduced is determined in such a way that the costs incurred are minimized. The real time balancing operations depend heavily on the day-ahead commitment schedule and real time conditions. However, it is worth mentioning that works such as the one in Ref. [54] has focused on the use DG ramping to deal with excursions in demand and prices. Here the ramping of DG sets beyond the traditional ramping rates to meet these wild excursions has been explored. Since this could affect the life of the rotor, a ramping cost has been formulated to address this.

Ref. [55] tells us about the long term effects of demand side control and management on system. Effects on capacity margin and transmission upgrades were demonstrated. These demand response resources as they were termed were also seen as an alternative to additional generation. The benefits of these applications in terms of reduced number of loss of load events as a result of voluntary load curtailments were also shown.

Chapter 3

System Overview

This section will introduce the reader to the system at hand. Following sections will present the general layout and components of the MG along with the different technical specifications of these entities. The MG essentially consists of a network of interconnected DG units and loads; all of which will be presented in this chapter.

3.1 Network Layout

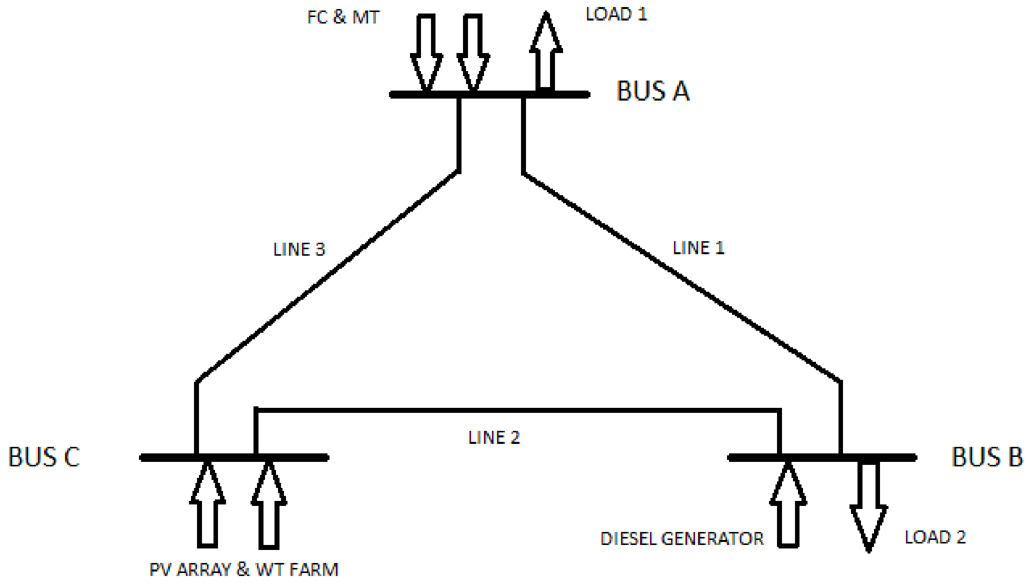

Figure 3.1: Layout of the test network

As stated earlier the MG presented here is nothing more than an interconnection of DG sets catering for the needs of the local loads connected to the network. Figure 3.1 depicts the network that is used in this work. The distribution voltage level of this MG is 415 V. As is seen from the figure a FC and a MT are connected to bus A. A diesel Generator is connected to bus B. Both the renewable sources, namely the WT and the PV panels are connected to bus C. The REGs are connected farther away from the loads as they require a lot of sitting space. The two sets of loads have been connected to bus A and bus B. Each load set further consists of various types of loads which have been classified. These will be described in a later section. For the case of my institute that has been considered in this work, the load readings from institute panel-1 and institute panel-2 have been clubbed to form LOAD-1 and the meter readings from the hostel and workshop panels have been aggregated to form LOAD-2.

Table 3.1: Specifications of power lines

Line	Reactance/km (Ω/km)	Resistance/km (Ω/km)	Length of the line (km)	Power rating (kW)
1	0.1	0.2	9	60
2	0.1	0.2	10	60
3	0.1	0.2	8	60

Table 3.1 showcases the various specifications of the connecting lines that have been used in the MG. The lines have been numbered in accordance to the Figure 3.1.

$$A_g = \begin{bmatrix} 1 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} \quad A_{gr} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 1 & 1 \end{bmatrix} \quad A_l = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix}$$

The above three matrices represent the incidence of the three conventional DG sets, the two REG sources and the two loads respectively on the three bus network.

3.2 Generator specifications

There are two types of DG units available in this MG setup namely- the dispatchable and the non-dispatchable DG set.

Dispatchable generation refers to sources of electricity that can be dispatched at the request of power grid operators; that is, generating plants that can be turned on or off, or can adjust their power output on demand. The main reasons for which dispatchable power plants are needed are:

- Load matching - slow changes in power demand between, for example, night and day, require changes in supply too, as the system needs to be balanced at all times.
- Peak matching - short periods of time during which demand exceeds the output of load matching plants; generation capable of satisfying these peaks in demand is implemented through quick deployment of output by flexible sources.
- Lead-in times - periods during which an alternative source is employed to supplement the lead time required by large coal or natural gas fueled plants to reach full output; these alternative power sources can be deployed in a matter of seconds or minutes to adapt to rapid shocks in demand or supply that cannot be satisfied by peak matching generators.
- Frequency regulation or intermittent power sources - changes in the electricity output sent into the system may change quality and stability of the transmission system itself because of a change in the frequency of electricity transmitted; renewable sources such as wind and solar are intermittent and need flexible power sources to smooth out their changes in energy production.
- Backup for base-load generators - Nuclear power plants, for example, are equipped with nuclear reactor safety systems that can stop the generation of electricity in less than a second in case of emergency.

Non-dispatchable generation is a term for an energy system that cannot be expected to provide a continuous output to furnish power on demand, because production cannot be correlated to load. Hydrocarbon-based or nuclear power plants are dispatchable, but solar and wind power are non-dispatchable (without some added component for storage), since the supply of sunlight or wind is periodic and cannot be predicted and controlled. Hence they fall under the category of non-dispatchable generation. In general the only types of renewable energy which are dispatchable are biofuel, biomass, hydropower with a reservoir, and concentrated solar power with thermal storage.

In the following sub-sections the reader will find a few notable characteristics about the dispatchable and non-dispatchable DG sets used in this test MG. The term dispatchable generation will be used interchangeably with the term conventional generation.

MTs are very popular as generating units in DG systems and as energy producers in combined heat and power systems. At present they hold maximum prospect to be used as micro sources for MGs. They are small and simple cycle gas-turbines with output ranges varying from 25 to 300 kW. They are designed to operate for extended periods of time and have little maintenance. They can run on most commercially available fuels. Here we will be considering one working on natural gas and another diesel based generator.

The FC serves as a micro-source by directly converting the energy in a fuel into electrical energy. It consists of two electrodes (an anode and a cathode) and an electrolyte which is retained in a matrix. The operation is similar to that of a storage unit except that the products and reactants are not stored, but are continuously fed to the cell. Fuel is fed to the anode and the oxidant is fed to the cathode. The two streams are separated by an electrode-electrolyte system. Electrochemical oxidation and reduction take place at the electrodes to produce electricity. FCs have several advantages over mechanically rotating DG units. Due to higher efficiency and lower fuel oxidation temperature, FCs emissions are minimal. Also since they are free from moving parts, they are free from vibrations and noise. A single FC produces an output voltage of barely 1V, hence they are connected in series and parallel depending on desired rating to form a FC system.

The two non-dispatchable units used in this work are a WT energy conversion system and a photo-voltaic panel system. The main part of the wind energy conversion system is the WT which converts wind energy into electrical energy. The wind turbine captures the kinetic energy of the wind and transfers it to the induction generator through the gearbox.

Solar PV systems are yet another eco-friendly micro-source. They are especially attractive because solar energy is free and inexhaustible. However, they do have certain disadvantages such as high installation cost and low energy efficiency. Studies have shown that smaller solar farms are more cost effective than large ones. This further indicates the effectiveness of connecting this generation directly into the customer circuits at low voltage distribution networks.

The following tables hold the specifications of the conventional DG units. The cost function of these DG units is modeled as a quadratic function $C(P) = \mu + \phi P + \lambda P^2$

Table 3.2: Conventional generator cost parameters

DG unit	μ (Rs)	ϕ (Rs/kW)	λ (Rs/kW^2)	Startup cost (Rs)	Shutdown cost (Rs)
FC	5	3.5	0.02	15	15
MT	7	4	0.05	17	17
Diesel Generator	18	5	0.08	21	21

Table 3.3: Conventional generator operational parameters

DG unit	P_{max}(kW)	P_{min} (kW)	Ramp up (kW/h)	Ramp down (kW/h)	MUT (h)	MDT (h)
FC	65	24	45	45	3	3

MT	60	24	45	45	3	3
Diesel Generator	100	35	60	60	3	3

The above two tables show the various economic and technical parameters of the conventional generators. In Table 3.3 $P_{\max}$ and $P_{\min}$ represent the maximum and minimum generation levels of each generator. Ramp up and ramp down constraints restrict the magnitude of rise or fall in generator level during consecutive intervals. MUT and MDT represent the minimum up time and minimum down time of the generators.

The REGs are connected to bus C of the bus 3 of the MG. Their forecasted production is assumed to be available in this study. Fig 3.2 shows the predicted production of these non-dispatchable generation sources.

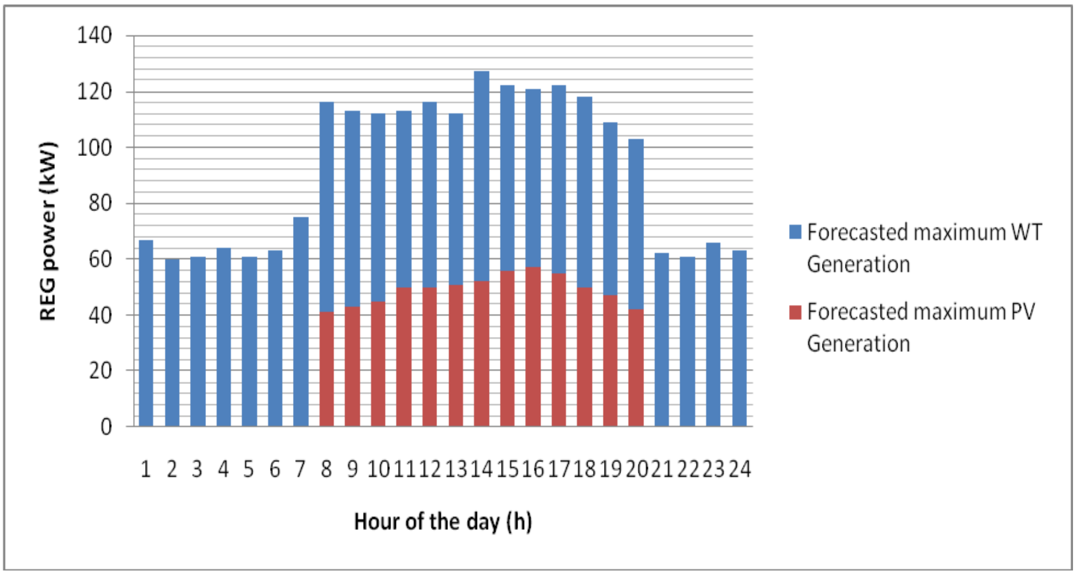

Figure 3.2: Maximum REG production levels

However, the power from the REGs is restricted by their installation capacities (Table 3.4). The specifications of the installed REGs are as follows. The parameters discussed in Table 3.4 and Table 3.5 are analogous to those discussed in Table 3.2 and Table 3.3.

Table 3.4: REG cost parameters

DG unit	α_r (Rs)	β_r (Rs/kW)	γ_r (Rs/kW^2)
PV array	18	0.5	0
WT	23	1.15	0.025

Table 3.5: REG operational parameters

DG unit	P_{max}(kW)	P_{min} (kW)	Ramp up (kW/h)	Ramp down (kW/h)
PV array	50	0	--	--
WT	75	16	40	40

3.3 Load specifications

Although the loads are aggregated from the unit commitment point of view, the loads at bus A and bus B are categorized as critical loads, lower priority curtailable loads and lowest priority adjustable loads.

The critical loads include the power supply to hospitals, banks, indoor lighting etc. The critical loads of the MG are prioritized above all other loads. The local power supply and ES systems should ensure that the critical loads are met at any cost. Since they hold the highest priority these loads are catered to even at the expense of the other classes of loads.

The curtailable loads are prioritized just below the critical loads. As mentioned earlier, these loads are fed from separate feeders. Curtailable load control is analogous to on-off control. These loads can either be connected or disconnected for a particular time interval. From optimization algorithm perspective, curtailable loads add as many binary variables as the loads themselves. Such large number of binary variables result in combinatorial explosion and such optimization problems are hard to solve. One may consider simplifying the problem by lumping all the curtailable loads as a single entity. However, such simplification is not considered in this paper. Furthermore, these arms have been provided with their own priorities (penalties for disconnection) in the objective function formulation. These priorities include energy constrained loads, i.e. they will fail to provide their primary-end use function if they do not receive sufficient amount of energy. Loads such as refrigerators, escalators in shopping complexes and segments of street lighting can be included in the curtailable loads section.

The adjustable loads include clusters of low priority loads whose curtailment lead only to a compromise in the quality of comfort experienced by the end user. These include classes of loads which respond quickly to control commands. Heating and cooling loads like water heaters and air-conditioners can be categorized into adjustable loads. To further elucidate the operation of these loads, let us take the example of a central air conditioning system in a building that is subjected to this scheme. Power usage of the system is a minimum when ambient temperature is to be maintained. Maintaining temperatures other than the ambient temperature require more power. The larger the difference between the ambient temperature and set point the more power is required. Any compromise in set point can result in power savings. A mere change in the set points of these devices can be seen as a means of load control.

