DYNAMIC CONTROL AND OPTIMIZATION OF DISTRIBUTED RESOURCES IN MICROGRID

A DISSERTATION

Submitted in partial fulfillment of the requirements for the award of the degree

of

MASTER OF TECHNOLOGY

in

ELECTRICAL ENGINEERING

(With specialization in System and Control)

By

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CANDIDATE'S DECLARATION

I hereby declare that this thesis report entitled **DYNAMIC CONTROL AND OPTIMIZATION OF DISTRIBUTED RESOURCES IN MICROGRID**, submitted to the Department of Electrical Engineering, Indian Institute of Technology, Roorkee, India, in partial fulfillment of the requirements for the award of the Degree of Master of Technology in Electrical Engineering with specialization in System and Control is an authentic record of the work carried out by me during the period June 2015 through May 2016, under the supervision of **Dr. BARJEEV TYAGI, Department of Electrical Engineering, Indian Institute of Technology, Roorkee.** The matter presented in this thesis report has not been submitted by me for the award of any other degree of this institute or any other institutes.

Date:

Place: Roorkee

ANJALI SHARMA

CERTIFICATE

This is to certify that the above statement made by the candidate is true to the best of my knowledge and belief.

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ABSTRACT

Existing economic dispatch mechanisms fails to operate effectively in case of microgrid with high penetration of renewable energy resources (RESs). An intelligent control technique is required that can tackle both variability and unpredictability of RESs while satisfying time varying load demands without violating operation constraints. In this paper, we propose a MPC scheme for islanded microgrid for hourly economic dispatch of generators, storage units and RESs. MPC, subjected to constraints and forecasts, aims at minimizing running cost of microgrid along with rewarding renewable power infeed. In order to have higher forecasting accuracy, SVM approach is adopted for day ahead hourly load forecasting. Multi-layer perceptron based neural network is used for PV array output forecast. System is modelled using MILP. MPC uses load and solar output forecast data and solves optimal control problem subjected to constraints and generates optimal power dispatch plan at each time instant.First generated sequence is applied and horizon is shifted to next time instant after executing the first step of the previously determined schedule thereby dynamically adjusting and self-correcting itself for future time steps. The results depict the effectiveness of this method.

Acknowledgements

I would like to express my deep sense of gratitude and sincere thanks to my guide **Dr. Barjeev Tyagi**, Department of Electrical Engineering, Indian Institute of Technology Roorkee, for his valuable guidance and support. I am highly indebted to him for his encouragement and constructive criticism throughout the course of this project work. Inspite of his hectic schedule, he was always there for clarifying my doubts and reviewed my dissertation progress in a constructive manner. Without his help, this thesis would not have been possible.

Anjali Sharma

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Notations

C_{swt}	Cost coefficient of switching
C_{om}	Cost coefficient of maintenance
C_{tr}	Cost coefficient of Transmission
$E_{storage}$	Energy stored in storage unit
w_{load}	Forecasted hourly load data
P_{tr}	Power flowing through transmission line
$\mathbf{Y}$	Admittance matrix
P_g^{nom}	Nominal power rating of generator
P_g	Power supplied by generator
P_{ren}	Power supplied by PV array
P_v	Power supplied or absorbed by a node

Chapter 1

Chapter 1

Introduction

Use of renewable energy resources like solar, wind etc. is increasing rapidly due to growing environment problems and unsustainability of fossil fuel[1]. This led to advancement in the field of green power that in turn led to the initiation of advanced research programs in order to provide innovative as well as economical penetration of green power in todays power system scenario. This gave rise to the concept of microgrid. Microgrid is a cluster of loads, renewable energy resources and storage units, which may or may not be connected to main grid. An intelligent energy management system assists microgrid in making power allocation decisions. The main objective of energy management system is to allocate power to different energy sources in the microgrid such that the cost of energy production is optimized. As the integration of renewable energy resources increases, the obscurity in bringing about load scheduling also increases. Due to high uncertainties in renewable energy output, it is necessary that controller design must be robust enough to deal with variabilities and unpredictability of energy sources.

1.1 Introduction to Microgrid

A microgrid architecture is shown in fig 1.1 The local ac loads and dc loads are the group of consumers that includes residential buildings, factories, institutes etc. Wind turbines, solar arrays, micro turbines, fuel cells and storage units serve as sources of electric energy. We also have macrogrid utility connection to purchase electricity when there is a lack of electricity generated from local generators or to trade electricity back when generated electricity is surplus in amount. In cases of emergencies or massive faults, the macrogrid gets disconnected and the microgrid works independently to provide electricity in the islanded mode. In places like remote islands or deserts where it is not feasible to have a main grid connection, small islanded microgrid can function as the source of electricity in such regions.

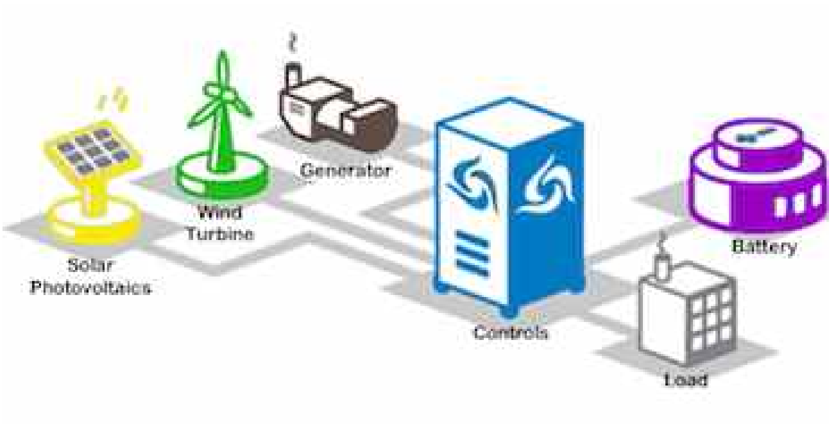

FIGURE 1.1: Microgrid Architecture

1.2 Optimal design and planning for Microgrid

The microgrid optimal operational planning involves making decisions on how to schedule power generated by various DERs, storage units as well as controllable loads optimally, in order to fulfil load demands and minimize the entire operating costs of the grid. At every time step, the microgrid controller generates decision variables. They are:

1. When should DG be turned on or off (unit commitment)
2. How much power should different unit deliver to satisfy these loads at minimum cost
3. When should storage devices be charged or discharged?
4. how much power should be bought from or sold to the main grid (if the microgrid is in the grid-connected mode)?
5. which loads must be shed/curtailed and when?

As analogous to the utility grid operation, microgrid operation can also use unit commitment (UC) and economy dispatch (ED) technique. The UC is executed from one day to one week ahead offering the start-up and shutdown schedule for each generation and storage unit that can minimize the running cost of the microgrid. ED executes itself in advance from few minutes to one hour to allocate the demand to the running units economically, considering all unit and system constraints. The recommended methods for the conventional power system optimization cannot be utilised directly to micro-grids with high penetration of renewable energy resources and ES devices due to higher variability and uncertainties in power curves. There may be huge difference between the forecasted and actual value so controller must know to deal with this stochastic behaviour of renewable sources of energy. A block diagram for energy management system is shown in fig.1.2 when a microgrid has more than two DERs; the energy management system (EMS) is required to take the power allocation decisions.

