SWARM INTELLIGENCE BASED ECONOMIC OPERATION OF HYDRO-THERMAL POWER SYSTEM WITH FORECASTED DEMAND: A CASE STUDY

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THESIS CERTIFCATE

This is to certify that the thesis entitled **'SWARM INTELLIGENCE BASED ECONOMIC OPERATION OF HYDRO-THERMAL POWER SYSTEM WITH FORECASTED DEMAND: A CASE STUDY'** submitted by **Pramelakumari K** to the Cochin University of Science and Technology, Kochi for the award of the degree of Doctor of Philosophy is a bonafide record of research work carried out by her under my supervision and guidance at the Division of Mechanical Engineering, Faculty of Engineering, Cochin University of Science and Technology. The contents of this thesis, in full or in parts, have not been submitted to any other University or Institute for the award of any degree or diploma.

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DECLARATION

I hereby declare that the work presented in the thesis entitled '**SWARM INTELLIGENCE BASED ECONOMIC OPERATION OF HYDRO-THERMAL POWER SYSTEM WITH FORECASTED DEMAND: A CASE STUDY'** is based on the original research work carried out by me under the supervision and guidance of **Dr. Jagathy Raj V.P**, (Guide), Professor, School of Management Studies, and **Dr. Sreejith P.S.** (Co-guide), Professor, Division of Mechanical Engineering and Dean, Faculty of Engineering, Cochin University of Science and Technology for the award of degree of Doctor of Philosophy with Cochin University of Science and Technology. I further declare that the contents of this thesis in full or in parts have not been submitted to any other University or Institute for the award of any degree or diploma.

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ABSTRACT

Power sector plays a pivotal role in all developmental activities of a State. Kerala power system signifies with its higher availability of hydro-power at a relatively cheaper rate compared to other States of India. However, the cost of generation and power purchase are being increased recently on account of the imbalance of generation and power consumption. The Kerala power system has not yet applied any scientific tools for its economic operations and hence results in huge revenue loss. This thesis work addresses the above problem by formulating the economic operation and suggests solution using selected intelligent tools in load forecasting, generator scheduling and cost optimization, so that a substantial amount of revenue can be saved by reducing the import of power.

In this study, the performance evaluation of the statistical and intelligent methods for load forecasting such as, time series, multiple linear regression, artificial neural network and support vector machine have been carried out. It is found that the prediction errors in time series is less than that of multiple linear regression. The most efficient technique for load forecasting is proved to be artificial neural network (ANN) in comparison with support vector regression and statistical tools. The swarm intelligence based economic operation of hydro-thermal power system with forecasted demand has been done in this study by using particle swarm optimization with time varying inertia weight (PSO-TVIW) and genetic algorithm (GA).

The results show that generation can be properly scheduled and hence the cost of imported power can be reduced, thereby a large amount of money towards the energy cost can be saved. It is observed that PSO-TVIW gives better results compared to

GA. The case study concludes with a proposal for using the ANN based scientific tools for load forecasting. It also proposes PSO-TVIW based intelligent techniques utilizing the forecasted data for cost optimization by proper generator scheduling.

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ABBREVIATIONS

ACO	-	Ant Colony Optimization
AGO	-	Accumulated Generating Operation
AGA	-	Atavistic Genetic Algorithm
ABT	-	Availability Based Tariff
ARR	-	Annual Revenue Requirement
AR-SVR	-	Auto Regressive Support Vector Regression
ARMA	-	Auto Regressive Moving Average
ARIMA	-	Auto Regressive Integrated Moving Average
ARMAX	-	Auto Regressive Moving Average with Exogenous Variables
ARIMAX	-	Auto Regressive Integrated Moving Average with Exogenous Variables
ARX	-	Auto Regressive Exogenous Variables
ANN	-	Artificial Neural Network
APCPL	-	Aravali Power Company Pvt Ltd
BDPP	-	Brahmapuram Diesel Power Plant
CPP	-	Captive Power Project
CGS	-	Central Generating Station
DSM	-	Demand Side Management
DE	-	Differential Evolution
DED	-	Dynamic Economic Dispatch
ESO	-	Evolutionary Strategy Optimization
ELD	-	Economic Load Dispatch
FEP	-	Fast Evolutionary Programming
GA	-	Genetic Algorithm
GM	-	Grey Model
HT-LT	-	High-Tension - Low-Tension
IIM-K	-	Indian Institute of Management, Kozhikode
IPP	-	Independent Power Project