The practicality of dispatching these prioritized loads depends much on how they are modeled. Various priority loads discussed above can be further elucidated through a couple of examples. First let us consider an example of street lighting. While modeling the street lighting load we can have one in every three street lights belong to critical load. The other two can belong to two different sets of curtailable loads. Since one in every three street lights belong to a critical load we can ensure that even in case of large disturbances, the streets will still be lit to a certain extent. Next, consider modeling air conditioners for large buildings. The power required to maintain the temperature of a centrally air conditioned office building at 25 °C will be much less compared to the power required to maintain the temperature at 21 °C. Additional power required to lower the temperature of the building to 21 °C for end user comfort can be treated as an adjustable load which can be compromised (given low priority) to maintain power balance. The same ideas can be extended to the operation of heating loads such as water heaters. Thus in case studies presented later, the air conditioners and water heaters have been considered as purely adjustable loads.

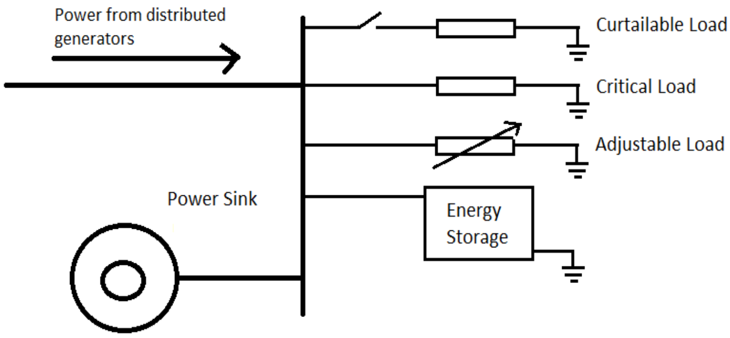

Figure 3.3: Load side layout

As seen in the above figure, along with the above mentioned loads there also exist an energy storage unit and a power sink. Having an ESS (i.e. battery) gives the added advantage of leveraging stored energy to maintain power balance and to minimize the curtailment of priority loads. Further, batteries can also help achieve fault tolerance against failure of a small generation unit. Batteries provide opportunity for the operator to store energy when it is in excess and use the stored energy to compensate for increased load demand or decreased energy generation. As stated earlier, excessive discharging or charging of a battery can adversely affect battery health. Therefore, certain constraints on charging and discharging rate, as well as on the maximum and minimum energy level of the ES have been modelled. The details of which are given in Table 3.6. The battery power is considered positive when it is charging and it is negative when it is discharging. Here $P_{bat-\max}$, $P_{bat-\min}$, $E_{\max}$ and $E_{\min}$ are maximum and minimum battery power flow rates and energy levels respectively.

Table 3.6: ESS Specifications

$P_{bat\text{-}max}$ (kW)	$P_{bat\text{-}min}$ (kW)	E_{max}(kWh)	E_{min} (kWh)
20	-20	50	10

The power sink is seen as an energy dump. It is where all the excess energy that is generated is dumped. Since this is a wasteful practice, the proposed strategy will minimize the use of the power sink. However, in the case of system operation without energy storage, it becomes imperative to use this provision to maintain power balance and mitigate over-voltages.

3.4 Sum of all components

Figure 3.4 brings forth all the different functional blocks in the MG and assembles them in the IEEE smart grid conceptual model [11]. The entire architecture of the MG has been layered into computer & IT layer, communication layer and physical layer. In the figure the green, blue and red arrows stand for information transfer, control stream and power flow respectively. As seen in the figure, information about past load is used to determine the day-ahead forecast and also set day-ahead prices which are a reflection of the stress on the system. This function falls under the market operations section. This information about the dynamic day-ahead prices is made available to the end-users. The customers may choose to schedule a set of loads in order to help alleviate the stress on the system while reaping some economic benefits. This optimal scheduling is done one day in advance and in the accumulator the load prediction is modified in accordance to the customer's choice. Communication channels are made available between the customer and this module to transfer information regarding the customer's decision and the load subjected to scheduling. Along with the REG forecasts, the predicted value of load helps plan the generation schedule for the following day. Control signals from the unit commitment and economic load dispatch module govern the generation levels of the DG sets in the MG.

However, owing to inevitable mismatches in generation and demand, the real-time load balancer module has been constructed. As the name suggests this module operates as an online control over load values. It has also been provided with control of the supporting ESS. Options for sudden ramping of online generator are also governed by this module. These interactions between the operator and the end user which is an integral part of demand side management come under the service provider domain.

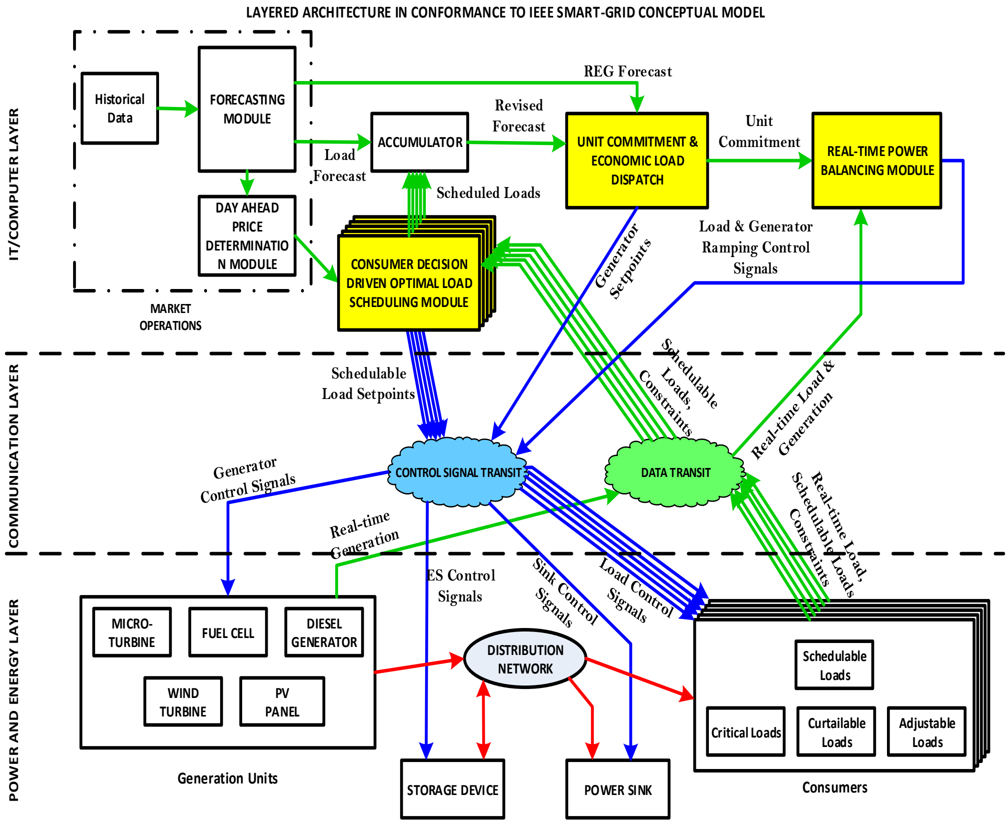

Figure 3.4: MG optimization workflow

Chapter 4

Load forecasting module

In this section, the first functional block of the workflow diagram will be explained and obtained results will be introduced. Here we have used the time series multiplicative model to predict future load demands.

In this section, the first functional block of the workflow diagram will be explained and obtained results will be introduced. Here we have used the classical time series multiplicative model to predict future load demands. These models however, cannot capture the complex relationships between load demand and other factors like weather conditions and operational contingencies which may affect the system. However, these are simpler and faster and more importantly perform satisfactorily even with limited data to work with. Considering the window of time in which this module was commissioned, only a month's worth of real-time load data from the institute was available.

Time series models can developed in much the same way as a regression model. In our case the observation were considered as a product of components namely- Seasonal, irregularity and trend component.

4.1 Time series model

In this work, load demand data was collected over a month and sorted according to the day of the week. This constitutes a time series. A time series is a collection of observations of well-defined data items obtained through repeated measurements over equally spaced intervals of time. Data collected irregularly or only once are not time series.

Our observed time series can be decomposed into three components namely: trend component, seasonal component and irregular component.

First off, if we are going to use a time series for prediction we need to find any trend that might exist in the data. As trends tend to be obscured by the random errors, some smoothing method is needed to iron out some of the “ups" and “downs". The simplest way of smoothing a time series is to use a moving average, which is based on averaging adjacent time periods. It essentially creates a series of averages of different subsets of the full data. Since the time period for our time series is 24, the moving average is going to average 24 observations while dropping down and capturing a new observation. That is, when calculating successive values, a new value comes into the sum and an old value drops out. It is important to note that here the mean is normally taken from an equal number of data on either side of a central value. This ensures that variations in the mean are aligned with the variations in the data rather than being shifted in time.

$$MA_i = \frac{O_{i-12} + O_{i-11} + ...O_i + ...O_{i+10} + O_{i+11}}{24} \tag{4.1}$$

In the above equation MA_i and O_i refer to the moving average the measured power at the instant i. However, since the time period is an even number, the moving average values are not centered. Hence we need to perform a centered moving average of the given set. This is done by simply averaging 2 values of the moving averages while dropping down and capturing a new moving average value. This essentially helps smooth out the time series. This essentially takes out the seasonality and the irregularity components from the time series. The equation for centered moving average represented as CMA_i at instant i

$$CMA_i = \frac{MA_i + MA_{i+1}}{2}$$

(4.2)

The seasonal and irregular components are obtained from the equation below:

$$S_i, I_i = \frac{O_i}{CMA_i}$$

(4.3)

The seasonal component consists of effects that are reasonably stable with respect to timing, direction and magnitude. It arises from systematic influences such as: demand during the hour of the day, end-user patterns, institute time table etc. Seasonality in a time series can be identified by regularly spaced peaks and troughs which have a consistent direction and approximately the same magnitude every similar day, relative to the trend.

The irregular component (sometimes also known as the residual) is what remains after the seasonal and trend components of a time series have been estimated and removed. It results from short term fluctuations in the series which are neither systematic nor predictable.

Smoothing gets rid of both the irregular component and the seasonal component. What we might like to do is just remove the seasonal effect and leave any trend and random ups and downs in the data.

$$DS_i = \frac{O_i}{S_i}$$

(4.4)

The resulting series gives us what is called the "deseasonalized" data and it may give us a better idea of what is happening.

As mentioned earlier, the cycle lasts 24 hours; hence we will have 24 seasonal components. Averaging each of the combined seasonal and irregular components combined for each of the 24 hours over the given observed data set is going to give the seasonal component.

Next we need to find the trend component. This requires us to perform simple linear regression with the deseasonalized set is going to serve as the Y-variable and number of the observation as the X-variable.

Linear regressions suggests an approximation of the form $c + dt = f$

Over the entirety of the observations this can be written in matrix form as

$$A_{(NX2)}U_{(2X1)} = F_{(NX1)} \tag{4.5}$$

Here the first column of A matrix is filled with ones and the second column sequentially extends from 1 to N, where N is the total number of observations or measurements. The matrix U contains the coefficients c and d. The matrix F is a column matrix, which holds all the observed values.

As the case may be, not all there may not be an exact solution to this system of equations. The objective thus translates into finding the best value of c and d ($\hat{U}$) such that the error e or $\lVert F - A\hat{U} \rVert$ is minimized. This is essentially called the method of least squares. If $(F - A\hat{U})$ is the error in our approximation, the least square minimization becomes

$$\min\{e^T e\} = \min\{(F - A\hat{U})^T (F - A\hat{U})\} \tag{4.6}$$

This can be solved either as an optimization problem or geometrically. Solving it geometrically has proven to be an easier option and it is as follows.

Our system of equations is essentially $AU = F$. The LHS basically gives a combination of columns. All possible combinations will give a plane of exact solutions. However, RHS is not an exact solution. Here we use the principle of projection to find the shortest distance between the desired point and a point on the plane. This shortest distance or error between the two is going to be a perpendicular.

Let a_1 and a_2 be the columns of the matrix A. The combinations of a_1 and a_2 will give the plane of exact solutions.

This gives

$$a_1^T e = 0 \tag{4.7}$$

$$a_2^T e = 0 \tag{4.8}$$

The combination of the two will give

$$\begin{aligned} &A^T e = 0 \\ &\Rightarrow A^T (F - A\hat{U}) = [0] \\ &\Rightarrow A^T A\hat{U} = A^T F \end{aligned} \tag{4.9}$$

This is the solution for the least square regression method. This can also be obtained by performing optimization.

In recursive least squares algorithm, we would like to use the calculations that have already been made, in contrast to starting over from the beginning. The subscripts old and new have been used to signify this in the following equation.

With the new entries, system becomes of the form $\begin{bmatrix} A_{old} \\ A_{new} \end{bmatrix} \hat{U} = \begin{bmatrix} F_{old} \\ F_{new} \end{bmatrix}$ or $[A_1]\hat{U}_1 = [F_1]$.

In such a case the update procedure is as follows:

We additionally define another variable P

$$P_0^{-1} = A^T A \tag{4.10}$$

and it is updated as follows:

$$P_1^{-1} = P_0^{-1} + A_1^T A_1 \tag{4.11}$$

From this we get the Kalman matrix according to the equation

$$K = P_1 A_1^T \tag{4.12}$$

The update equation for the vector $\hat{U}$ is as follows:

$$\hat{U}_1 = P_1 (A_0^T F_0 + A_1^T F_1) \tag{4.13}$$

The coefficients obtained c and d, are used to obtained the trend component of the given time series. Once this is obtained a mere multiplication gives the predicted values and this can be extended to include the forecast of a number of days.

4.2 Results of the forecasting module

The data from 3 weeks was used to develop the time series multiplicative model and it was tested against the data from the 4th week. Some load predictions may appear to be far more accurate than others and this partly because of exogenous factors, such as festival holidays, weather conditions and special technical workshops.