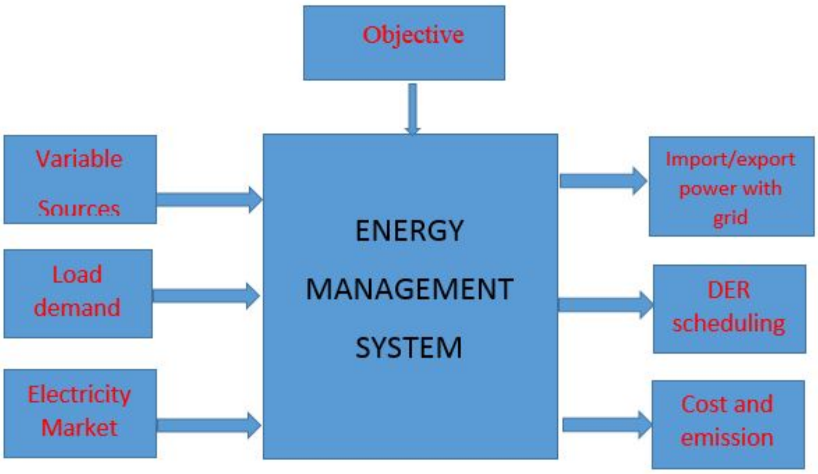

FIGURE 1.2: Energy Management System

1.3 Literature Survey

A lot of focus is shown in the field of cost optimization and suitable controller design for economic dispatch of differnet generators in microgrid. The reason behind this is the complexity and unpredictability to the entire system and the economic profit that could be made if the process of cost optimization perform effictively.Different heuristics and metahueristics algorithms have been proposed[3]. This mainly include Genetic Algorithms[4], PSO technique[5], evolutionary methods and tabu search algorithms. In order to perform effictively, controller for microgrid must use advanced control algorithm which takes into account predicted future values and uncertainities along with deploying demand responses.It should optimally use storage units without violating any physical constraints. So this makes the problem computationally intensive and unappropriate for real time use. Optimization problem remains nonlinear (MINLPs). MPC [6]turns out to be a effective tool to solve such problems as 1) It uses a predictor which is significant as forecasted renewable energy and load data are used to solve the problem. 2)Its robust due to feedback mechanism. 3)It does not violate physical system constraints[7]. An MPC method is proposed for power allocation in microgrid using wind power[8]. Stochastic MPC[9], Scenario based MPC[10], Minimax MPC[11] etc. have been discussed in different papers. Some work have been found in literature which uses two techniques simultaneously such as ADMM along with MPC framework to bring about power scheduling[12]. Hooshmand et al.[13] uses an MPC for cost optimized dynamic economic dispatch.A mutlirate MPC is also used for coordinating regulation and demand response[14]. An MPC is used for household power management[15]. Control stategies for islanded microgrid is discussed[16] In various works the nonlinear objective cost function is approximated to a linear one. Piecewise linerisation is used to convert MINLPs to MILPs. This approximation gives us suboptimal solutions. A large amount of work is still required in this field. As to reduces complexity sometimes some important parameters are not considered. The stability and protection of microgrid is very vital. A influential developement is needed in both the feilds.

1.4 Objectives

The objective of thesis is to bring about day ahead economic dispatch of energy sources in an islanded microgrid. The islanded microgrid consist of :

1. Storage unit
2. PV array
3. Thermal generator
4. Electric load

The aim is to design a controller which allocates power to different energy sources in microgrid such that entire running cost of microgrid is minimized. The focus here is also on using storage units effectively so as to minimise thermal generator infeed and maximize the renewable energy infeed in presence of uncertain forecast. Unit Commitment decision and economic dispatch are the two major task that will be performed by the controller to be designed. In order to design MPC we need approximate value of unknown variable. So we go for day ahead load and solar energy output forecasting. This is termed as short term forecasting where in we use historic data to predict the future forecast. Perfect forecasts or a formal statistical model to characterise uncertainty are not required for the MPC to perform robustly. The predictions that hold general trends are adequate since MPC generate power schedules at each time step after executing the first step of the previously calculated schedule, dynamically adjusting thereby self-correcting itself. Optimization control problem mainly comprises cost function that penalises thermal generation and rewards power infeed from pv array over K time steps.so the objectives can be summarised as follow:

1. To conduct Short term load forecasting using artificial intelligence techniques like neural network and SVM [17] so as to generate day ahead hourly load Forecast data[18]

2. Forecast pv array electric day ahead hourly output so as to set upper and lower limit constraints on power that can be extracted from solar energy resources.

3. Design a MPC which can handle uncertainties in forecast data as well as take care of physical constraints subjected to the optimal control problem.

4. Discuss results and check effectiveness of the proposed methodology

1.5 Thesis Organisation

The outline of the thesis is as follows: Chapter One entails basic concepts of microgrid. It introduces microgrid and describes the main objective of the thesis. Chapter two is dedicated to short term load forecasting. It describes neural network algorithm and SVM technique to perform forecasting and then compares the result obtained by both the methods. Chapter third consist of forecasting day ahead hourly PV array electric output data and the process used to set upper and lower limits on renewable energy power output. This bounds are used in controller design. Chapter Four involves modelling of components present in microgrid. MILP is used for problem formulation. Chapter Five mainly focuses on MPC and formulation of optimal control problem. Chapter Six discusses results and conclusions drawn from the entire work done thereby suggesting future works and improvements that needs to be conducted in this field of research.

Chapter 2

SHORT TERM LOAD FORECASTING

2.1 Introduction

Load forecasting is mainly used by electric utility to configure important aspects of power industry like infrastructure expansion, load switching, and setting up market price for electric power, power scheduling etc. The process of forecasting extracts information from historic load and weather data to make future predictions. Load forecasting is divided into three broad categories:

1. Long term load forecast
2. Medium term load forecast
3. Short term load forecast

Short-term load forecast is used in the process of unit commitment and power dispatch. It majorly generates hourly day ahead forecast. Methods for short-term load forecast comprises of two approaches:

1. Conventional Approach
    (a) Regression models

   (b) Stochastic time series

   (c) Exponential smoothing

   (d) Extrapolation

2. Mordern Approach

   (a) Neural networks

   (b) SVM and SVR

   (c) Fuzzy logics

   (d) PSO

   (e) Genetic algorithms

2.2 ANN Approach

The entire forecasting process is broken into four main steps. These steps are:

1. Identification of input: These steps include selecting number of features for input data.

2. Pre-processing data: This step involves Normalisation of data. Inputs are normalized in the range of [0,1]

3. Selection of training set: This is breaking of data into training testing and validation data. 70 percent of data is training data. 15 percent of data is validation data and rest 15 percent is testing data.