ITS	-	Interval Time Series
IGA	-	Immune Genetic Algorithm
KDPP	-	Kozhikode Diesel Power Plant
KSEB Ltd	-	Kerala State Electricity Board Limited
LTA	-	Long Term Access
LSHS	-	Low Sulphur High Stock
LDIW	-	Linear Differential Inertia Weight
MAE	-	Mean Absolute error
MPE	-	Mean Percentage Error
MAPE	-	Mean Absolute Percentage Error
MAD	-	Mean Absolute Deviation
MW	-	Mega Watt
MTOA	-	Medium Term Open Access
MLR	-	Multiple Linear Regression
MA	-	Moving Average
MLP	-	Multi-Layer Perception
MRA	-	Multi-Regression Analysis
MPSO	-	Modified Particle Swarm Optimization
MU	-	Million Unit
NTPC	-	National Thermal Power Corporation
NLC	-	Neyveli Lignite Corporation
NCEMC	-	North Carolina Electric Membership Corporation
PSO- TVIW	-	Particle Swarm Optimization with Time Varying Inertia Weight
PSO	-	Particle Swarm Optimization
PPA	-	Power Purchase Agreements
PGCIL	-	Power Grid Corporation of India Limited
PACF	-	Partial Auto-Correlation Function
RGCCPP	-	Rajiv Gandhi Combined Cycle Power Project
RMSE	-	Root Mean Square Error

SED	-	Static Economic Dispatch
SRLDC	-	Southern Region Load Despatch Center
SLDC	-	State Load Dispatch Center
STLF	-	Short Term Load Forecasting
SVR	-	Support Vector Regression
SVM	-	Support Vector Machine
SA	-	Simulated Annealing
SGA	-	Simple Genetic Algorithm
SPSS	-	Statistical Package for Social Sciences
SOFNN	-	Self-Organizing Fuzzy Neural Network
TS	-	Time Series
TS	-	Tabu Search
VAR	-	Vector Auto Regressive
UI	-	Unscheduled Interchange

CHAPTER 1

INTRODUCTION

The electric power is generated, transmitted and delivered to the user instantly on demand as storage of large amount of electrical energy is a formidable challenge. The electrical demand forecasting is a central process for planning periodical operations and facility expansion in the electricity sector. Accurate forecasts, in turn, lead to substantial savings in operation and maintenance costs, increased reliability of power supply and well-founded decisions for future development. The correct dispatch decision depends on the accuracy of forecast with the extent of the permissible variation in generation limits. Thus, electrical load forecasting has become a vital process in the planning and operation of electric power systems.

Power sector plays a dynamic role in all developmental activities of a State. The Kerala State Electricity Board Limited (KSEB Ltd), is the statutory body responsible for generation, transmission and distribution of electricity in the State of Kerala. Kerala is abundant in hydro power which results in relatively low-priced energy. The electricity generation in Kerala began in 1940 by the commissioning of Pallivasal Hydro-electric Project with an installed capacity of 37.5MW (Economic Review, 2008). During the seven and half decades thereafter, the progressive developments of various projects mainly hydro, thermal, wind and solar, witnessed remarkable achievements in generation, transmission and distribution of electricity. At present the installed capacity reached to 2791.25MW (KSEB Ltd website).

At the initial stages of development of power projects, the energy was surplus till 1980s. The excess energy was sold to the neighboring states and there was a fillip to the power intensive industrial sections in the State. Over the years, the per capita consumption of electricity has also been increasing in Kerala, without enough simultaneous capacity addition. The high increase of energy consumption by the consumers – industrial as well as domestic– necessitated further increase of production of electricity. However, due to several environmental factors, the KSEB Ltd could not proceed with hydro-electric projects such as Silent Valley, Pooyamkutty and the latest pending Athirappilly. The situation, thus, paved the way for much depending on power purchase from different sources. The development of power grid at the regional and national level helped the State to purchase a large proportion of power from outside the State. This resulted in huge financial liability of the State apart from the transmission and distribution loss of electricity and other related issues. But the KSEB Ltd had to adopt strategic initiatives for improving the power management and overall productivity coupled with cost reduction efforts. This resulted in reducing the revenue deficits to a considerable extent. For instance, the revenue deficit of 2006-07 was reduced from Rs. 142.23 crores to Rs. 91.29 crores in 2007-08 (Kerala State Electricity Regulatory Commission, 2017; Khurana and Banerjee, 2015).

Thus, there emerged the significant challenges of demand forecasting and cost optimization through generation scheduling. The State Planning Board in its review of power sector in Kerala has rightly observed:

> "The new challenge is to be able to find an adequate basket of sources, suitably distributed over time and hours of the day, with advance purchase agreement so that the net cost of purchased power is suitably optimized."
>
> (Economic Review, 2016, p.296)

In 2014, a World Bank Report depicted Kerala as one of the best performing electricity sectors in India with a consistent rank among the top utilities. However, the increasing demand of electricity without adequate capacity addition forced the Board to purchase the power from external sources and drew down surpluses earned in earlier years. The World Bank Report rightly identified the Board's problem in the following words:

> "Inadequate planning for power procurement to address demand growth has exacerbated the change in fortunes of the utility, which remains well managed but is now suffering in the face of external shocks."
>
> (Pargal and Banerjee, 2014, p.93)

The study conducted by the Indian Institute of Management, Kozhikode (IIM-K) in 2015 also revealed and emphasized the need for reducing the cost of generation including the proper utilization of man power (IIM-K, 2015). One more study of the World Bank in 2015 further highlighted that the State's financial performance in power sector was critically linked with power purchase costs (Khurana and Banerjee, 2015). The above reports conclude the need of proper planning for power procurement and cost optimization.