4.2.1 Friday forecast

The following graph shows the load prediction for Friday using time series forecasting with linear regression in the recursive least square sense.

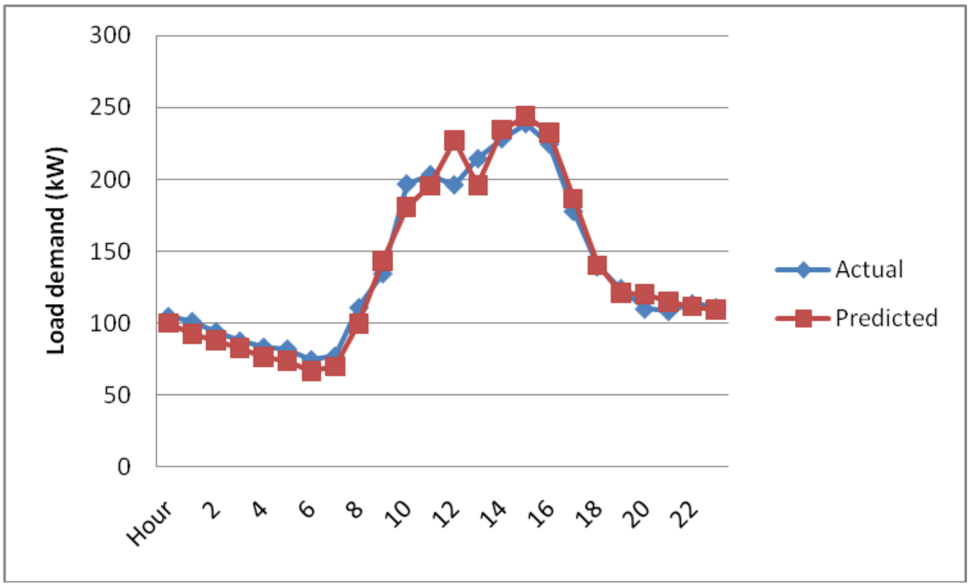

Figure 4.1: Friday load demand forecast

MAPE = 6.31%.

4.2.2 Saturday forecast

The following graph shows the load prediction for Saturday using time series forecasting with linear regression in the recursive least square sense.

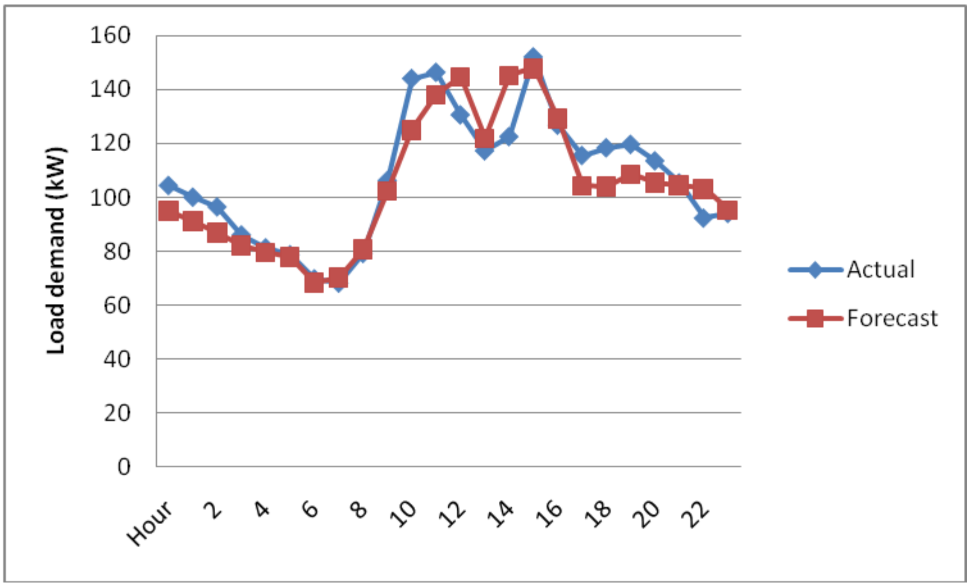

Figure 4.2: Saturday load demand forecast

MAPE= 6.42%.

4.2.3 Sunday forecast

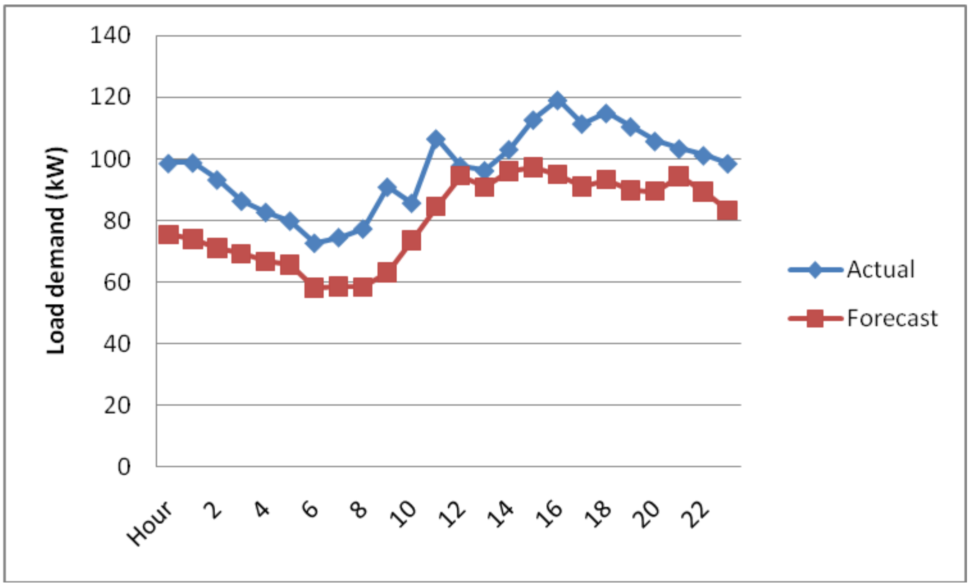

Figure 4.3: Sunday load demand forecast

The above graph shows the load prediction for Sunday using time series forecasting with linear regression in the recursive least square sense.

MAPE= 17.34%.

4.2.4 Monday forecast

The following graph shows the load prediction for Monday using time series forecasting with linear regression in the recursive least square sense. The forecast on Monday was not very accurate as two out of the three previous Mondays used to develop the model were holidays.

MAPE= 15.81%.

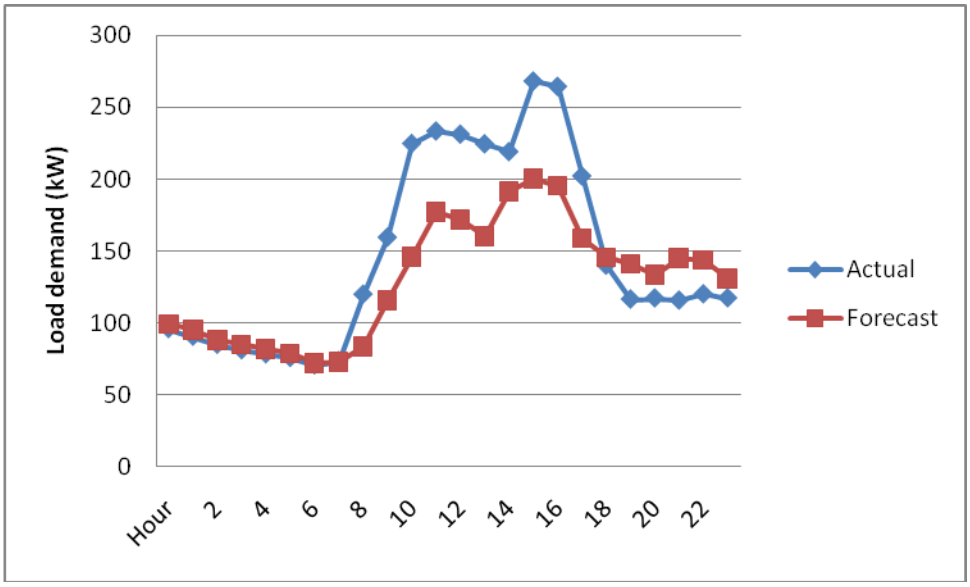

Figure 4.4: Monday load demand forecast

4.2.5 Tuesday forecast

The following graph shows the load prediction for Tuesday using time series forecasting with linear regression in the recursive least square sense.

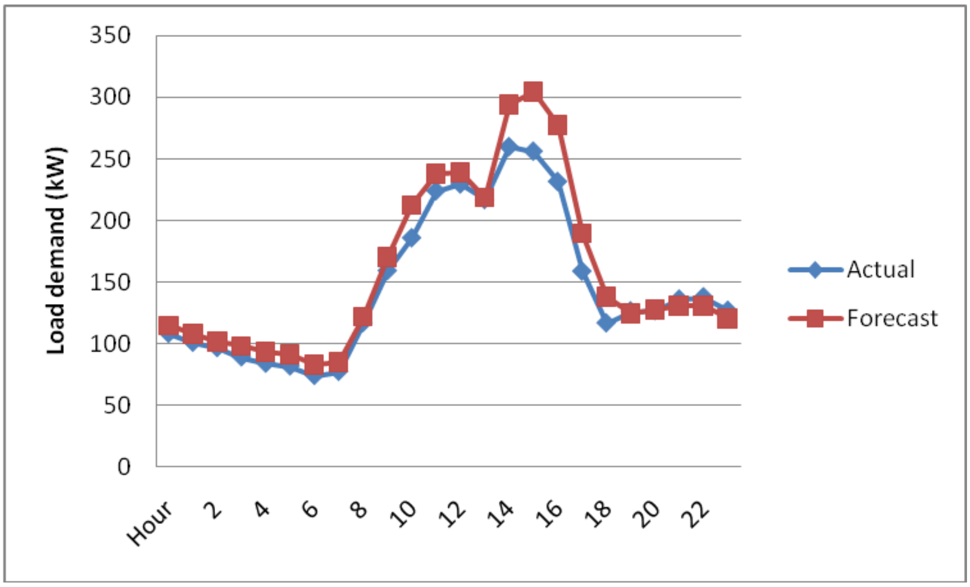

Figure 4.5: Tuesday load demand forecast

MAPE= 8.93%.

4.2.6 Wednesday forecast

The following graph shows the load prediction for Wednesday using time series forecasting with linear regression in the recursive least square sense.

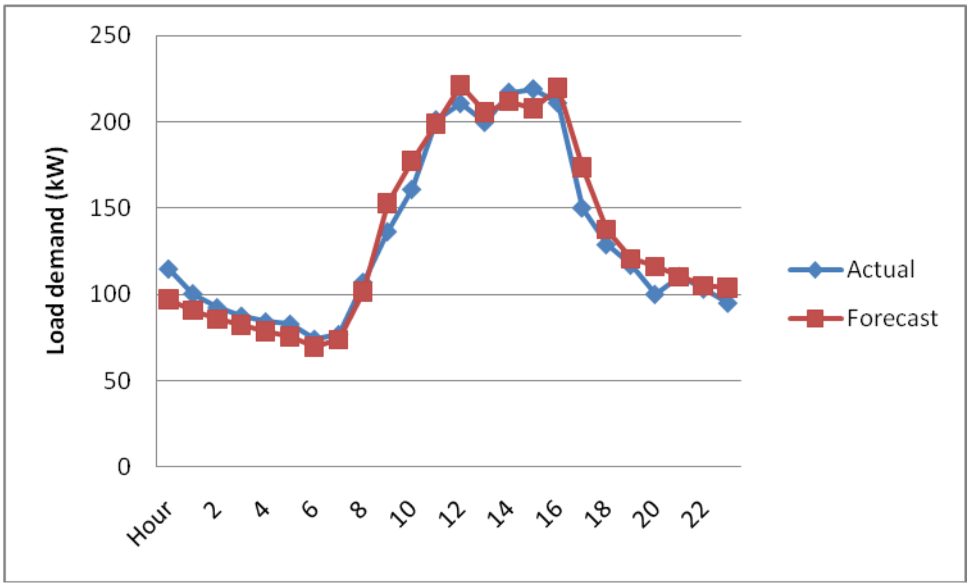

Figure 4.6: Wednesday load demand forecast

MAPE= 6.81%.

4.2.7 Thursday forecast

The following graph shows the load prediction for Thursday using time series forecasting with linear regression in the recursive least square sense.

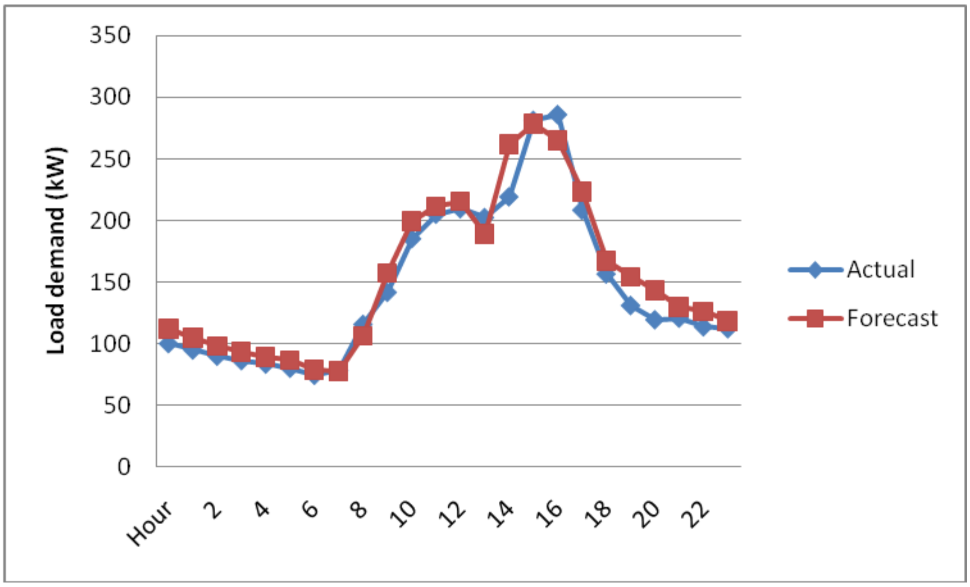

Figure 4.7: Thursday load demand forecast

MAPE= 8.55%.