4. Testing the results: At last, Plot the results and calculate MAPE for test data.

The input features are the factors on which electricity consumption is depends. These features correlates to generate forecast. They are:

1. Historic Hourly load data

2. Min/Max/ Average daily temperature

3. Min and Max daily Humidity

4. Weekday or weekend

The historic hourly load data is taken from California ISO[19]. Weather data is taken from San Francisco region of California as it gives sufficient representation to the change in weather parameter across the state. The climate data depicting weather conditions is shown in table 2.1 and 2.2.

Table 2.1: Input Features Part1

DATE	HOUR	MIN TEMP	MAX TEMP	MIN HUMID	MAX HUMID
1/06	01	20	11	55	87
1/06	02	19	11	54	86
31/09	24	16	14	67	79

Table 2.2: Input Features Part2

holiday/ working day	samehr. prev.day	prev.day avg.	last hr. sameday	hourly load data
0/1	load	data	from	caiso
0/1	load	data	from	caiso
0/1	load	data	from	caiso

Neural Network model used here is a Multi-Layer Perceptron (MLP) network with a single hidden layer. The number of neurons in the hidden layer can be varied between 11 and 23. It is set to 15 neurons as this gave better results. The activation function used in the hidden layer neuron was Tan-sigmoid. To set the learning rate, the network was made to run with a large number of different learning rates before settling on 0.07, which gave us the best results. For each hour, train a neural network. The outputs of 24 network clubbed together and gave day ahead forecasting. Back propagation technique trains neural network in this model. The neural network model used is depicted in fig.2.1

2.3 SVM Approach

SVM algorithm is a machine-learning tool that can be effectively used to solve classification and regression problems. Initially, it was used for classification and pattern recognition purpose. Later it was modified to solve regression problems. Training data provide a supervised learning to SVM model and thereby helping it to learn about the correlation between inputs and outputs. In case of linear classification, the aim is to find

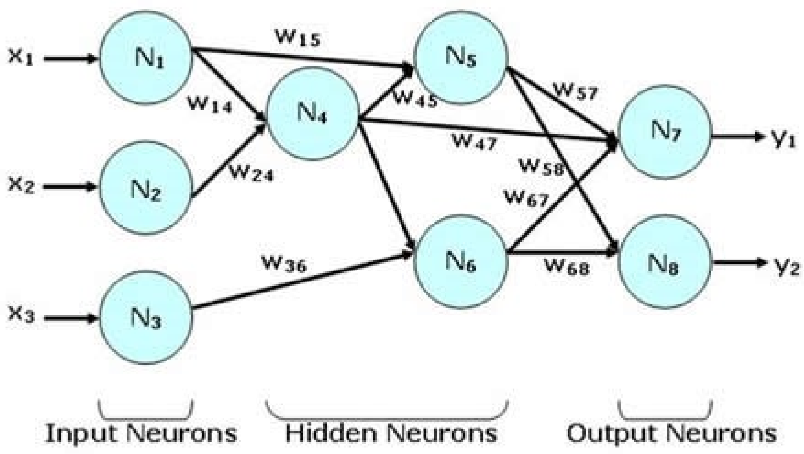

Figure 2.1: Neural network

maximum margin hyperplane that classifies the data into groups. In case of nonlinear decision boundary, data is mapped into a higher dimension feature space where it becomes linearly separable. The problem now is converted into an optimization problem, which aims at maximizing distance between hyperplanes also termed as support vectors. The problem statement is now a quadratic equation subjected to linear constraints. The

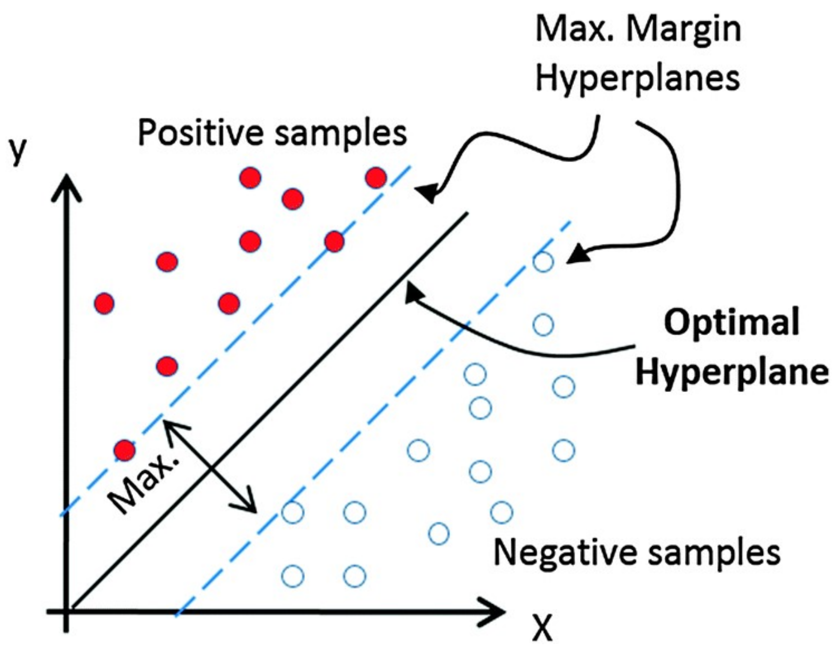

Figure 2.2: Linearly Separable Dataset

problem may be solved using lagranges multiplier. Let (x_i, y_i) denote data point of training set, b be the bias and w be a vector perpendicular to two parallel lines shown in fig

4. The margin, distance between the support vectors is mathematically given as

$$\frac{2}{\sqrt{w^t w}} \tag{2.1}$$

The distance can be maximized by minimising

$$\frac{1}{2} w^t w \tag{2.2}$$

Problem: Find w, b so as to Minimise

$$\frac{1}{2} w^t w; subjectedto : y_i(wx_i + b >= 1)(\forall x_i \in trainingdataset) \tag{2.3}$$

The problem may be solved using lagranges multiplier. Kernel Function: Original Feature space is mapped into higher dimensional feature space where data is linearly separable. Kernel functions are used for performing this task.
$\varphi : x \rightarrow \phi(x)$ The common kernel function used are