The Kerala power system is still following a conventional method of forecasting the load demand. From the past experience the demand is calculated. That is, for a particular day or week or month, the previous year's position is taken into account. No scientific tools are adopted for demand forecasting and cost optimization.

1.1 DEMAND FORECASTING

Demand forecasting is usually a sort of method to identify the electrical demand from a specified number of consumers in a specified period. Electrical demand and electrical supply system could be in terms of average system demand, maximum system demand, load demand in MW or energy demand in MWhr. Demand forecasting is usually undertaken with the prediction of hourly, daily, weekly, monthly and annually of the system demand and peak demand. Such forecasts are categorized into three (Charyotoniuk *et al.*, 1999; Adepoju *et al.*, 2007). One is the short-term forecasting which takes a few hours ahead to a few weeks. It concerned mainly with unit commitment, economic dispatch, hydro-thermal coordination and load management. The second is mid-term or medium-term forecasts usually from a week to one year. It relates to the planning of operation, maintenance, energy contracts and fuel management (Shrivastava and Misra, 2008). The third one is long term forecasting which can be valid from 5 years to 20 years and concerned with system generation and transmission. For the economic and secure operation of power system, an accurate load forecasting technique is essential.

1.2 APPLICATION OF SCIENTIFIC TOOLS

Demand for electricity is closely linked to economic growth and depends on the industrial development as well as increase in population. No serious study has been undertaken to optimize the operation of the Kerala power system. Some of the computations are on the basis of thumb rules. In this work computational efficiency of various scientific tools used in load forecasting is analyzed and compared.

Various scientific methods are in vogue for prediction of load demand and optimization of cost. They are statistical tools such as: time series, multiple regression, trend analysis etc., and artificial intelligence techniques such as: artificial neural networks, fuzzy logic and support vector machines etc. (Warwick *et al.*, 1997). In this study, the forecasting methods used for short-term, mid-term and long-term load forecasting include time series, multiple regression, artificial neural networks, and support vector machines. The particle swarm optimization and genetic algorithm are used as tools for solving the economic load dispatch problems.

1.2.1 Time Series and Multiple Regression

Time series regression is a statistical method used for forecasting the electric load demand. This method is based on the assumption that a load pattern is nothing more than a time series signal with seasonal, weekly and daily periodicities. The data has some internal structure such as auto-correlation, trend or seasonal variation (Park *et al.*, 1991; González-Romera *et al.*, 2007).

Linear regression is a statistical technique used for finding a relation between two or more variables. If the relation is found between two variables, it is the simple linear regression and the multiple linear regression is the relation among more variables. After finding the relation between the variables, it is assumed that the parameters are varying with same relation. Hence the same relation is applied to the forthcoming parameters, which will give the values of dependent variable for the corresponding forthcoming independent variables (Hong *et al*., 2011). The dependent variables considered in this work includes weather factors such as minimum and maximum temperature, humidity and rain fall. Linear regression is a quite simple method to fit the curve and find the coefficients.

1.2.2 Artificial Neural Network

A neural network is a machine that is designed to model the way in which the human brain performs a particular task i.e., each neuron receives input from neighbours or external source and use this to compute an output signal which is propagated to other units. Once a neural network is trained to a satisfactory level it may be used as an analytical tool on the other data.

The neural network has been an increasingly important approach to artificial intelligence (Rumelhart *et al.,* 1986; Smolensky 1987; Feldman *et al*., 1988; Freeman and Skapura, 1991).

1.2.3 Support Vector Machine

Support Vector Machine (SVM) is the most powerful and new technique for the solution of data classification and regression problems. This approach was based on the Vapnik's statistical learning theory and structural risk minimization principle to estimate a function by minimizing an upper bound of generalization error (Zhu *et al.*, 2007). While the neural network and other intelligent systems try to define the complex functions of the inputs, support vector machines use the nonlinear mapping of the data into higher dimensional features by using the kernel functions. In support vector machines, simple linear functions are used to create linear decision boundaries in the new space (Islam, 2011). In the case of neural network, the problem is in the choosing of architecture and in the case of support vector machine, problems occur in choosing a suitable kernel.