These forecasts are then used in subsequent modules to set the unit prices in the MG and also as an input to the unit commitment and economic load dispatch module. The dynamic prices set by the operator will also be used by the customer to optimally schedule his load if he wishes to. Both these day-ahead modules will be looked into detail in the next chapter.

Chapter 5

Day-ahead optimization module

In this section, the day-ahead optimization schemes in the presented setup will be discussed. This basically includes a day-ahead consumer driven optimal load scheduling unit and a unit commitment and economic load dispatch unit. There is a sequential flow of information from the load forecasting unit to the first and the second unit of this module.

The Information from the load forecasting unit may be used to define the day-ahead prices that the customers may be charged.

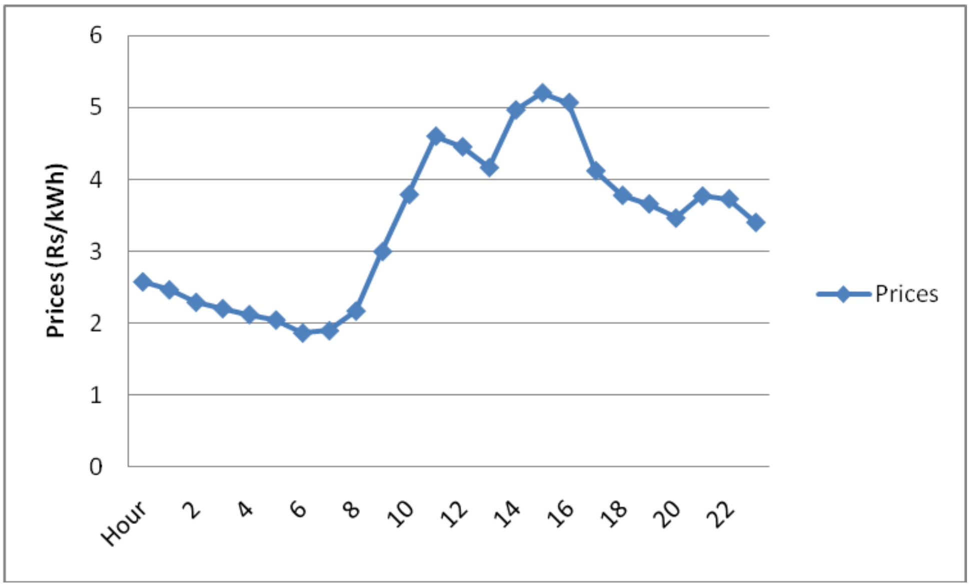

Figure 5.1: Day-ahead (Monday) prices

These prices are going to be directly proportional to the load demand or the stress on the system. This is done to discourage the use of electricity during the peak hours. Here the maximum price that the customer can be charged is multiplied with the normalized load demand forecast to get the day-ahead prices. All further analysis will be performed for the 4th Monday whose forecasted value is available in the previous chapter.

The maximum price per unit in the S1 area (Andhra Pradesh and Karnataka) were obtained from the IEX [56]. It was taken as Rs 5.205/kWh.

5.1 Offline optimization blocks

5.1.1 Day ahead load scheduling

This information about the dynamic day-ahead prices is going to be made available to the customer one day in advance (Sunday) via communication links. The customer has the choice to reschedule some of his loads away from the peak hours. This kindness towards the operator's need to reduce the stress on the system which will eventually improve the reliability of the system and reduce the maintenance required is rewarded here. The dynamic prices itself provide an incentive to shift loads away from the forecasted peak hours as it will help reduce the bills incurred by the customer. The prices are a direct reflection of the stress on the system, i.e. consumers are charged higher prices when the stress (demand) on the system is higher.

Here three loads have been identified for the purpose of load rescheduling. The details of these loads have been tabulated in the table below. These tasks or loads are all constant power loads with a fixed energy requirement. The customer also has the prerogative to set windows of operation for each of these tasks. These windows define the time window in which the task has to be started and completed. Also it has been assumed that once the task has been started it has to run continuously till the end.

Table 4.1: Schedulable load specifications

Schedulable Load	Energy Required (kWh)	Power Level (kW)	Earliest (time of Day)	Deadline (Time of Day)
Washing Machine Service	45	15	18	24
Electric Vehicle Charging	150	30	1	8
Maintenance Service	40	8	9	15

The process of optimal scheduling is solved as a MILP problem. The governing equations are as follows:

$$\min_{\{x(sl,j)\}} \sum_{j=1}^{t} \sum_{sl=1}^{SL} K(j) P_{const}(sl) x(sl,j) \tag{5.1}$$

The above equation will serve as the objective function that is to be minimized. Here SL refers to the total number of schedulable loads. $K(j)$ is the dynamic price at instant j. $P_{const}(sl)$ and $x(sl,j)$ are power requirement of schedulable load sl and status (on/off) of the load sl at time j.

The following equation determines the time required to complete each task. Here $E(sl)$ is the energy requirement of the load sl.

$$\sum_{j=1}^{t} x(sl,j) = \frac{E(sl)}{P_{const}(sl)} = T(sl) \tag{5.2}$$

The following three equations ensure that each task is initiated only once and completed within the stipulated time frame and to ensure the preemptive nature of the load. Here $d(sl,j)$ is the switch-on variable. It is 1 when the task is switched from being inactive to being active.

$$\sum_{j=1}^{t} d(sl,j)=1 \tag{5.3}$$

$$d(sl,j)\le x(sl,t) \quad \forall t=j,j+1,\cdots,j+T(sl)-1 \tag{5.4}$$

$$x(sl,j)=0 \quad \forall j\notin \left(T_e(sl),T_d(sl)\right) \tag{5.5}$$

The optimization program proceeds to relocate the schedulable loads in such a way that the customers incur minimum bills.

5.1.2 Unit commitment and economic load dispatch unit

Since In this section we define the MG economic scheduling problem. At every time step, the MG scheduler must take high level decisions regarding the status and also the generation level of each DG unit. The information from the revised forecast is going to be used by this unit to generate set points for the various DG units.

MG economic optimization is achieved by designing the decision variables so that a cost functional representing the operating costs is minimized. The problem is solved as a MINLP problem. The governing equations of the optimization problem are as follows :

$$\begin{gathered}\min \sum_{j=1}^{t}\sum_{i=1}^{CG} u(i,j)C\left(P(i,j)\right)+\sum_{j=1}^{t}\sum_{r=1}^{R} u_r(r,j)C_r\left(P_r(r,j)\right)+ \\ \sum_{j=1}^{t}\sum_{i=1}^{CG} d(i,j)S_{up}(i)+\sum_{j=1}^{t}\sum_{i=1}^{CG} f(i,j)S_{dn}(i)\end{gathered} \tag{5.6}$$

This will serve as the objective function to be minimized. i and r are the indices of conventional DGs and REG sources respectively while CG and R will serve as the total number of conventional and non-conventional (REG) DG sets. $P(i,j)$ and $P_r(i,j)$ represent the generation levels of the conventional and renewable DG sets. C and C_r are the quadratic cost functions of the conventional DGs and REG sources respectively. Similarly $u(i,j)$ and $u_r(r,j)$ are the statuses of the conventional DGs and REG sources respectively. d and f are the switch-on and switch-off variables of conventional DG sets. $S_{up}(i)$ and $S_{dn}(i)$ are the costs associated with these two respective actions.

$$P_{\min}(i) \le P(i,j) \le P_{\max}(i)$$

(5.7)

$$P_{r,\min}(r) \le P_r(r,j) \le P_{r,\max}(r)$$

(5.8)

The above two equations lay limits on the generation of both conventional DGs and REG sources available.

$$R_d(i) \le P(i,j) - P(i,j-1) \le R_u(i)$$

(5.9)

$$R_{r,d}(r) \le P_r(r,j) - P_r(r,j-1) \le R_{r,d}(r)$$

(5.10)

The above two equations restrict the ramping up and ramping down of the DG sets which restrict the increase or decrease in generation level with reference to its previous generation level.

$$\left(T_{on}(i,j) - MUT(i)\right)\left(u(i,j-1) - u(i,j)\right) \ge 0$$

(5.11)

$$\left(T_{off}(i,j) - MDT(i)\right)\left(u(i,j-1) - u(i,j)\right) \ge 0$$

(5.12)

$$\left(T_{r,on}(r,j) - MUT_r(r)\right)\left(u_r(r,j-1) - u_r(r,j)\right) \ge 0$$

(5.13)

$$\left(T_{r,off}(r,j) - MDT_r(r)\right)\left(u_r(r,j-1) - u_r(r,j)\right) \ge 0$$

(5.14)

$T_{on}(i/r,j)$ and $T_{off}(i/r,j)$ represent for how long each DG set has been on or off at time instant j.The above four equations implement the minimum up time and minimum down time of the DG units installed in the MG.

The following equations have been used for developing the Load flow model of the MG. It is to be noted that the load balance equality constraint has also been included in this power flow formulation.

$$P_{inj}(n,j)=\sum_{i=1}^{CG}A_g(n,i)u(i,j)P(i,j)+\sum_{r=1}^{R}A_{gr}(n,i)u_r(i,j)P_r(i,j)$$
$$-\sum_{l=1}^{L}A_l(n,l)load(l,j) \tag{5.15}$$

$$P_{inj}(n,j)-\frac{V^2}{1000}\left(\sum_{k=1}^{N}\frac{\sin(\delta(n)-\delta(k))}{X(n,k)}\right.$$
$$\left.+\sum_{k=1}^{N}\frac{\cos(\delta(n)-\delta(k))}{R(n,k)}\right)=0 \quad \forall k\neq n \tag{5.16}$$

$$-fl_{\max}(line)\leq\frac{V^2}{1000}\sum_{k=1}^{N}\frac{\delta(n)-\delta(k)}{X(n,k)}\leq fl_{\max}(line) \tag{5.17}$$

In the above equations n,k and l stand for indices of buses and lines. V is the operating per phase voltage of the distribution system in volts. $P_{inj}(n,j)$ represent the power injected in bus n and time instant j. $R(n,k)$ and $X(n,k)$ represent the resistance and reactance of the line connecting bus n and bus k. $\delta(n/k)$ is the power angle at the particular bus. $fl_{\max}(line)$ is the maximum power handling capability of a line. The first equation serves to define the power injected at each node. The second accounts for nodal balance, which also encompasses the traditional load balance constraint that is so pivotal in every unit commitment and economic load dispatch model. The third equation sets flow limits on power flow between lines due to line limitations.

5.2 Results for offline optimization module

5.2.1 Results for load rescheduling module

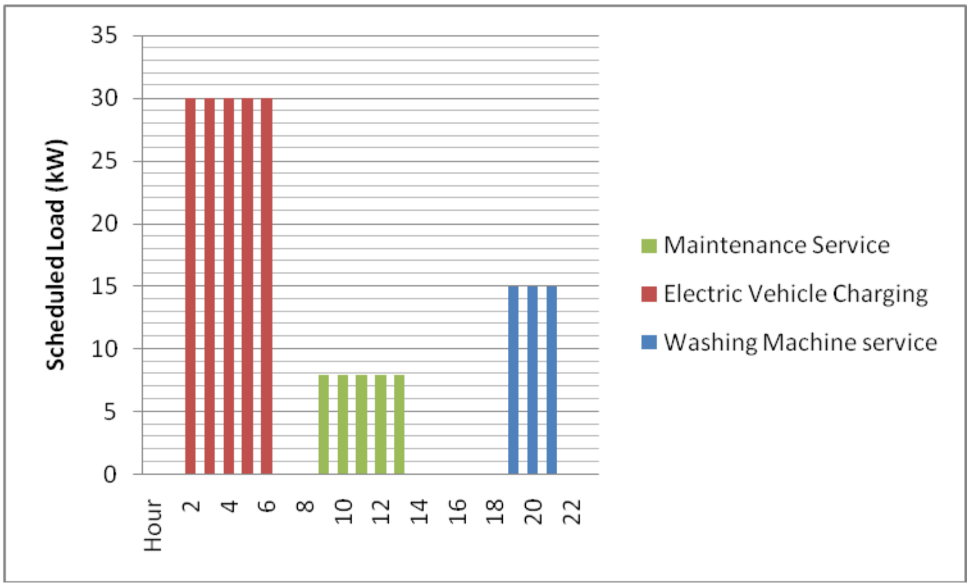

Figure 5.2 Scheduled load values

The results of the optimization problem are shown above and this becomes instrumental in revising the existing forecast. The forecast from the forecasting module and the revised forecast are also shown in the figure below. There is an obvious reduction in the peak demand of the system. It is important to keep in mind that the operation window plays a key role in determining the magnitude of peak reduction.