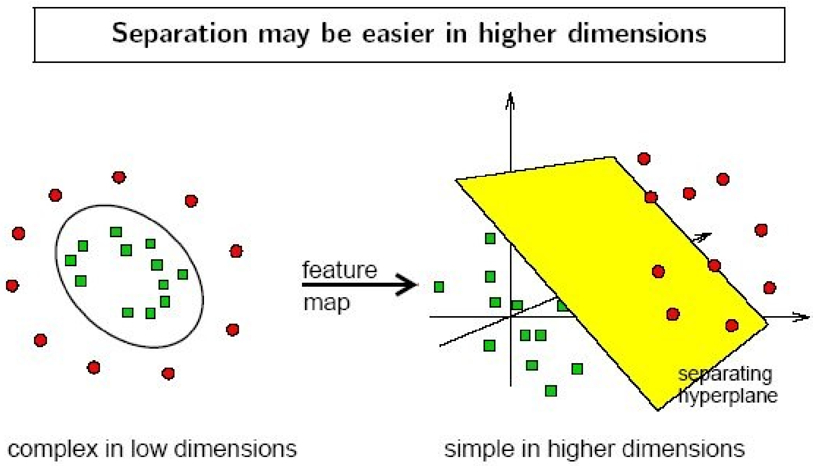

Figure 2.3: use of kernel

1. Guassian RBF(infinite dimensional space)
2. Hyperbolic tangent
3. Polynomials (homogeneous and non homogeneous)

When we work in high dimensional feature spaces, the problem of expressing complex functions get solved automatically. But it leads to two problems. Computational problem arises due to increase in dimensionality and along with it comes the curse of dimensionality which in turn ruins the generalization of model. Generalization bounds on the risk of overfitting. The best hyperplane is always the one with maximum margin. The choice of kernel affects the width of margin. large margin suggest that the choice of kernel function was right. There are no solid rules that decides which kernel function should be used. Choice of kernel function varies with datasets and algorithms used.

2.4 Short term load forecasting using SVM

The model uses concept of clustering for forecasting the next day hourly load demand. Forecasted weather parameters plays a crucial rule in clustering of available data. Load demand is also affected by time factors along with temperature and humidity. Time factors include data that represent hour of the day, time of the year, and data that states wheather its a weekday or weekend. The aim of SVM model is to recognize this factors and cluster data accordingly in order to predict future values. While carrying out load forecasting, there are no strict rules to follow for selecting input feature space. The feature selection is largely dependent on personal judgement and preliminary experimentation[20]. A support vector regression model is proposed here. The input feature are given in table 1 and table 2 of this thesis. The optimization problem is defined as follows

$Minimize : \frac{1}{2}w^t w + \gamma\Sigma_{i=0}^{k}(\varepsilon_i + \varepsilon_i^*)$

subjected to

$y_i - (wx_i + b) \leq \epsilon_i + \varepsilon_i^*$

$(wx_i + b) - y_i \geq \epsilon_i + \varepsilon_i^*$

$\gamma > 0$, cost function is a trade off between accuracy and the amount by which the any deviation is tolerated. The constraints mentioned tries to maintain the error in ϵtube. If it exceeds out of this tube, the deviation upto ϵ_i or ϵ_i^* is tolerated. The objective function strieves to minimise this slack variable ϵ_i^* . The parameters which control regression are cost function,ϵ-insensitive loss function and mapping function. Mapping function used here is guassian RBF

ϵ-insensitive loss function,$|\epsilon|$ is described as

$if : \varepsilon < \epsilon, |\epsilon| = 0,$

$else : \varepsilon < \epsilon, |\epsilon| = \epsilon - \varepsilon$

2.5 Result

Mean absolute percentage error (MAPE) is used in statistics as a measure of prediction accuracy of forecasted data. It is also known as Mean Absolute Percentage Deviation. MAPE= $\frac{1}{n}\Sigma_{i=1}^{i=n}\left|\frac{r(t)-f(t)}{r(t)}\right|$
Where r is actual value and f is forecasted value. From ANN approach, MAPE is 4.22The graph below shows predicted output in blue and actual output in green. The historic hourly data was from 1/01/15 to 1/04/16.

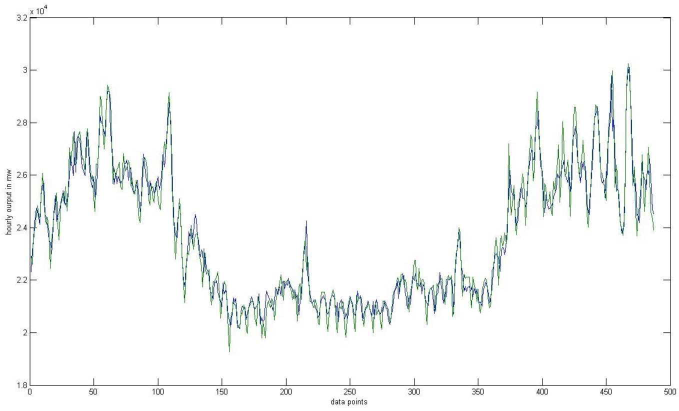

Figure 2.4: Linearly Separable Dataset

Chapter 3

PV ARRAY OUTPUT FORECAST

3.1 Power output of PV Array

Last few decades led to developement of large-scale and medium scaled photovoltaic system across the world. PV arrays generate electricity without pollution and hence termed as green energy. The accurate forecasting of solar energy output is very crucial as it can affect both stability and operating cost of the grid. Mordern forecasting approach uses evolutionary methods and machine learning techniques to predict day ahead solar output using historic data. This seems to provide better result as compared to methods which only depends on solar irradiance forecastinng model.

FIGURE 3.1: PV array

In order to study or model PV modules, four basic electrical characteristics of PV system must be described[21]. These important features are: 1) short circuit current of the module, 2)open circuit voltage generated by the module 3) fill factor and 4)maximum power output.

1. Short circuit current I_{sc} : It depends on solar irradiance and temperature of the module. The mathematical model of PV module is expressed by the following equation

$$I_{sc}(t) = I_{sc,ref}(1 + \alpha(t - t_0))\frac{GHI}{GHI_0} \tag{3.1}$$

   GHI_0 is the standard solar irradiance value of module.$I_{sc,ref}$ is the reference short circuit current calculated at STP and GHI_0. t is the temperature ino_C. α is given in the list of module specifications and its unit is $\frac{A}{o_C}$. GHI is Global Horizontle Irradiance. Its measured in $\dfrac{W}{m^2}$

2. Open Circuit voltage :

$$V_{oc}(t) = V_{oc,ref}(t)(1 + \beta(t - t_0)) \tag{3.2}$$

   $V_(oc, ref)$ is the reference open circuit voltage calculated at STP. $\beta$is available in specificaton details of module.

3. Fill Form: It is the ratio of the maximum power that can be generated by a PV module to the output power generated at any instant of time.

$$FF = \frac{V_{mxp}I_{mxp}}{V_{oc}I_{oc}} \tag{3.3}$$

PV Array: Let this array have M_p and M_s number of parallel and series units of PV module. The power is given as:

$P_{array} = P_{module}M_pM_s$

Inverter is used to convert DC power output of PV array to ac power. Its efficiency is given as η_{ac}. The ac output power is given as

$P_{out} = \eta_{ac}P_{array}$

Using these equations, Power output can be directly calculated. This is called as direct method. But this method is not robust. It cannot perform well in case of forecasted irradiance data. The uncertanities in forecasted data can be tackled efficitively by techniques like ANN and fuzzy logics.