1.3 ECONOMIC LOAD DISPATCH

The economic operation in power system planning plays a major role in deciding electricity price in both regulated and de-regulated market. Economic dispatch is the name given to the process of apportioning the total load on a system between the various generating plants to achieve the greatest economy of operation (Stevenson Jr., 1982). Thus, the economic load dispatch problem controls the committed generating unit outputs so as to meet the required load demand at minimum operating cost while satisfying the power demand and system equality and inequality constraints (Wood and Wollenberg, 2005). The economic load dispatch is a non-linear constrained optimization method whose complexity increases when constraints such as system power balance constraints, generator constraints, reserve constraints, valve-point effect and generator's prohibited zones are considered (Gaing, 2003; Parassuram *et al.*, 2011).

An optimal solution to the economic load dispatch problems leads to remarkable saving in the power system's operational cost. The main problem is to decide when and which generating units to start up and shut down, in order to minimize the total fuel cost over specified period subject to a large number of constraints. The most important goal is that the total generation must be equal to the forecasted demand of power (Cohen and Wan, 1987).

1.3.1 Particle Swarm Optimization

A new optimization technique using an analogy of swarm behavior of natural creatures was started in the beginning of 1990s. It was the Particle Swarm Optimization (PSO) technique, a simple optimization concept compared to other techniques, was introduced by Kennedy and Eberhart in 1995. In this method paradigms are implemented in a few lines of computer code. The original objective of this technique was to mathematically simulate the social behavior of bird flocks and fish schools.

PSO was aimed at treating non-linear optimization problems with continuous variables. Schools of fishes and swarms of birds can be modeled with such simple models. If the behavior rules of each individual (agent) are simple, the behavior of the swarm can be complicated. The behavior of each agent inside the swarm can be modeled with simple vectors. The position of each agent is represented by its x, y axis position and also its velocity is expressed by v_x and v_y. Modification of the agent position is realized by the position and velocity information. Bird flocking optimizes a certain objective function. Each agent knows its best value (*pbest*) and its x, y position. This information is an analogy of the personal experiences of each agent. Moreover, each agent knows the best value so far in the group (*gbest*) among *pbest*. Birds and fish adjust their physical movement to avoid predators, seek food and mates, optimize environmental parameters as temperature, humidity etc. (Eberhart *et al.,* 1995b; Lee and El-Sharkawi, 2008; Al-Rashidi and El-Hawary, 2009; Jaini *et al.*, 2010).

1.3.2 Genetic Algorithm

Heuristic technique seeks good solutions at a reasonable computational cost without being able to guarantee either feasibility or optimally. Most modern heuristic search strategies are based on some biological metaphor. Evolutionary algorithm is based on genetics and evolution. All genetic algorithms (GA) consist of following components such as chromosomal representation, initial population, fitness evaluation, selection, cross over and mutation (Sivanandam and Deepa, 2008).

In order to apply a GA to a given problem, decision must be taken on how the parameters of the problem will be mapped in to a finite string of symbols known as genes (with constant or dynamic length), which encoding a possible solution in a given problem space. The symbol alphabet used is often binary, though other representations including character-based and real-valued encodings. When using binary coding, the positions of the genes in the chromosome are very important for a successful GA design, unless uniform crossover is applied. The binary gene position problem is to use an operator called inversion. Inversion can freely mix the genes of the same string in order to put together the building blocks, automatically during evolution. Each string is evaluated and assigned a fitness value after the creation of an initial population (Walters *et al.*, 1993). The objective function and fitness function can be distinguished by the use of genetic algorithm. In short, genetic algorithm is found to be an efficient tool in solving the economic load dispatch problem (Tofighi *et al.*, 2011; Sewtohul *et al.*, 2004).

1.4 MOTIVATION OF THE RESEARCH WORK

KSEB Ltd has been running at a huge loss due to the power purchase for meeting the needs of the State. The cost of power purchase alone is 70% of the total revenue. The Board has not yet adopted any scientific tools for forecasting the load demand. Forecasted peak demand of power by conventional method of KSEB during 2017-18 was 2645MW. But the actual peak demand reached upto 4468MW. If the Board is using scientific tools for forecasting the load demand and optimization of economic dispatch, it can reduce the import of power and thereby substantially decrease the financial loss.

1.5 SCOPE OF RESEARCH WORK

The existing strategy followed by KSEB Ltd is the conventional method which includes the following: Reserving the storage of water in reservoirs for the use in summer season. For prediction of the load the demand of a day is calculated on the basis of the demand of that day in the previous week and previous year. This calculation is subjected to the occurrence of rain during previous day, week or year. The present strategy adopted by the KSEB Ltd is not accurate due to the absence of using scientific tools for predicting the load. Therefore, an effective load forecasting based on scientific methods and use the of forecasted data are essential in cost optimization of economic operation of Kerala power system. The research study undertakes this work.