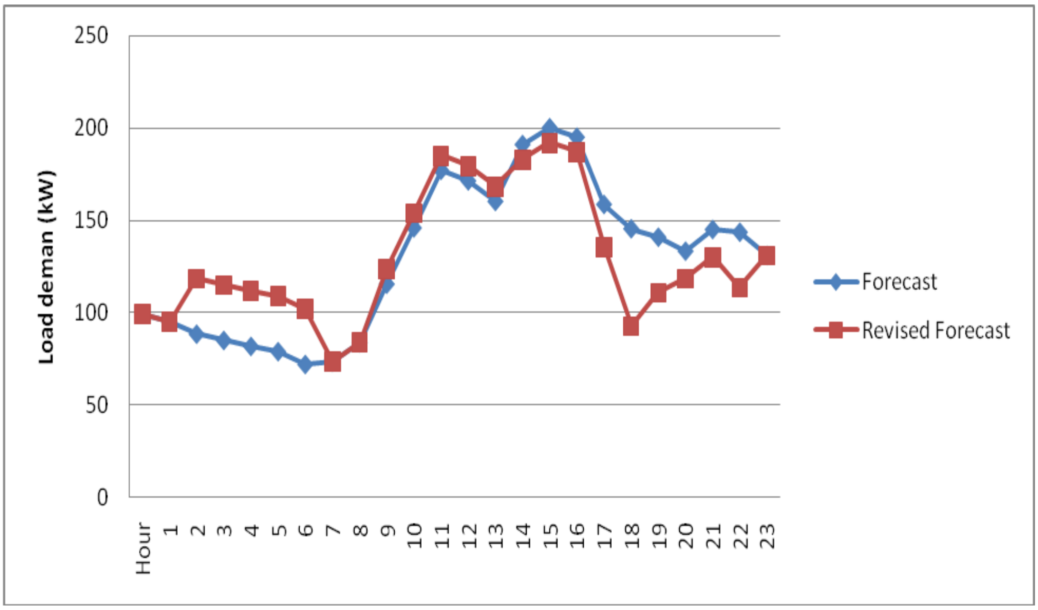

Figure 5.3: Forecast and revised load forecast values

The problem was solved in the GAMS environment. Similar scheduling was also done for variable power schedulable loads. However, solving the objective function for non-preemptive nature of these loads was found to be NP hard.

5.2.2 Results for unit commitment and economic load dispatch

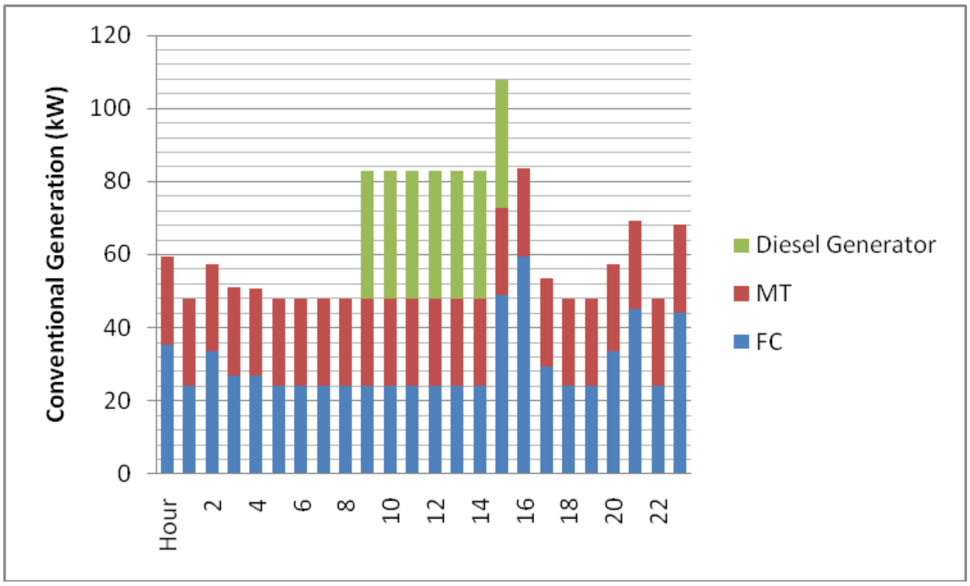

Figure: 5.4 Conventional generation levels

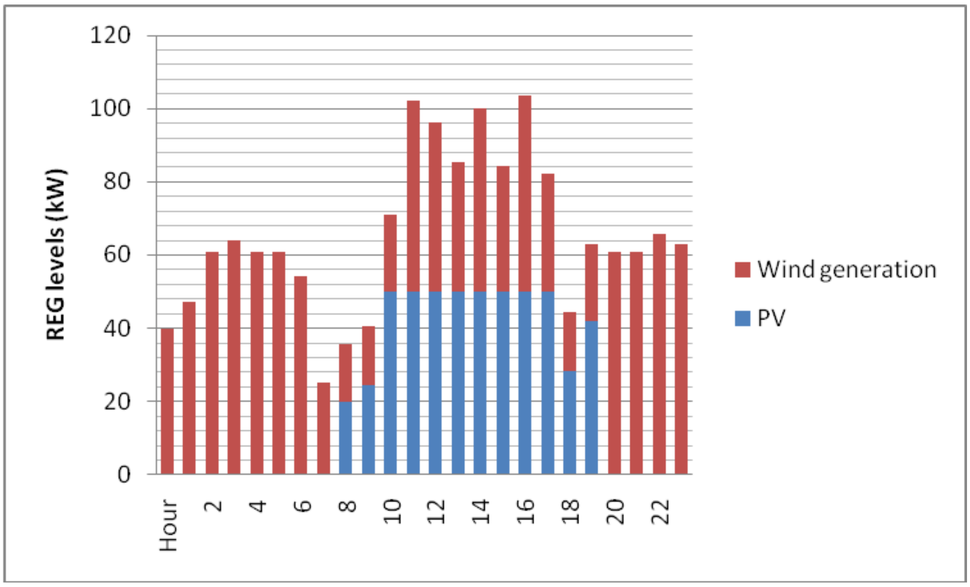

Figure: 5.5 REG levels

The above two diagrams show the generation of the conventional DGs and the REGs. It is to be noted that REG levels are not at their maximum even thought they are the cheapest. This is set so that all the constraints for the present hour and coming hours may be satisfied.

Chapter 6

Fault tolerant power balancer

In this section, the online optimization module will be discussed. Here we focus on the prioritization and advanced control of load in conjunction with a controlled use of an energy storage device. Direct load control can often respond to the requests of the operator instantaneously whereas the generators are usually lugged down by their larger time constants. Such a use of load as a system service can also circumvent the use of fast ramping but inefficient generators. In many cases an unforeseen increase in electrical demand causes the operator to bring increasingly inefficient generation online. Under such circumstances, it is possible that the supply side generation costs will be greater than the retail price. The use of direct load control under pre-agreed terms and conditions can help alleviate this problem. The ESS is also introduced to improve system reliability. Before delving deeper into the topic, the communication infrastructure which is an important pre-requisite for this module will be briefly discussed.

The control architectures discussed in the following sections have their own demands on the supporting communication infrastructure. The communication networks need to take into account the highly distributed nature of the loads. These loads are already embedded in the power system and communication platforms ranging from broad band connections to advanced metering infrastructure are becoming widely available. It may soon be the case that the only technical impediment to reliable realization of utilization of loads for system services might be the development of necessary load models and control strategies. The most practical forms of load control tend to utilize control commands that re broadcast across all loads, rather than targeted to specific installations.

The objectives of this method is to develop a novel load side operation and control method for the proposed system. Here we are going to explore opportunities to use load control schemes to achieve power balance that are competitive with conventional generator based approaches. Also we will be taking into consideration a large penetration of REG and rather realistic variations between forecasted load and actual load resulting in larger power imbalances compared to conventional power grids. Here the whole energy balancing issue as a real-time optimization problem which runs every 15 minutes. However, owing to the low run time of the algorithm the same can also be executed for smaller time intervals.

6.1 Optimization module

This section will give an overview of the optimization module. Three separate optimization problems have been constructed for cases depending on use of generator ramping and energy storage use. Here we taken the luxury of lumping the all adjustable loads as a single adjustable load whose value can be varied from full load value to zero. However, the curtailable loads have disunited and have been presented as three separate entities with their own separate priority values. Priorities refer to the penalty faced by the operator for compromising the end use performance of the load. The figure below is a representation of the optimization problem we will be looking at.

Figure: 6.1 Online optimization module

Figure 6.2 shows the actual load demand on the 4th Monday that was collected from LOAD 1 (institute panel 1 and institute panel 2) and LOAD 2 (hostel panel and workshop panel). As mentioned earlier, the forecast on Monday is not the finest since the previous data sets used to develop the model included exogenous factors like holidays which were not taken into account during forecasting. However, this proves to be a good platform to depict the efficacy of the proposed power balancing scheme. The figure also shows actual generation values. There is bound to be some mismatch between the two owing to varying solar and wind conditions. Since we are not operating the REGs in maximum power point tracking fashion, the deviation in actual and anticipated REG level is going to be negative.

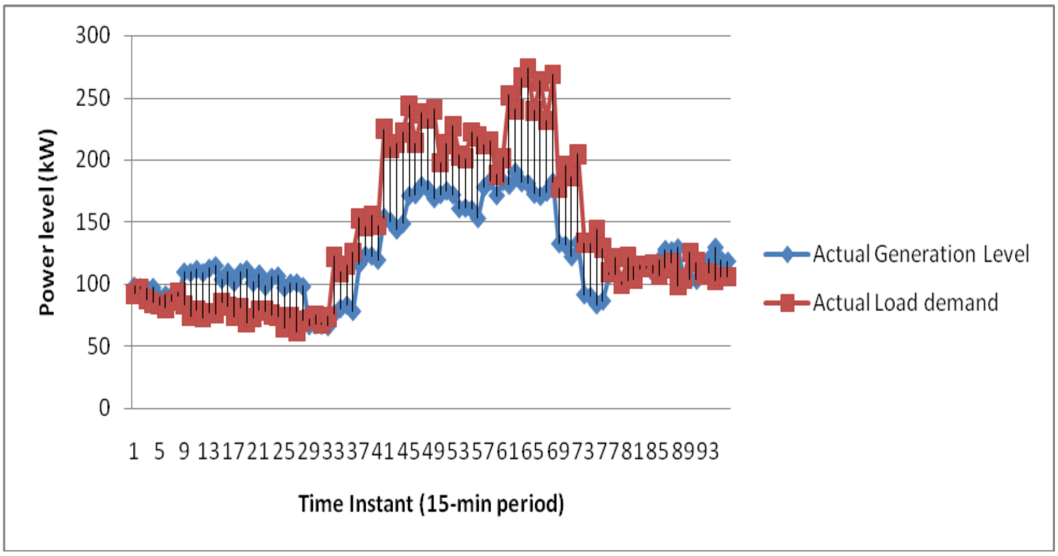

Figure 6.2: Actual load demand and generation levels

Figure 6.3 shows the real-time distribution of load demand over 96 of these 15 minute intervals. The load classification is in accordance to the briefing done in the System overview chapter.

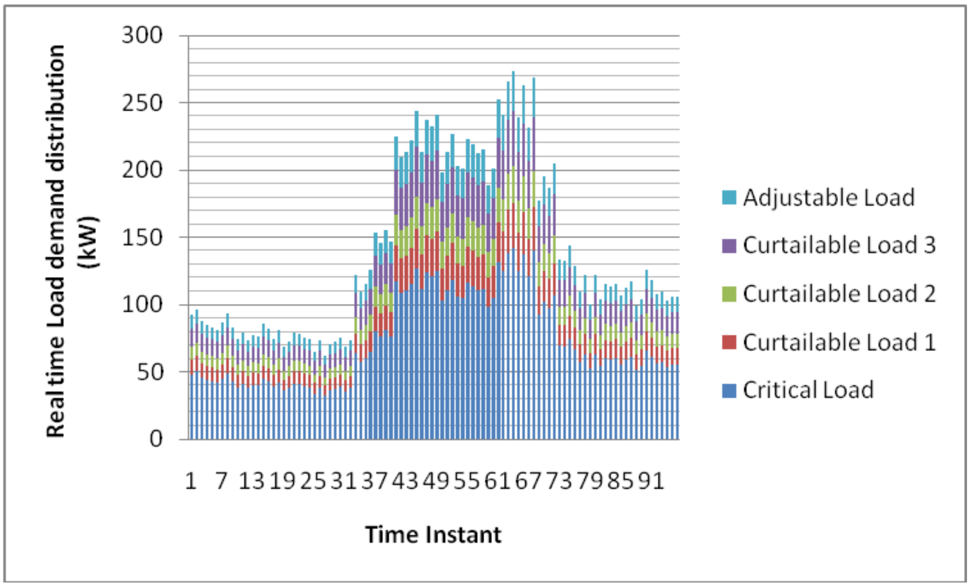

Figure 6.3: Actual load demand distribution

6.2 Real-time power balancer problem formulation

Here we will be looking at the general power balancer optimization problem. We will also be looking at variants of the generalized problem under specific cases in the following subsection.