3.2 Prediction of PV array output using ANN

A feed forward MLP model with one hidden layer 17 neurons is used to predict the output. It was trained using supervised back propogation training method. Activation function of neuron is TAN Sigmoid. Learning rate was decided by hit and try method. The output vector is the Historic hourly ac pv array output data taken from California ISO solar data. This output vector along with input features forms training data set. The input feature consist of parameters on which output of solar cell depends. They are as follow:

1. Hourly GHI data
2. Air temperature
3. Cell temperature
4. Short circuit current
5. Open circuit voltage
6. Time of the day
7. Month of the year

Table 3.1: Input Feature for PV output forecast

Date	hour	GHI	air temp	cell temp	PV output
1/06	01	data	from	sa[22]	data
1/06	02	data	from	sa[22]	from
31/09	24	data	from	sa[22]	caiso

The SolarAnywhere[22] offers world-class irradiance and weather data, and solar energy simulation services. Developers, system owners, utilities, operators and state governments, use it to condense the risk of solar asset proprietorship by enumerating renewable resource ambiguity. This website is used to extract solar irradiance data for forecasting as it is easily available and has high accuracy. The input is a (n7) matrix, where n is no. of data points in training set.

3.3 Result

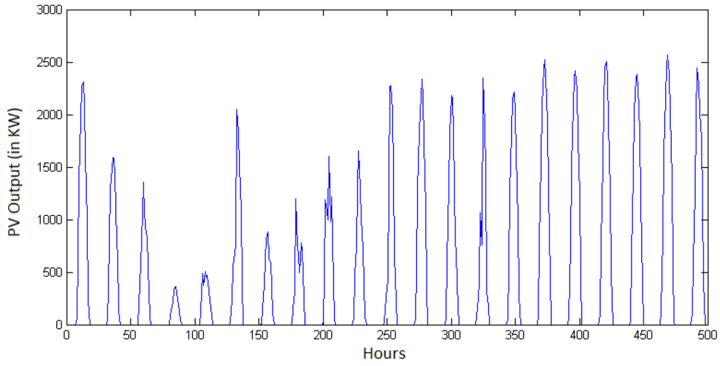

FIGURE 3.2: PV output forecast

Chapter 4

MODELLING OF MICROGRID

4.1 Microgrid Control Structure

Microgrid control structure is highly complex. It involves different control stages that operates at different time scale. Controller that manages voltage stability, frequency, power quality etc. must operate in time scale of seconds or milliseconds. There is longer time scale (hours) for controller that take unit commitment decisions and brings about economic dispatch of generating units and storages. A hierarchical control structure is required for effective microgrid operation[23]. The Microgrid controller must fulfil the following issues:

1. Frequency and Voltage Management: The system must control power through voltage and frequency control loops using different droop control schemes.

2. Demand and supply balancing: All the load demands must be satisfied at every instant of time without violating voltage and frequency constraints.

3. Power Quality: Microgrid must support power quality of main grid by bringing about Reactive power compensation and harmonic compensation at the PCC

Fig.7 describes the control structure with three levels. Primary Level Control is fast with time scale in seconds. Secondary control level is slightly slower than primary control level whereas tertiary operates in time range of hours. We aim at tertiary control level wherein we solve cost optimization problem. The objective is to determine suitable set points for all generating units and storages present in islanded microgrid such that all demands are satisfied and power dispatched is economic. The Tertiary level control actions are weakly dependent on fast dynamics and transient behaviour of lower level control schemes hence steady state assumption of different components can be made without ample loss of accuracy. The higher-level control scheme must not violate the voltage and frequency limits established by primary controller and must not result in line congestion. The outline of further task to carry out successful cost optimization of

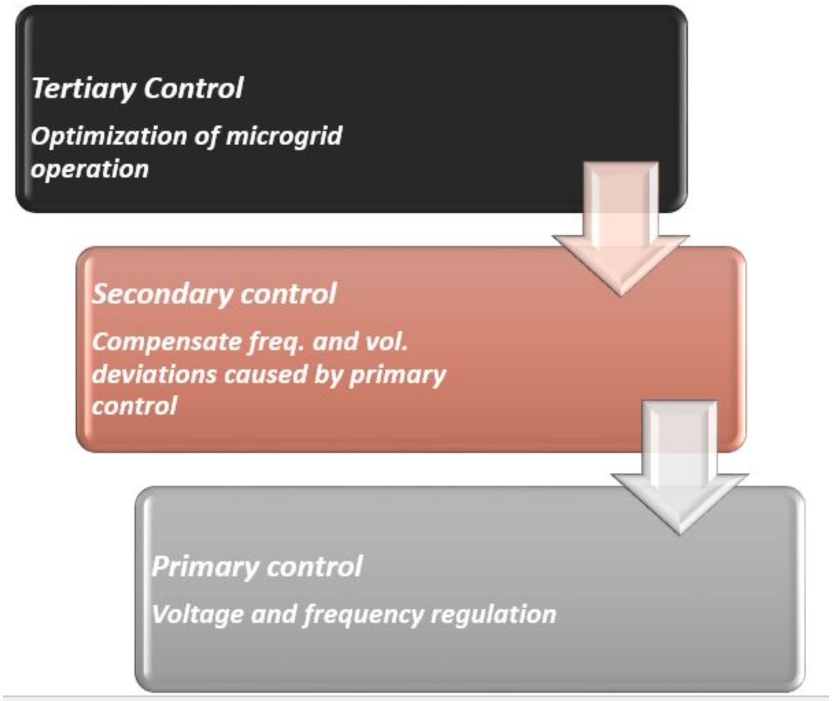

FIGURE 4.1: Control Structure

microgrid operation include the following steps:

1. Modelling of microgrid: We strive to develop a novel model of the complete microgrid using mathematical equations and setting up physical constraints.

2. MPC Scheme: We aim to develop a MPC mechanism for optimizing running costs.

3. Presentation of simulation results: The final step presents simulation results to show the effectiveness of this MPC-MILP approach in cost optimization of microgrid operations.

4.2 System Description and Modelling

We use a MPC-MILP approach for solving cost optimization problem. The reason for modelling microgrid by MILP are as follows[12]:

1. The problem statement uses both continuous and discrete decision variables. Unit commitment decisions need binary value 1 or 0 to depict on/off status of different generating units whereas Economic dispatch problem uses continuous decision variables.

2. Both differential or difference equations and logical statements can describe the behaviour of a microgrid system and its components. MILP approach can model this effectively. It transforms Logical statements into mixed-integer linear constraints[24].

The reasons for using MPC are as follows:

1. It develops feedback mechanism, that makes system effectively robust to uncertainties.

2. It is based on future behaviour of the system and predictions, which is important as systems highly depend on demand and PV array generation forecast.