1.6 THE RESEARCH PROBLEM

The major research challenge is to predict the timely demand so as to find an adequate resource in advance, distribute them over a period of time in a cost optimized and fitting mode meeting load demand, so that the advance power purchase agreement can be met with minimum net cost of power purchase. This thesis work is an attempt to address the challenges of improvements to be made in load forecasting of a typical power system and to utilize the forecasted demand of electrical power for optimization of load dispatch. The data from Kerala power system, where the existing system has not yet adopted any scientific tools in load forecasting and cost optimization, is utilized for executing this research attempt.

1.7 RESEARCH OBJECTIVES

The major objective of the study is the optimization of power system with reference to Kerala. More specifically, the objectives are:

i. To review of Kerala power system operation, existing load survey and forecasting methods;

ii. To analyze the performance of load forecasting and optimization in order to identify an apt tool, which can be applied for a real power system data;

iii. To analyze the load demand forecasting for short-term, mid-term and long-term by using the data taken from Kerala power system;

iv. To optimize the cost of generation based on the forecasted load demand;

v. To reduce the import of power and attempt to induce self-sustainability in Kerala power system; and

vi. To develop a strategy for cost optimization that can be used for Kerala power system.

1.8 METHODOLOGY

An assessment of the Kerala power system is required in this study. On the basis of the data obtained from Kerala power system, the short-term, medium-term and long-term demand forecasting are carried out. The algorithm of artificial neural network, time series regression, multiple linear regression and support vector regression are used for load demand forecasting. The forecasted demand is taken for minimizing the cost of generation. The particle swarm optimization and genetic algorithms are used for optimization of the cost of generation. The Figure 1.1 represents the working model of the research.

Step 1: The actual load demand is collected from utilities (Kerala State Electricity Board Ltd and India Meteorological Department). This data is preprocessed to suit as input to the selected computational tools - statistical method and artificial intelligence method.

Step 2: Two algorithms are used under statistical method, which are, time series and multiple linear regression for load forecasting. Time series analysis is accounted here since the data points in a series of particular time periods that may have internal structure such as autocorrelation, trend or seasonal variation. The multiple linear regression is used to explain the relationship between one continuous dependent variable, in this case load data, and two or more independent variables like temperature and rainfall.

Step 3. Artificial neural network and support vector regression algorithms are chosen as artificial intelligence method for load forecasting. Artificial neural network, which simulates the way human brain analyzes and process information, is considered to be a nonlinear statistical data modeling tool where the complex relationship between inputs and outputs are modeled. Support vector regression is a supervised machine learning algorithm which tries to fit the error within a threshold value.

Step 4: In this step, compare the results obtained with statistical method versus artificial intelligence method. The error term such as MAE, MAPE, MPE, MSE and RMSE are calculated and compared for short-term load forecasting (one hour ahead load prediction, one day ahead load prediction), mid-term load forecasting (one week ahead load prediction, one month ahead and one year ahead load prediction) and long-term load forecasting (five year and ten year ahead load prediction).

Step 5: A strategy for cost optimization that can be used for Kerala power system which includes combined cost optimization of hydro and thermal units with particle swarm optimization and genetic algorithm is developed. A detailed comparison of the effectiveness of the developed methods are done with ANN forecasted demand.

Figure 1.1 depicts the different topologies used in research work.