6.2.1 Operation with ESS and generator ramping support (Case 1)

The objective function formulation of the energy management system for real time power balancing for each instant with the use of battery and generator ramping is discussed in this section. The decision variables used here include $P_{adj}(k)$ which is the total adjustable load aggregate available for reduction at the time instant k, $u(i,k)$ which is the on/off status of the curtailable load i at the time instant k. Here $P_{cur}(i,k)$ is the value of demanded curtailable load i at time instant k. The number of distinct curtailable load sets is N. $P_{crit}(k)$ is the value of demanded critical load at time instant k. $P_{\sin k}(k)$ gives the value of power dissipated in the dump. Where α, β and γ are the priority values of the adjustable, curtailable loads and the sink respectively. The number of distinct curtailable load sets is N. The f denotes a fraction of the adjustable load that should be curtailed for power balancing and naturally it varies from 0 to 1. The objective function has also gone ahead and incorporated the ESS in such a way that its energy state always tries to always tries to return to a user specified value E_o. A penalty δ has also been defined for any deviation of the battery state $E(k)$ at time k from this specified value. In addition to the load side support units, the ramping ability of the dispatchable DG sets are also used in the power balancing scheme. The use of these ramping generators further helps quality of service enjoyed by the end-user. In the equation below, $P_{ramp}(cg,k)$ and $status(cg,k)$ refers to ramping power and on or off status of conventional generator cg at time instant k. The total number of these dispatchable DG sets available is G. The formulation is such that only generators that have already been brought to run by the unit commitment module are made available for this ramping exercise. This has been done to avoid wasteful startup costs during the process of load balancing. A penalty $\sigma(cg)$ has also been set on this sudden ramping of generators. The problem is solved as a MINLP problem and solved using couenne solver in GAMS. The formulation is as follows:

$$\min_{\substack{f,u(i,k)\\ P_{sink}(k),E(k),P_r(cg)}} \alpha f P_{adj}(k)+\sum_{i=1}^{N}\beta(i)\left(1-u_{curt}(i,k)\right)P_{cur}(i,k)+$$
$$\gamma P_{\sin k}(k)+\delta\left|E(k)-E_0\right|+\sum_{cg=1}^{CG}\sigma(cg)\left(\left|P_{ramp}(cg,k)\right|\right)status(cg,k) \tag{6.1}$$

Subject to:

$$0\le f\le 1 \tag{6.2}$$

The f denotes a fraction of the adjustable load that should be curtailed for power balancing and naturally it varies from 0 to 1.

$$E(k)=E(k-1)+\frac{s}{60}P_{bat}(k) \tag{6.3}$$

$$E_{\min}\le E(k)\le E_{\max} \tag{6.4}$$

$$P_{bat\_\min}\le P_{bat}(k)\le P_{bat\_\max} \tag{6.5}$$

The above three equations deal with the dynamics and constraints of the battery. $P_{bat}(k)$ is the power output of the battery. It may be positive or negative depending on whether the battery is charging up or discharging. s refers to the sampling time in minutes, here it is 15 minutes. The above constraints ensure that the battery energy levels and power flow are within the permissible lower and upper limits namely ($E_{\min}, E_{\max}$) and ($P_{\min}, P_{\max}$) respectively.

$$P_{C\_\min}(cg)\le P(cg,k)+P_{ramp}(cg,k)\le P_{C\_\max}(cg) \tag{6.6}$$

$$P_{ramp-\min}(cg)\le P_{ramp}(cg,k)\le P_{ramp-\max}(cg) \tag{6.7}$$

The above two equations refer to the spinning reserves of the dispatchable units. Equation 6.12 defines a capacity of the generator which is slightly broader than the generation limits imposed on the sets during unit commitment problem. $P_{c\_\min}$ and $P_{c\_\max}$ are the minimum and maximum capacities of the conventional generation limits. $P_{ramp-\min}(cg)$ and $P_{ramp-\max}(cg)$ are minimum and maximum ramping values of a conventional DG unit in the sampling time s. A small scope for ramping is also included in Equation 6.7. The restriction on the value of this online ramping is to ensure that it is within the hourly ramping capacity of the generator. It is to be noted that $\mathrm{P}_{ramp}(cg,k)$ is used to update the value of generation level of the dispatchable DG sets and this value is used in subsequent runs of the algorithm.

The equation given below gives the power balance equation of the system at each sampling instant.

$$\begin{aligned}&(1-f)P_{adj}(k)+P_{crit}(k)+P_{sink}(k)+\sum_{i=1}^{N}u_{curt}(i,k)P_{cur}(i,k)+P_{bat}(k)+\\&\sum_{cg=1}^{CG}\left(\mathrm{P}_{ramp}(cg)\right)status(cg)=P_{gen}(k)\end{aligned} \tag{6.8}$$

Although the formulation gives the user complete flexibility to set different relative priorities for the different components, in my run of the algorithm, curtailable loads have higher priority compared to adjustable loads. Additionally, the priority levels of the curtailable loads increase from 1 to N. The wasteful dumping of power when generation is greater than demand is highly discouraged and a large penalty value (γ)is set on it. Furthermore, the value of δ is chosen greater than α but less than all the βs. As a consequence the battery will try to attain its optimal energy value even at the expense of the adjustable load, while curtailable loads are provided for even if battery energy level deviate from its desired value. However, the choice of these weights are completely flexible and they may be chosen differently for a given application.

Also, here the curtailable loads have been lumped together to form three controllable loads. The priorities of these loads with respect to the ramping of the three generators in this study follow the inequality: $\sigma(1) < \beta(1) < \sigma(2) < \beta(2) < \sigma(3) < \beta(3)$. So in case of an energy shortage, the diesel generator will ramp up only to cater for the highest priority curtailable load.

In this mode of operation the optimization module dictates the levels of various loads with the provision of standby power in the form of ESS and generator support. Here the loads are adjusted and curtailed according to their priorities. In all the cases catering for the critical load is imperative and no compromise can be made.

6.2.2 Operation under the occurrence of a fault (Case 2)

In this scenario, the operation of the power balancer is studied under the occurrence of a fault. Here a fault refers to the outage of one of the DG sets.

6.2.3 Operation with only ESS support (Case 3)

The problem formulation in this section is the same as the one in the previous section except for the fact that the option of generator ramping has been removed. So the power balancer can only avail support from the ESS. This has been logically implemented by increasing the penalty for using the generator ramping to a very large value. This in effect becomes the same as denying access to the ramping capabilities of the conventional generator. This is going to result in slightly deteriorated performance as far load reliability is concerned. Also since the option of ramping down production is not available the excess power dissipated at the power sink is also going to be more.

6.2.4 Operation without ESS or generator ramping support (Case 4)

This case features an additional handicap where the support of the ESS is also removed. This can be the representation of the scenario where the ESS is not available due to its inherently high installation cost. The scenario translates into mathematics by setting the value of δ along with those of σs to a very high value.

6.3 Results for power balancing module for various cases

6.3.1 Results for Case 1

This subsection will hold the results for the first case study in this chapter namely, the operation of the load balancer with ESS and generator ramping support. Figure 6.4 shows the catered curtailable load profile. The lower priority adjustable loads are controlled to accommodate both the curtailable loads and the return of the battery to its specified state. The use of power sink is done so only when the generation is greater than demand and if dealing with that is beyond the technical constraints of both the ESS and the ramping generators. Hence not a lot of power is wasted at the sink. Figure 6.5 shows the catered adjustable loads and the power dissipated at the sink.

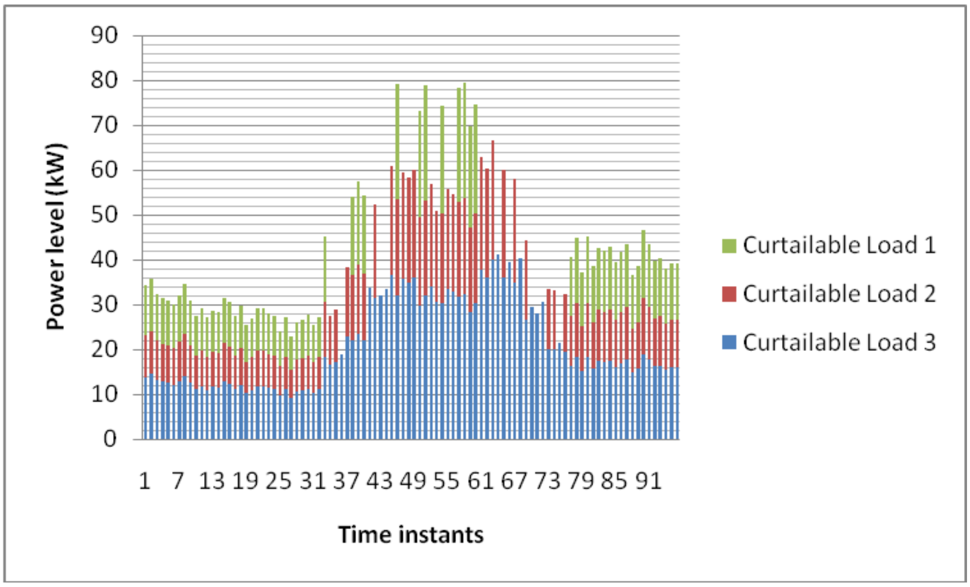

Figure 6.4: Catered curtailable loads (Case 1)

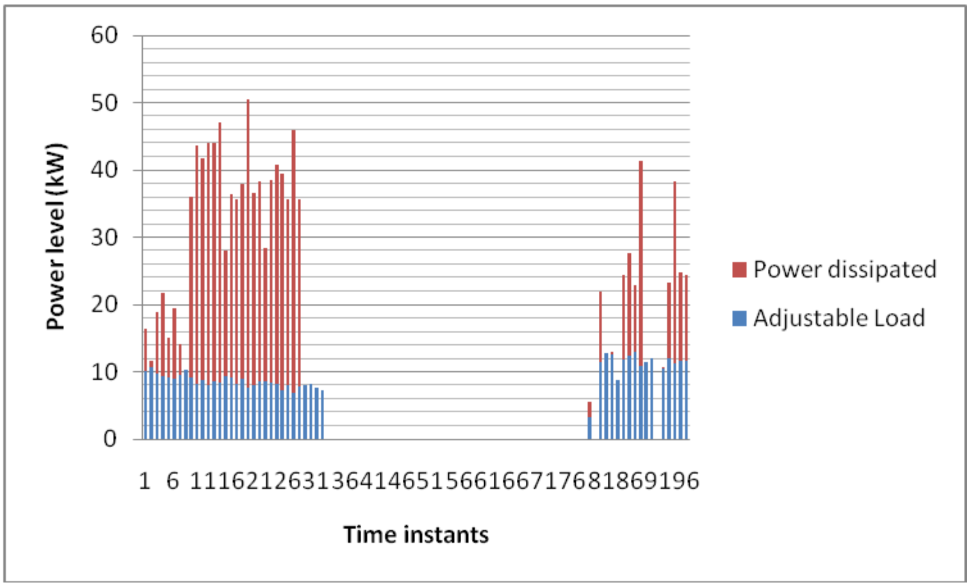

Figure 6.5: Catered adjustable loads and power dissipated (Case 1)

Figure 6.6 and 6.7 are depictions of the battery energy level and power level respectively. The next figure 6.8 shows the real time ramping of the three dispatchable generators. It is seen that the larger diesel generator which is not online (according to the unit commitment scheme) most of the time does not contribute much to this online load balancing. This is also because the penalty for ramping the unit is large and hence utilized only to provide for the higher priority loads.

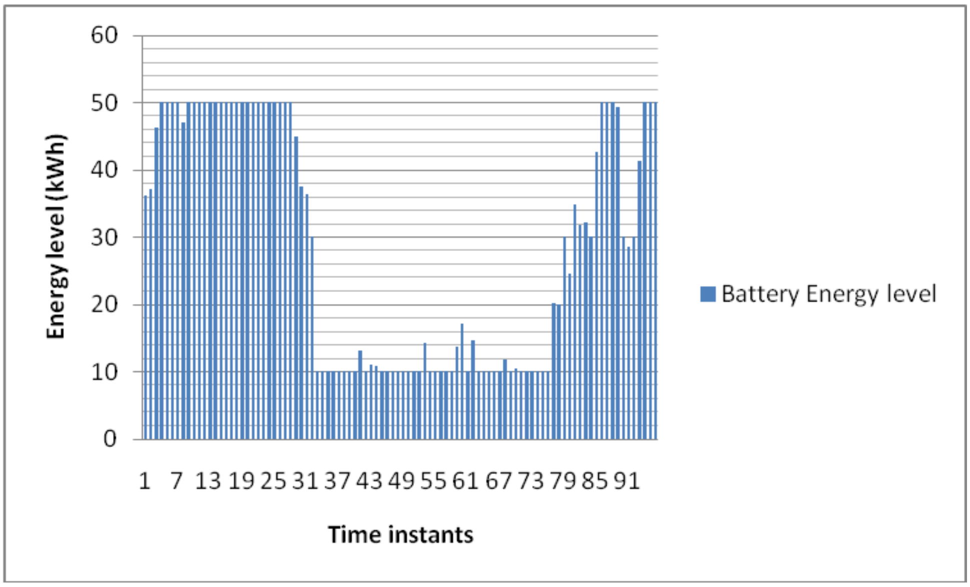

Figure 6.6: Battery energy states (case 1)

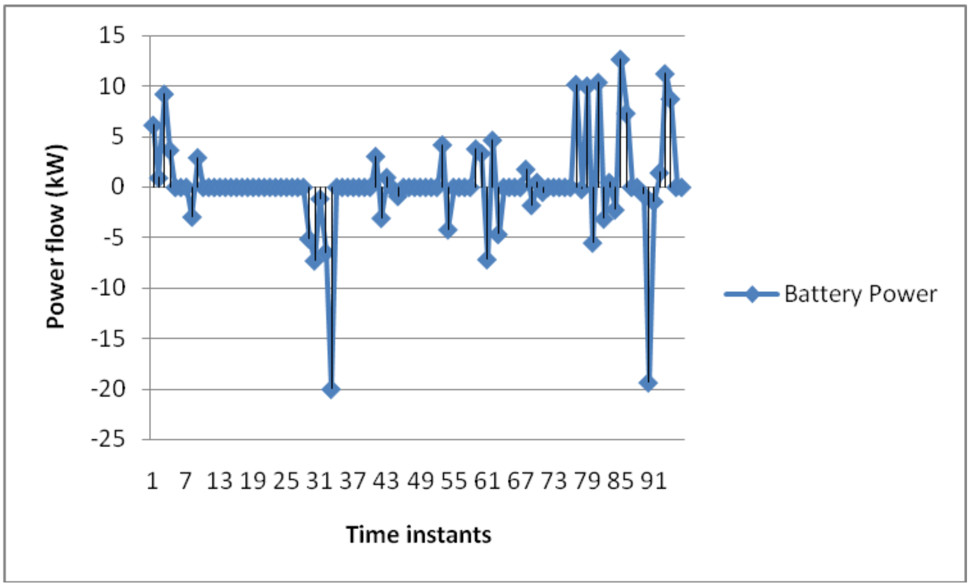

Figure 6.7: Battery power flow (Case 1)