3. It can handle power system constraints.

Real world control problems are subject to various constraints. Some common constraints are cost constraints, capacity constraints and actuator constraints (amplitude and slew rate limits). Several problems also impose constraints on state variables like minimum tank levels, maximal pressures that cannot be exceeded etc. These constraints may be ignored in some cases, at least in the initial design phase. But in some problems, these constraints cannot be violated as the system operates near a constraint boundary. Model Predictive Control is used to solve online optimal control problem. It uses receding horizon approach which can be summarized in the following steps:

1. At time k and present state x(k), solve online open loop optimal problem is solved over time interval taking into account current and future constraints

2. Implement first step of optimal control sequences

3. Repeat the same at$(k + 1)_{th}$ time step using the present state x(k+1)

Model Predictive Control (MPC) uses an explicit dynamic model of the response of process variables to change the manipulated variables into calculated control moves. Control actions are such that it forces the process variables to follow a reference trajectory from the current operating point to the set target point. Future control action are taken on the basis of current measurements and future predictions. Optimal controller are designed to minimise error from set point Basic version uses linear model, but there are many possible models Corrections for unmeasured disturbances, model errors are included. It uses both Single step and multi-step versions. It drives some output variables to their optimal set points, while maintaining other outputs within specified ranges.Future values of output variables are predicted using a dynamic model of the process and present measurements. Decision variables, u(k), at the k-th time step are calculated so that they minimize objective function, J.Various Inequality constraints, and measured disturbances are included in the control calculations. Let M be control horizon and P be prediction horizon.At the k-th sampling instant, the values of the manipulated variables, u, is calculated upto the next M sampling instants.This set of M control moves calculated so as to minimize the predicted deviations from the reference trajectory over the next P sampling instants while satisfying the constraints.Usually an LP or QP problem is solved at each sampling instant.Then the first u(k) is implemented and horizon is shifted.An inportant property of MPC is that stability of the resultant feedback system can be established. This is made possible because of the fact that the value function of the optimal control problem behaves as a Lyapunov function for the closed loop system. Usually the optimization problem is a convex problem due to the quadratic cost and linear constraints. some standard numerical procedures like Quadratic Programming algorithms are available to solve this problem.It can be observed that architecture described here gives a form of an integral action. In particularY_{actual} is taken to the set-point Y_{set} irrespective of the true plant description provided that a steady state is reached and u is unconstrained.It calculates the disturbance by comparing the actual controlled variable with the predicted ones. The flowchart is shown in fiig. The key elements of MPC for are:

1. state space model
2. on-line state estimation
3. prediction of future states

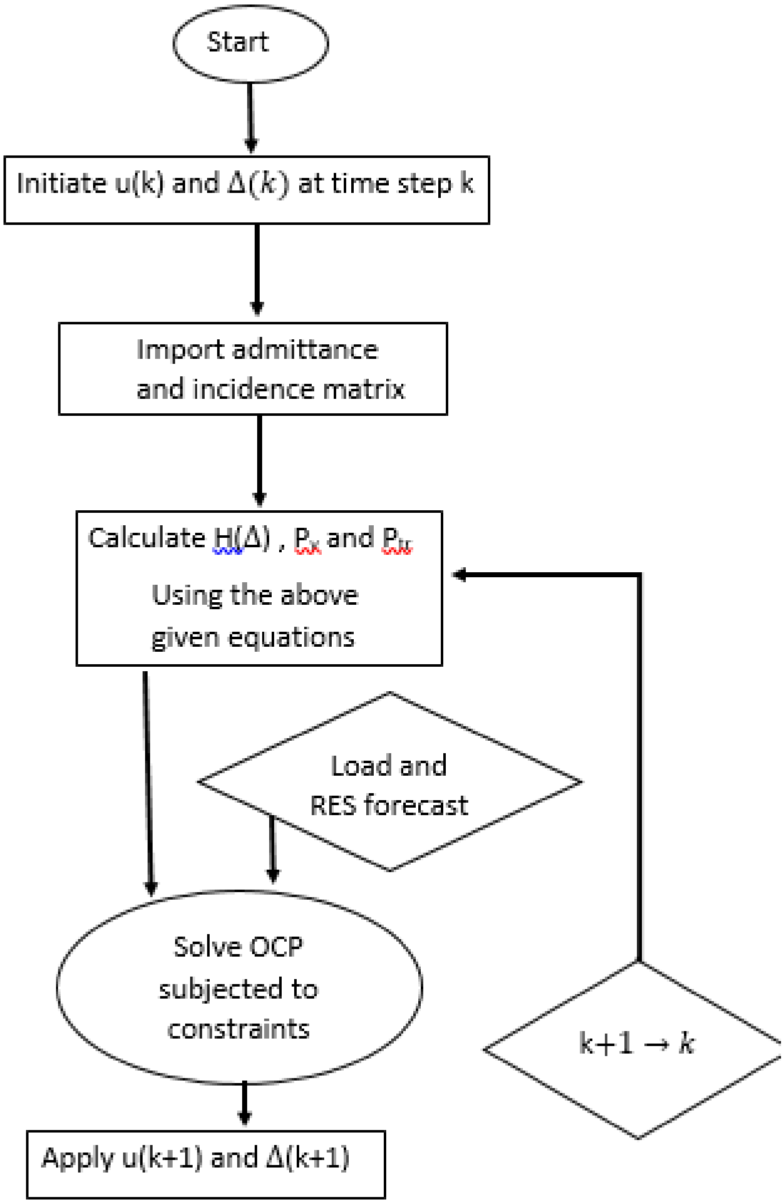

FIGURE 4.2: flowchart MPC

4. online optimization of future trajectory subject to constraints

The Islanded microgrid considered consist of:

1. Storage unit
2. Thermal Generator
3. Electric Load
4. Solar Panels as source of renewable energy
5. Transmission lines connecting them

We use the Power nodes modelling framework[25]. The foundation of the Power Nodes methodology is that any power sink or source connected to power system requires transformation of some form of energy into electric energy or power, or vice versa. These forms may be termed as supply-form or use-form of energy. It is necessary for us to fulfil the power balance in the electric grid. Conceptualizing from physical characteristics and the internal configuration of a use-process or supply- process that includes the associated energy conversion, we represent it from a grid perspection as a one lumped unit with specific parameters, a power node".