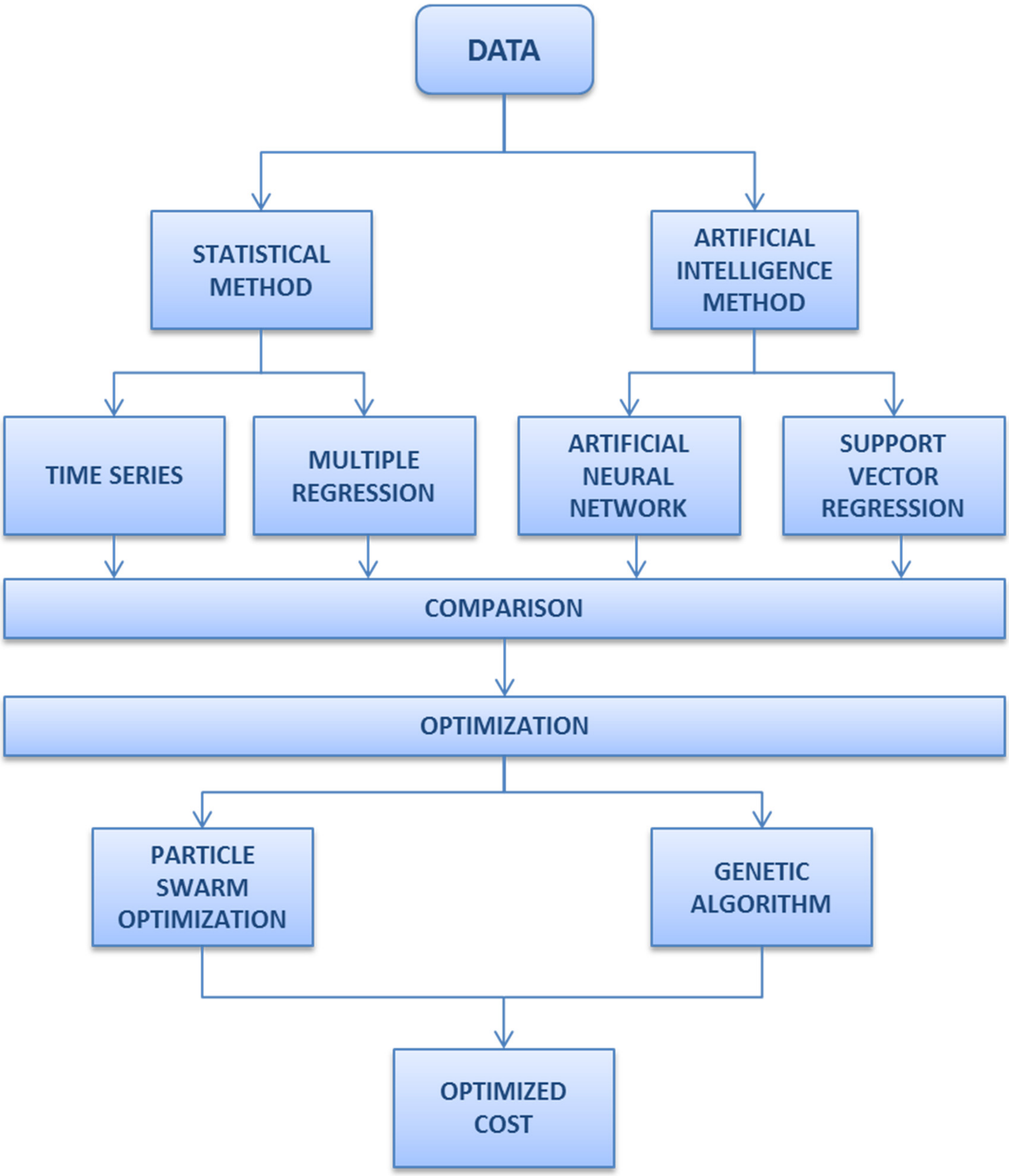


Figure 1.1 Flowchart of working model of research

1.9 ORGANISATION OF THESIS

The thesis is organized systematically with the following sections:

Chapter 1 gives an introduction to the research topic. The concept of load demand forecasting and economic load dispatch with the application of some selected scientific tools are briefly explained. The problem, objective and methodology of research are also discussed.

Chapter 2 reviews the literature on various demand forecasting and different modeling methods used for demand forecasting. The literature on forecasting tools, demand forecasting applications, economic load dispatch problems and finally the optimization techniques including particle swarm optimization and genetic algorithm are reviewed and discussed.

Chapter 3 analyses the state-of-the-art of Kerala power system with the existing practices of load forecasting. The performance evaluation of the statistical methods of time series and multiple linear regression for load forecasting in Kerala power system is also analyzed.

Chapter 4 evaluates the application of artificial intelligence technique such as neural network and support vector regression for demand forecasting in Kerala power system. An attempt is made for demand forecasting of both short-term and mid-term with support vector regression techniques. Demand forecasting of short-term, mid-term and long-term is made with artificial neural network. A detailed comparison of the results obtained has been made.

Chapter 5 deals with utilization of the forecasted demand of Kerala power system for optimization of the economic load dispatch operation by using the method of Particle Swarm Optimization and Genetic algorithm.

Chapter 6 summarizes the work presented in this thesis and provides the contributions, conclusions and the future scope of research.

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

A comprehensive literature survey was conducted to study the various approaches existing for different categories of load forecasting, different methods, modeling and analysis. The electric load forecasting is the process used to forecast the demand with historical load data and weather factors. This is an important and essential methodology for the operation, planning and sustainability of a good and managed power system. Load forecasting is categorized into three. They are short-term, medium-term and long-term load forecasting. Load forecasting of Kerala power system has also become an important mechanism for its planning and operation.

Different methodologies are adopted in this field for accurate performance prediction. In early days, the load models are used on the basis of extrapolation and the load behavior was represented by Fourier series or tends curves in terms of time functions. Later a variety of statistical methods such as: similar day approach, regression models, trend analysis, end use analysis, econometrics and time series models, and artificial intelligence methods such as artificial neural networks, expert system, fuzzy logic and support vector regression have been developed. The development and improvement of the appropriate mathematical tools were lead to the formation of more accurate load forecasting techniques. The evolution of these methodologies is reviewed in section 2.2 - 2.4.