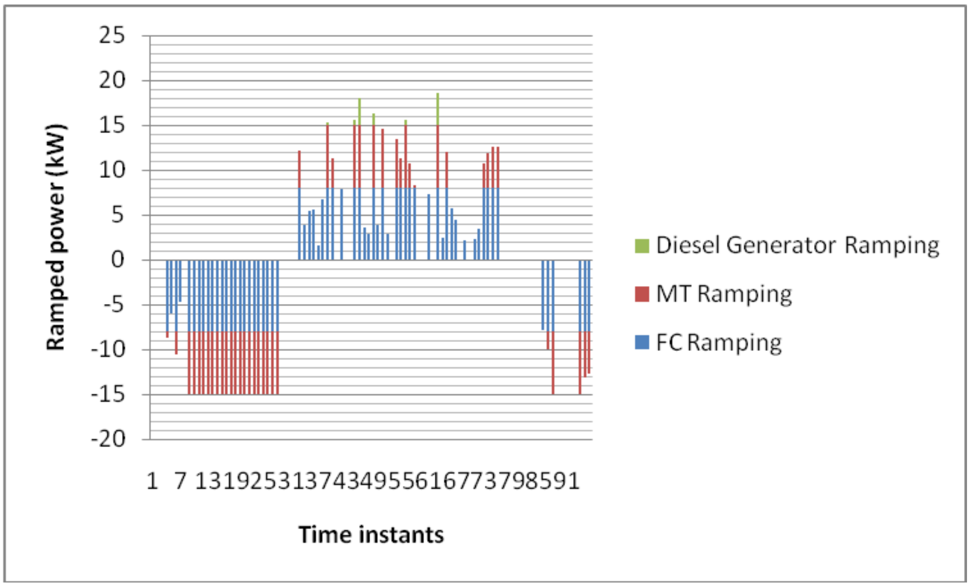

Figure 6.8: Conventional generator ramping (Case 1)

6.3.2 Results for Case 2

Here the MT is subjected to a fault which results in it being inoperative. This results in a fall in the real time generation fault as shown in Fig 6.15. This also implies that this DG set will not be available for providing reserves during real time power balancing operation. As is evident from the figure the fault occurs at 12 in the pm and persists for a good 3 hours. Figure 6.16 shows that in spite of this large reduction in generation, the curtailabe loads especially those falling under the higher priority are catered for even during most of the time instants from 49-60. It is also worth mentioning that even under these circumstances, serving the critical load is maintained as an imperative. The figures following show the behavior of the other elements included in our scheme in response to this drop in generation due to fault.

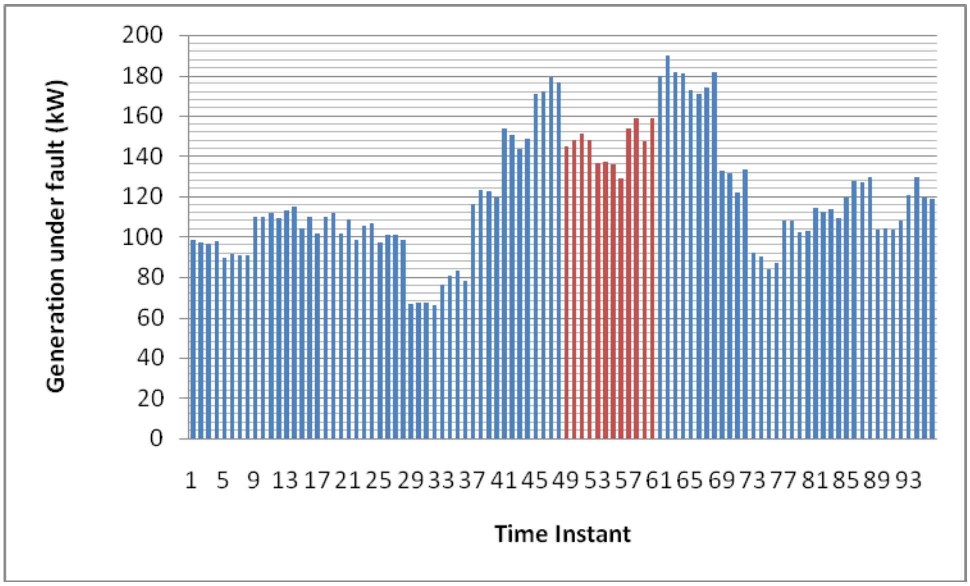

Figure 6.9: Generation under fault

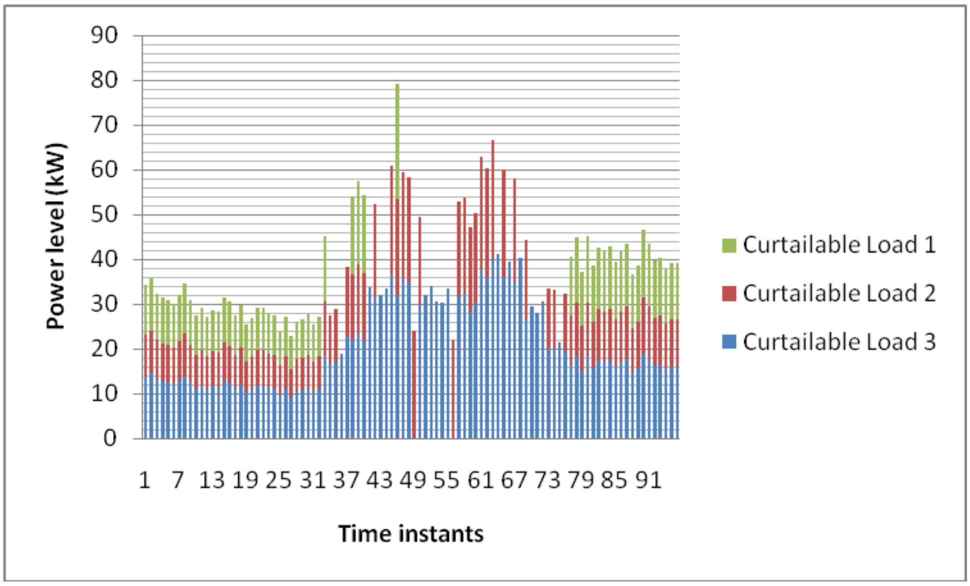

Figure 6.10: Catered curtailable loads (Case 2)

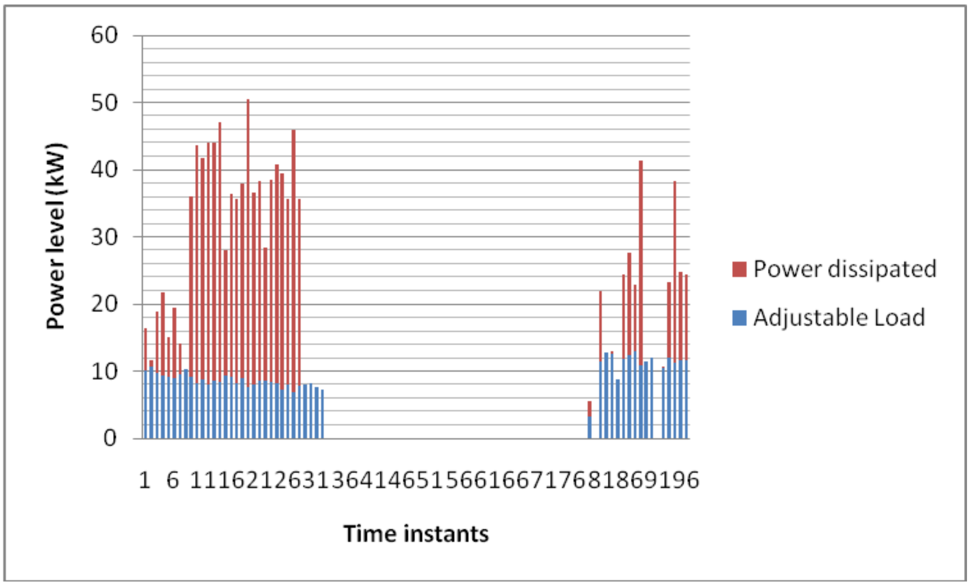

Figure 6.11: Catered adjustable loads and power dissipated (Case 2)

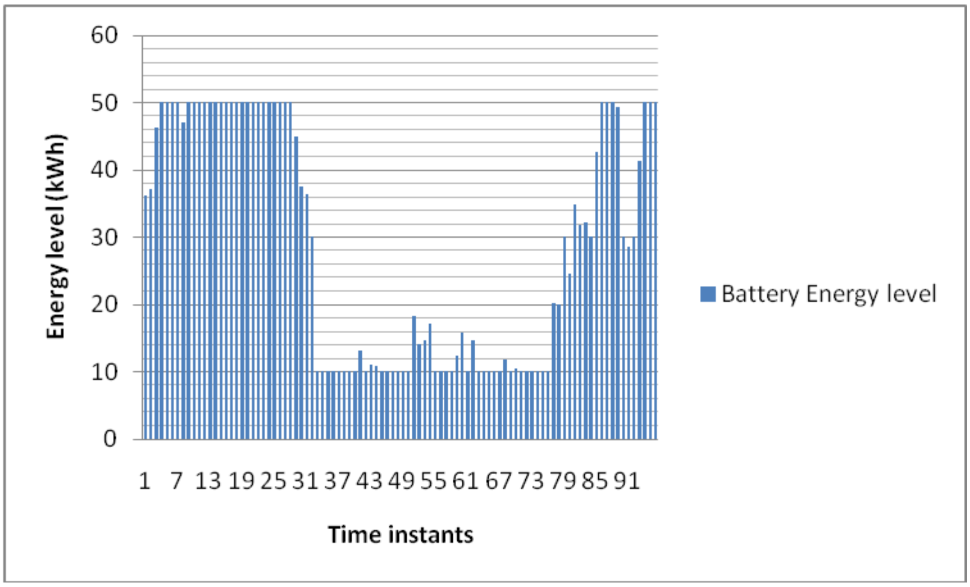

Figure 6.12: Battery energy states (Case 2)

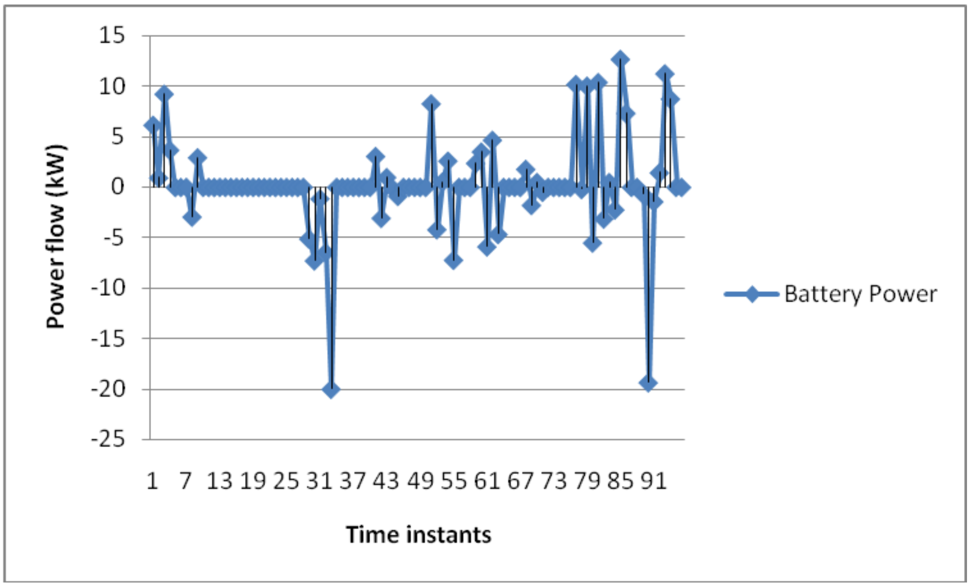

Figure 6.13: Battery power flow (Case 2)

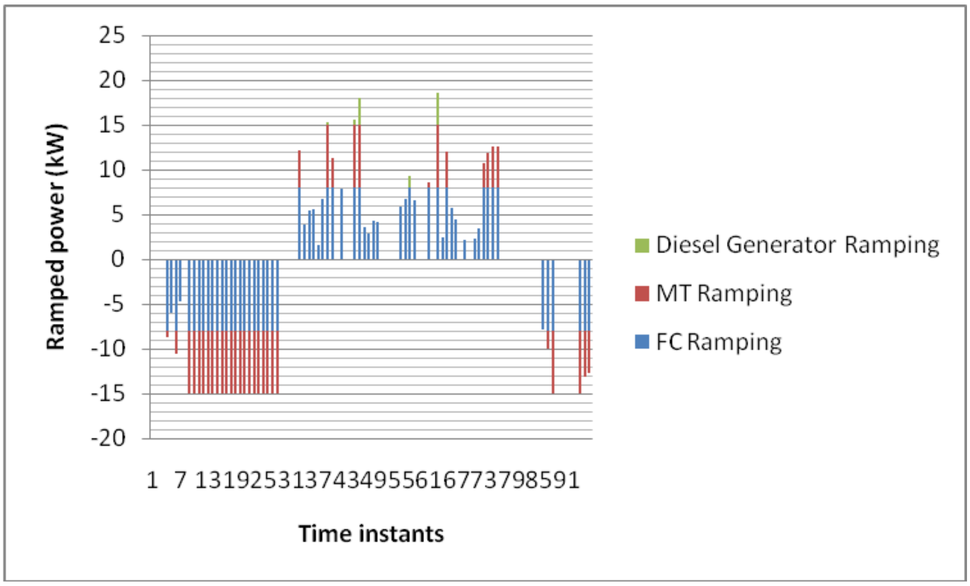

Figure 6.14: Conventional generator ramping (Case 2)

6.3.3 Results for Case 3

Here the performance of the proposed power-balancing algorithm for a system with only ESS support is considered. In this operation the optimization module dictates the levels of various loads with the provision of a standby energy source. The catered profiles of the curtailable loads under this scheme are shown in Figure 6.15. Although there is a deterioration in the end-user services, due to the ESS some of the curtailable loads are still catered for. Figure 6.16 shows the adjusted values of the adjustable loads and the power dumped. As was in the previous case, the adjusted loads have been controlled to accommodate the curtailable loads and the return of the battery energy state to the user specified state.