In this exemplary case study, the microgrid operates in islanded mode. All energy sources and sinks are represented as nodes. The microgrid model is shown in fig.8 Let

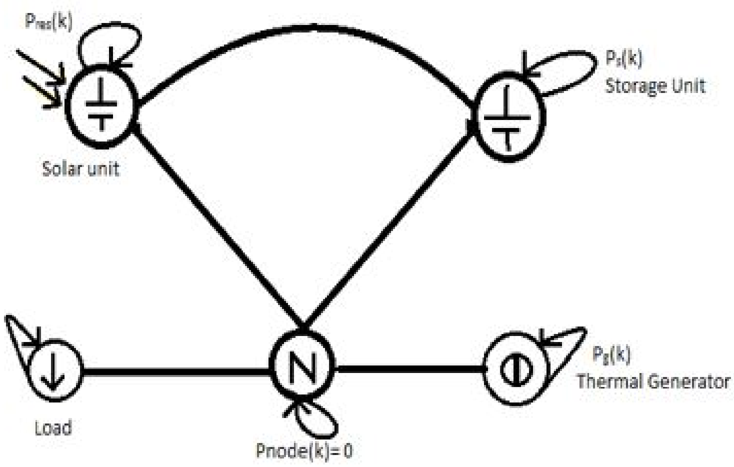

Figure 4.3: Microgrid Model

V be the set of nodes and E be the set of edges.
V $=1, 2, 3....v$ and
$E \subseteq V \times V$ Let B be the node-edge incidence matrix with element $b_{id} = 1$ if node i is a source and $b_{id} = -1$ if it act as sink. The power flow over the lines can be calculated using Linearized DC power flow equations explained in [26].

$$P_{tr} = diag(y_{ij}) \times B^{'} \times \theta \tag{4.1}$$

Where y_{ij} is the admittance of line connecting i^{th} and j^{th} node and $\theta$is the phase angle matrix with dimension $v \times 1$. The admittance matrix Y is generated using relation:

$$Y = B \times diag(y_{ij}) \times B^{'} \tag{4.2}$$

We define another matrixP_v with dimension $v \times 1$. It gives dc power between the nodes.

$$P_{tr} = diag(y_{ij}) \times B^{'} \times T^{-1} \begin{vmatrix} Y_{bar}^{-1} \times P_{vbar} \\ \theta_v \end{vmatrix} \tag{4.3}$$

P_{vbar} is $(v-1) \times 1$ P_{vbar} Is matrix obtained by eliminating last row from P_v.
$Y_{bar} is (v-1) \times (v-1)$ Matrix obtained by modifying Y matrix.

$$T = \begin{vmatrix} I_{4\times4} & -1_{4\times1} \\ 0_{1\times4} & 1 \end{vmatrix} \tag{4.4}$$

as the model that we considered consist of five nodes. Power flowing through transmission lines can be calculated using equation 4.1 Now we define state variables of the system. We have four parameters to consider. They are:
$u(k) = (P_g^{'}(k), P_{storage}^{'}(k), P_{ren}^{'}(k))'$
$\Delta(k) = (\Delta_g^{'}, \Delta_s^{'}, \Delta_{ren}^{'})$
$x(k) = E_{storage}(k)$
$w(k) = (w_{load}^{'}(k), w_{ren}^{'}(k))'$

u(k) is a real valued input control variable that conducts economic dispatch for different energy sources and $\Delta(k)$ is binary input variable which makes unit commitment decisions.
w(k) Matrix comprises of forecasted load and solar energy data. All the disturbances and fluctuations of solar power output are content in this matrix.
x(k) gives the energy stored in storage units at kth time instant

$$x(k+1) = Ax(k) + B(u(k) + H(\Delta)w(k)) \tag{4.5}$$

Using equation 4.5, we calculate the future value of energy stored in storage unit. We define a virtual slack. The variation of load and solar infeed can be handled with the concept of this slack. The storage unit and thermal generator share power among each other according to their nominal rating. The power sharing occurs such that load is satisfied fully[27]. The power balance is such that both the increase and decrease in demand and renewable infeed is tackled by the vector $H(\Delta)$.
$H(\Delta) = -inv(P_{nominal}^{'}\Delta(k)) \times diag(P_{nominal})\Delta(k) \times ones(1 \times 2)$

The total power of machine i is now u(k)+$H(\Delta)$w(k) where u(k) is the set point generated and $H(\Delta)$w(k) looks after power balance amidst the occurring variations. Now the power flowing between nodes is:

$$P_v = \begin{vmatrix} u(k) + H(\Delta)w(k) \\ w'_{load}(k) \\ P_{node} \end{vmatrix}$$

This equation is further used to calculate power flowing through the lines.

4.3 Problem Formulation

We define cost function that rewards renewable infeed and penalises thermal generation over k time steps.

$$J(x,u,w) = \Sigma_{k=0}^{K-1} \beta^k (P_g(k) - P_{ren}(k) + C_{tr}^T |P_{tr}(k)| + C_{om}^T \Delta(k) + C_{swt}^T |\Delta(k) - \Delta(k-1)|) \tag{4.6}$$

Subjected to constraints:

$x_{min} \leq x(k) \geq x_{man}$

$P_{tr}^{min} \leq P_{tr}(k) \geq P_{tr}^{max}$

$w_{min} \leq w(k) \geq w_{max}$

$P_{nominal} = (P_g^{nom}, P_s^{nom}, 0)$

$diag(u_{min}\Delta(k)) \leq u(k) + H(\Delta)w(k) \geq diag(u_{max}\Delta(k))$

$C_{tr}^T |P_{tr}(k)|$ Represents cost for power transport.

$C_{swt}^T |\Delta(k) - \Delta(k-1)|$ Represent switching costs. Start-up and shut down cost are included in it.

$C_{om}^T \Delta(k)$ Represent operating and maintenance cost of running machines. The above problem is formulated using Yalmip[28] in MATLAB and solved with CPLEX.

Chapter 5

Case study

The microgrid we consider is shown in Fig. 5.2; It is operating in islanded mode. The sampling time is 1 hour with control horizon of 6 hour and Prediction horizon of 24 hour.

The exemplary microgrid consist of:

1. RES : A PV unit with maximum capacity of 2.5 KW.
2. Thermal generator : Maximum power of this generator is 2KW. It has both switching cost and operating and maintenance cost coefficients.
3. Storage unit: 1 battery storage unit of 2.5-kW maximum power capacity is used.
4. Loads: The forecasted day ahead data serve as load data with maximum consumption around 4KW.

All the values were converted into pu system. Different cost coefficients are used in cost optimization function. This parameters used in case study and their values are shown in table 5.1.

Assumptions:

1. The hourly optimal plan is obtained by solving control optimization problem assuming no error in load forecast and PV array output forecast. Although hundred percent forecast accuracy can never be acheived but it helps in formulating optimal control plan for cost optimized economic dispatch of different resources in a microgrid.

Table 5.1: Parameters

Sr. No	Parameter	Value
1	C_{swt}	$0.2\times 1_3$
2	C_{om}	$0.1\times 1_3$
3	C_{tr}	$0.1\times 1_5$
4	x_0	0.2

2. The lower level controller controls voltage stability, power quality and frequency. So we assume that low level controllers were availble and high level control only deals with economic dispatch.

Solving optimization control problem

The OCP is a MILP problem. The branch-and-bound method are usually applied to such problems. The problem is formulated using YALMIP toolbox in MATLAB and it is solved using CPLEX 12.0

5.1 Results

Without a high level controller, the system is operated with only one aim of satisfying the load demands. It sometimes take power from the source with high operating cost rather than utilising a cheap available energy resource. Hence a high level controller is imployed. Model predictive approach is used and MILP-MPC controller is implemented to obtain the optimal solution for microgrid so as to reduce the running cost. The control strategy used formulate an optimal plan of 24 hours based on predictions of day ahead demand ,renewable power infeed and energy prices.