2.2 SHORT-TERM LOAD FORECASTING

The short-term load forecasting is an essential instrument in power system planning, operation and control. Over-estimation of electricity demand will cause over conservative operation, which leads to the start-up of too many units or excessive energy purchase, thereby supplying an unnecessary level of reserve. Load supply and load demand are fluctuating due to the changes of weather condition and as a result energy prices are increasing during peak situations. Short-term load forecasts vary from few hours ahead to a few weeks. There are different methods used for short-term, mid-term and long-term load forecasting. They are Artificial Neural Network (ANN), Multiple Linear Regression (MLR) technique, Time Series Regression model, Fuzzy technique and Support Vector Machine (SVM) etc.

2.2.1 Artificial Neural Network Approach

The ANN method is applied to a large power system for short term forecasting. The back-propagation algorithm is recommended as a methodology for electric load forecasting. Park and Park (1990) and other several researchers reported the effectiveness of the ANN approach. The input /output pairs were used to adjust the interconnecting weights until the error became negligible.

Park *et al.* (1991a) reported an algorithm of the combination of ANN and time series regression model and observed that the ANN is suitable to interpolate among the load and temperature pattern data of training sets to provide the future load pattern. But there was high error with test data and they have not considered the features such as load on weekdays and weekend days.

Lee *et al*. (1992) used two different methods of applications of ANN in the short-term load forecasting. They were: dynamic approach (forecast 24 hour load sequentially using previous time load) and statistical approach (forecast 24 hour load simultaneously). The week day load pattern was used three current week days and adjusted the weight as $y_{(i-1)}= F(w_i, yi_{(i-2)})$ by using back propagation neural network (BPNN) algorithm. The authors estimated weekend day load patterns, which are grouped into five different loads and in the statistical method, the auto-correlation function of hourly load over four weeks was used. The dynamic approach performs better than the statistical method and was found to be better as it was used much lesser number of neurons and weight and gave better results particularly for the peak period than the method used by Park *et al.* (1991). The proposed methods were tested by using a historical utility data and the forecasting error obtained was 2% for the percent relative error and thus showed an assurance for the use of ANN method in load forecasting. It can be noted that parameters of slope and threshold of the sigmoid function was not defined and weather variables were not used.

Peng *et al.* (1992) developed a strategy by using a minimum distance measurement to identify the appropriate historical patterns of load and temperature readings to estimate the network weights. The proposed ANN algorithm included a combination of linear and non-linear inputs to map the past and temperature outputs to the load forecast output. Selection of training data improved the efficient use of a limited number of historical data in learning the system with the relationship between weather changes and load shape. This selection procedure and the self-learning process of an improved network structure eliminated the need for a separate updating algorithm. The accurate forecast is investigated using data and three different forecast variables such as, peak load, total daily load and hourly load with different number of hidden nodes. Thus, the most recent historical days were used to train the network and produced an accurate forecast. The authors however observed that a large historical data of several years of holiday observations is needed to improve the forecasted accuracy (Kiartzis *et al.,* 1995; Bakirtzis *et al*., 1996).

In holiday load forecasting two basic methods were used. The first method was the data set consisting of a specific holiday data from previous years together with weekend data. The second method used data for week days load forecasting was also used for holiday load forecasting (Papalexopoulos *et al*., 1994; Bakirtzis *et al*., 1996). The authors concluded the work with an improved holiday forecasting model which reduced the forecast errors of consecutive holidays and the days following a holiday.

The current activation state is a function of previous activation state as well as the current inputs of recurrent neural networks which are feedback networks. The feasibility of implementing recurrent neural network for short-term load forecasting in electric power system was investigated by Mandal *et al.* (1995). The authors found that the weather condition had negligible effect in one hour ahead load forecasting.

The ANN based short-term load forecasting model was developed for the Energy Control Centre of the Greek Public Power Corporation (Bakirtzis *et al*., 1996). The model included daily load profile forecasts up to 7 days ahead for week days (normal) and holidays. Khotanzad *et al*. (1996) developed a temperature forecaster that provided hourly temperature forecasts and predicted daily high and low temperature.

Charytoniuk *et al.* (2000), proposed a new method to very short term load forecasting by the application of ANN to model load dynamics. The method had been successfully implemented and used for online load forecasting in a power utility. For implementing a very short-term load forecasting system, the load data were obtained from the automatic generation control system by every 4 seconds. The upcoming data were converted into one-minute integrated loads which were considered as 'instantaneous' loads. These loads were used as input information for coupling load predictions and they were also stored for training. The implementation of Artificial Neural Networks had been successfully used by the authors to forecast integrated load.

Adepoju *et al*. (2007) focused a study of short-term load forecasting using artificial neural network in a Nigerian Electrical Power System. This artificial neural network consisted of real time data of three layers, an input, one hidden layer and an output layer. The number of hidden layer neurons was ranging from 5 to 11. The neuron was finally utilized because it offered better model characteristics than the other methods. The short-term forecasting gave a forecast of one hour ahead of time.