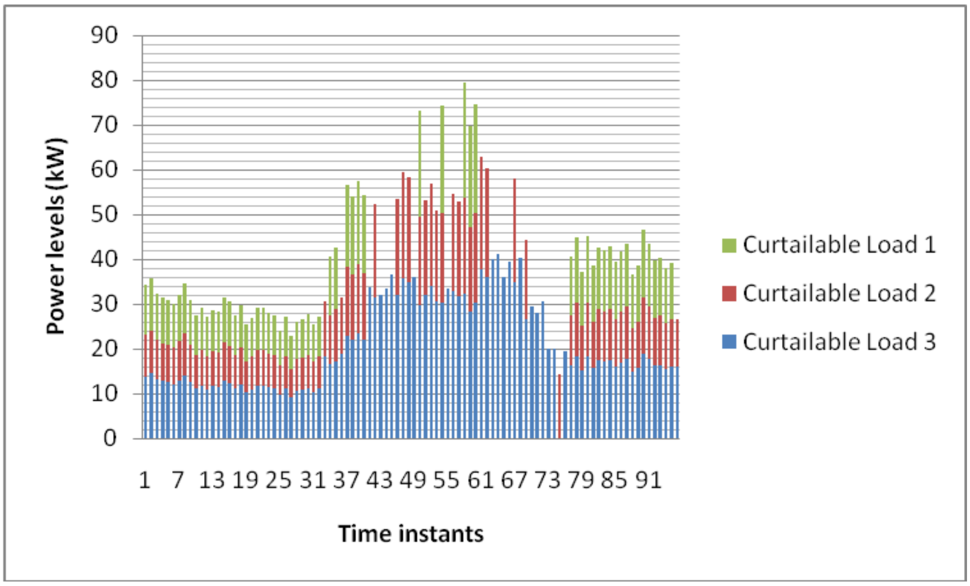

Figure 6.15: Catered curtailable loads (Case 3)

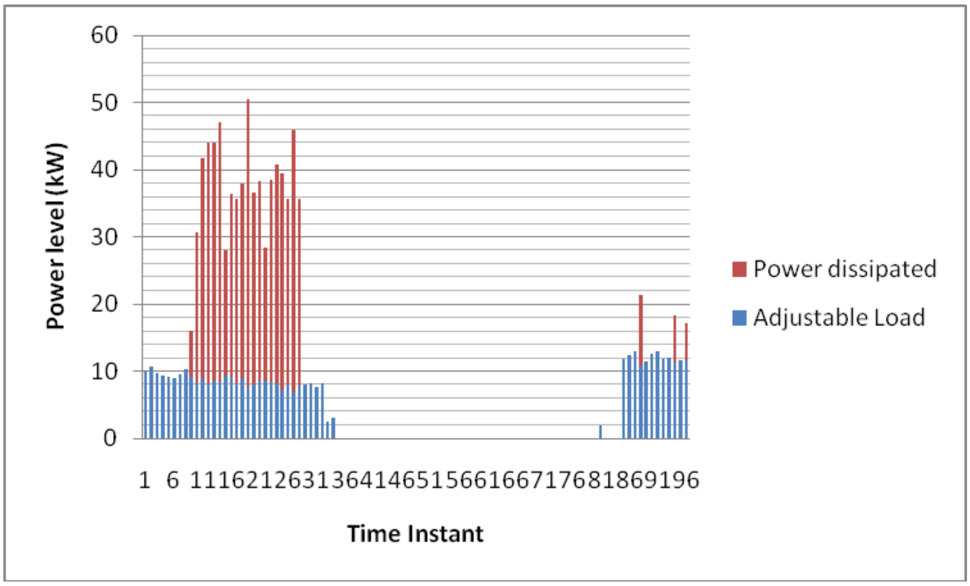

Figure 6.16: Catered adjustable loads and power dissipated (Case 3)

Furthermore, Figure 6.17 shows the variation of battery energy states during the span of this day. Corresponding power flow to and from the battery are also shown in Figure 6.18. Here positive values of battery power signify charging and negative values signify the discharging of the battery.

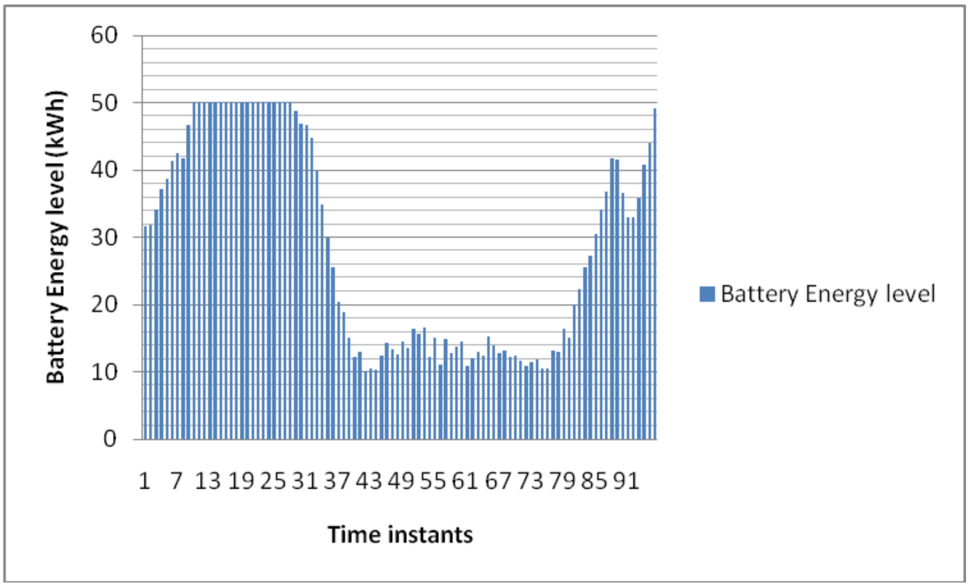

Figure 6.17: Battery energy states (Case 3)

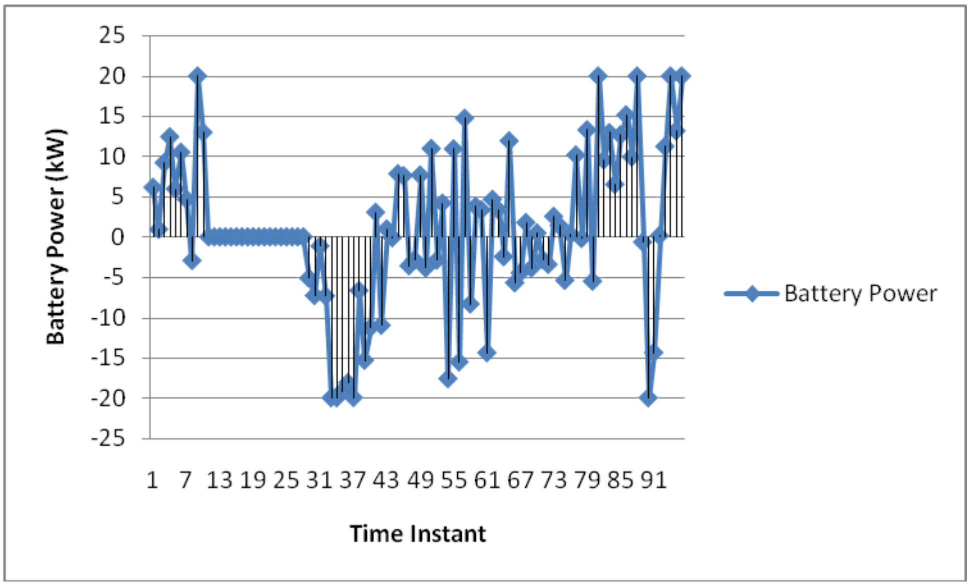

Figure 6.18: Battery power flow (Case 3)

6.3.4 Results for Case 4

Figure 6.19 and 6.20 represent the loads that have been catered for. It is seen that without the supporting units even the higher priority curtailable loads are not properly catered for. Also, there is a large unchecked dissipation of power whenever the generation exceeds the demand.

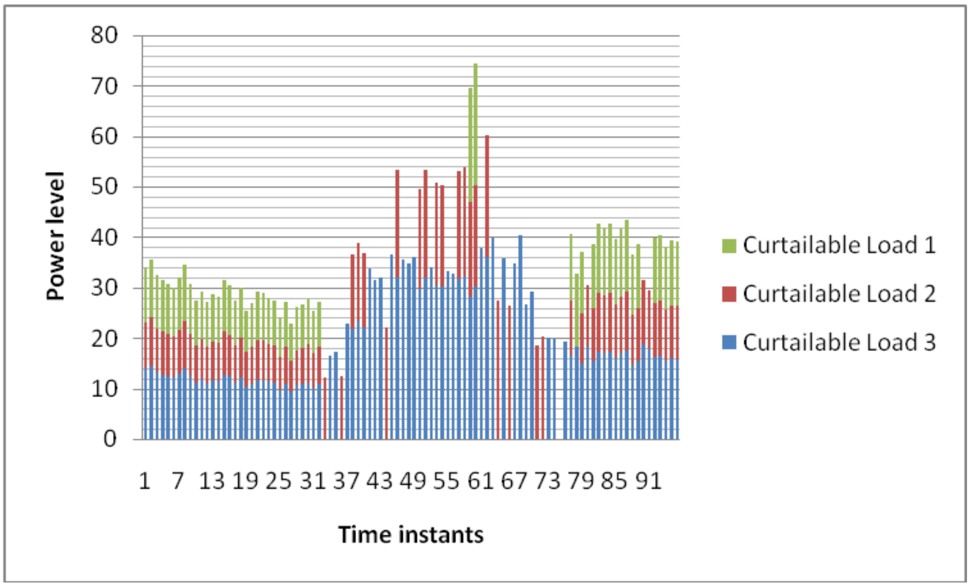

Figure 6.19: Catered curtailable loads (Case 4)

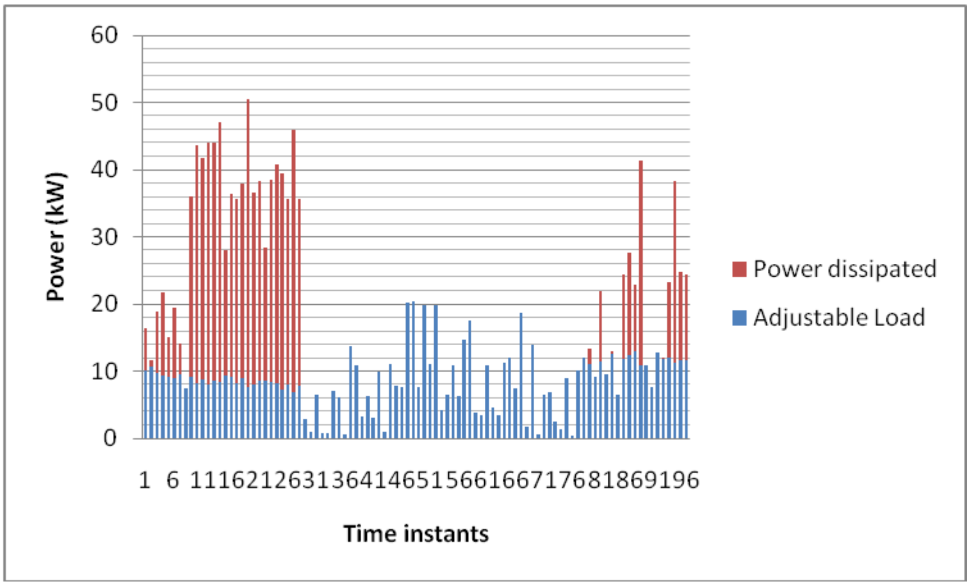

Figure 6.20: Catered adjustable loads and power dissipated (Case 4)

Chapter 7

Conclusions and Future work

This work has strived to bring together various optimization modules that could prove to be useful in the MG paradigm. It has also linked these modules and shown their tandem operation to generate meaningful results.

Provided with more data, the load forecasting module can be made more accurate. This is something worth looking into in the future. If more data regarding power consumption is made available there is also scope for developing more advanced forecasting modules like neural network modules, fuzzy system modules etc. This will also provide an avenue to take into account exogenous factors like weather, holidays, probability of special events etc.

In subsequent modules, a multi-period optimization scheme has been proposed to solve the problem of unit commitment and economic load dispatch in an isolated MG. Various constraints on the DG units were also included along with restrictions on inter-bus power flow. The distribution system was implemented using the power flow model of the MG. Participation from the consumer-side was also considered during objective function formulation. Load scheduling from the consumer side helped reduce the energy charges incurred by the consumers for specific tasks. It also helped reduce the stress on the system during peak hours. This served as a quid pro quo arrangement between end users and the MG operator. The fault tolerant load balancer scheme was proposed as a novel online optimization strategy for balancing generation and demand.

In the unit commitment and economic load dispatch module, only active power requirement of the system has been considered in the optimization problem; future work can include reactive power requirement of the system as well.

In the fault tolerant load balancer module we have explored various control strategies to attain power balance. Although the use of fast ramping generators is not particularly attractive considering the nature of this MG, this work has proposed a scheme in which a healthy balance between the various options is struck. The present operation of the fault tolerant balancer can be further be improved to increase end user performance. Although the present scheme prioritizes the loads and caters for the high priority ones, it may compromise end user comfort to a certain extent for considerable variations in generation and demand.

Another unexplored area is the pricing of energy and the remuneration the end-users will be awarded for tolerating various contingencies. Although a simplified price determination module was presented, it depends on various other factors which are worth exploring in this scenario. This work has also not looked into the compensation the customers should be given for participating in activities that could compromise their comfort like the power balancer operation.

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