1. As the sampling time is 1 hour, the day ahead time varying load forecast data of 24 hours is sampled at sampling time of 1 hour. Fig 5.1 shows the day ahead load forecast with upper and lower bounds.

2. Similarly PV array output is sampled with same sampling time and forecasted lower and upper bounds are calculated. This bounds serve as constraints while solving OCP. They are shown in fig 5.2

3. $\Delta(k)$ and u(k) are decision variable which makes the day ahead optimal control plan. At the first k^{th} time instance, both the decision variables are initialised with

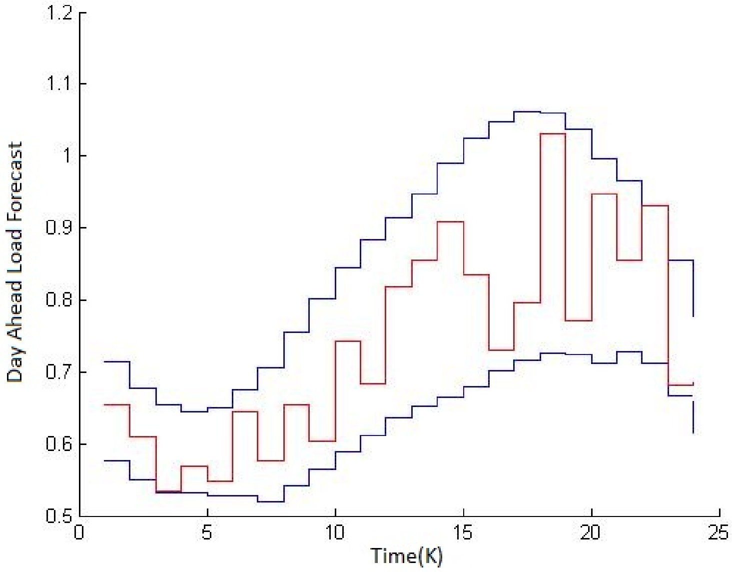

FIGURE 5.1: Load over time with predicted bounds

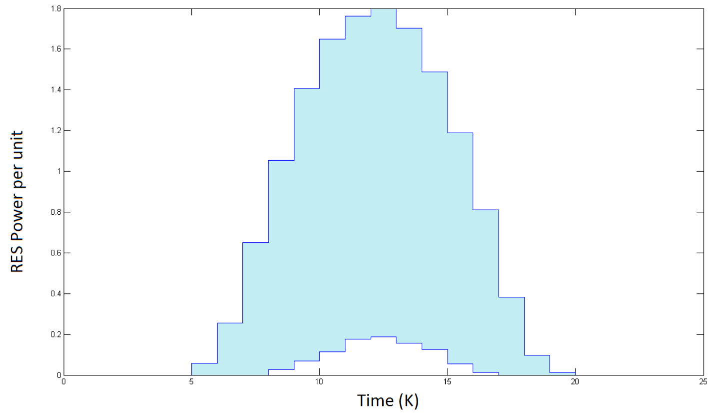

FIGURE 5.2: RES infeed over time

their current states. MPC-MILP based OCP is solved which generates the future decision variables (u(k+1),u(k+2),......u(k+m)) $(\Delta(k+1), \Delta(k+2), ...\Delta(k+m))$ where m is control horizon.Only the first decision variable generated are implemented and thereafter the horizon is shifted. At the next sampling instance, the new state of the system is considered, and optimization problem is solved again using this set of new information. using receding horizon approach, the generated optimal plan can compensate for disturbances that have recently arised. The entire process is repeated at $(k+1)^{th}$ instance.

4. The solution of MPC-MILP problem generated hourly economic power dispatch results. The optimal plan for thermal generator and storage unit is shown in fig

5.3 and fig 5.4

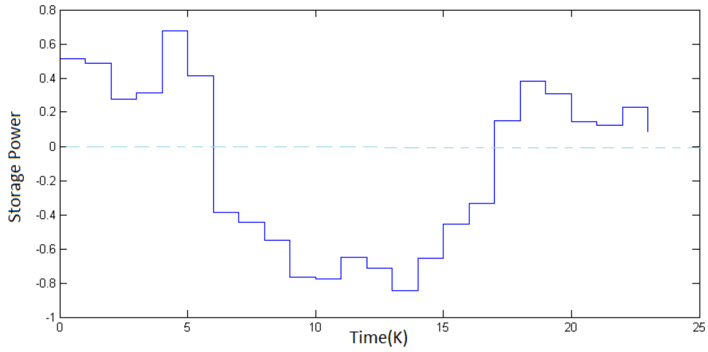

FIGURE 5.3: Optimised control input for storage unit

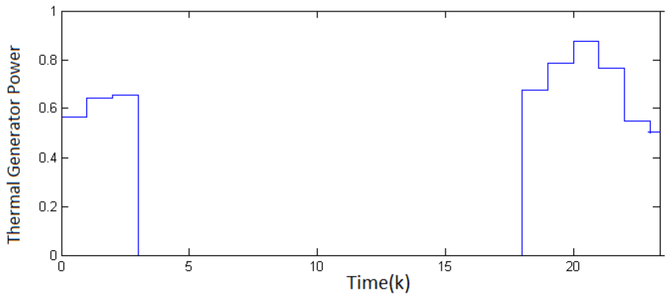

FIGURE 5.4: Optimised control input for thermal generator

As from k=0 to 5 and k=19 to 23, RES infeed is zero. Hence storage unit and thermal generator share the load on the basis of their nominal rating as decided by parameter $H(\Delta)$. From k=11 to 15 the storage unit is charged as RES infeed high and it supply power to load.

As OCP aimed at reducing runnning cost, thermal generator was used only once in a day k=19 to k=3 to reduce switching cost. Storage unit charged and discharged itself throughout the day depending on RES infeed.

5.2 Conclusion

This thesis proposed an MPC-MILP approach on modelling and optimization of an islanded microgrid. Mixed integer programming was used to model microgrid. Physical constraints were imposed on optimal control problem using MILP. The solution of OCP generated hourly economic dispatch plan for different energy sources in microgrid.The receding horizon approach of MPC made the economic dispatch plan dynamic and self correcting as it utilised both load and renewable energy forecast data. Machine learning techniques like SVM and ANN were used for forecasting. The proposed approach was implemented on an exemplary microgrid and this scheme is able to economically optimize microgrid operations. Unit commitment and economic dispatch decisions can be satisfactorily made using this approach. The hourly optimal plan was obtained by solving MPC based optimal control problem assuming no error in load forecast and PV array output forecast and assuming the availability of low level controller.

5.3 Future work

Future work include uncertainty modelling so as to deal with problem of errors in forecasting data. Weather conditions may lead to generation reduced power from renewable energy resources and this factors must be considered. Future work must also focus cost optimization and power scheduling of various distributed energy resources connected in grid connected mode of microgid. The cost function should encourage the use of renewable sources of energy and must bring about energy optimization.

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