Jain and Satish (2009) presented a new clustering technique based short term load forecasting using ANN for next day load forecasting. The daily average load of each day for all the training patterns and testing patterns was calculated and the patterns were clustered using a threshold value between the daily average load of the testing pattern and the daily average load of the training pattern. Important factors of this forecasting were stock of electricity using equipment, level and type of economic activity, price of electricity, and price of substitute sources of energy and weather condition. Different methods were implemented and observed that the ANN model was better than the other methods.

Fan *et al*. (2009) and Fan and Hyndman (2010) developed a composite learning technique to improve the forecasting accuracy and generalization performance. To improve the generalization capacity of ANN based forecasting model, an ensemble learning technique had been applied.

Gnana Sheela *et al*. (2013) reviewed the methods to fix a number of hidden neurons in neural networks. A new method was proposed to fix the hidden neurons in Elman networks for wind speed prediction. The statistical errors are calculated to evaluate the performance of network. Authors concluded that the selection of number of hidden neurons providing better frame work for designing Elman network.

2.2.2 Multiple Regression Technique

Multiple regression is one of the most widely used statistical techniques. Linear regression is a technique which examines the dependent variable to a specified independent variable. Dependent variables are demand and the independent variables are temperature, rainfall, wind speed, humidity or cloud cover etc. Multiple regression models include climate related and socio-economic factors to be used to improve the accuracy of forecast model.

Comparative analysis of regression and Artificial Neural Network models for wind turbine had been developed by Li *et al*. (2001). For improving the prediction of hourly load, the weather parameters such as temperature, wind speed, humidity precipitation and cloud cover were used. The selection of an appropriate function for regression model was extremely difficult and hence the neural network model showed better performance than regression model. The authors had not considered the training of neural network with more data for different seasons of the year which may be needed for better network performance.

The impact of weather parameter on monthly electricity demand has been investigated by Hor *et al.* (2005). Monthly electricity demand was forecasted based on a multiple regression model which was based on various weather parameters, gross domestic product and population growth.

Mingalev *et al.* (2006) developed an improved method called the Leven Berg Marquardt back propagation and used early stopping methods to reach the optimum network's parameters faster and to improve generalization. Its performance was satisfactory for one hour up to a week load forecasting.

Short-term load forecasting can be used to estimate load flows and to make decisions that can prevent over loading. Timely implementations of such decision led to the improvement of network reliability and to the reduced occurrences of equipment failures and black outs. Campbell *et al.* (2006), suggested that methods like similar day approach, various regression models, time series, neural networks, expert system, fuzzy logic and statistical learning algorithms could be used for short term load forecasting. The authors concluded that the enhancement of load forecasting would be achieved by the combination of two research areas - research in statistical and the artificial intelligence and the other is better understanding of load dynamic and statistical properties in order to improve modelling power. In time series method, special holiday encoding considered and its previous days load were used. In MLR, dependent variables were used. The disadvantages of this work were the requirement of much amount of historical data and less accuracy.

Rothe *et al*. (2009) attempted the statistical regression methods for existing studies on parameter impacts on electricity demands and described the assessment of rapidly growing Indian electricity sector. They concluded that the response of multi-linear regression techniques was much appreciable because the error was less than 5%.

Akole and Tyagi (2009) developed an algorithm based on ANN model for half hourly load forecasting and a day ahead load forecasting application. The authors compared the results of ANN forecasting model with the conventional Multiple Regression (MR) forecasting model. It was observed that ANN model worked more effectively than MR model. However, the authors correctly observed that care must be exercised as the response might not be identical from place to place and hence forecasting might not be so accurate.

2.2.3 Time Series Model Approach

Time series methods are based on the assumption that the data are having an internal structure, such as auto-correlation, trend or seasonal variation. The time series forecasting methods detect and explore such a structure. It has been used for decades in fields such as economics, digital signal processing, electric load forecasting etc.

Park *et al*. (1991b) applied time series regression combined with NN method by the use of weather variables that gave more accurate prediction than the use of Kalman filter, the Box-Jenkins method and Auto regressive moving average (ARMA) model.

But the following limitations were noted by the use of above two methods: the high non-stationary load pattern may not allow an accurate estimate by the use of Kalman filter, a longer computational time is required for the parameter identification by ARMA model and slow performance of Box-Jenkins method.

Aquino *et al.* (2007) reported two problems in the use of neural network i.e., poor load forecasting in holidays and lack of global models for both holidays and normal days. For solving these problems, a new special holiday encoding that considered holidays and its preceding day and following days load which are influenced by the holiday. The encoding was done in conjunction with quick propagation neural network and the result obtained by the proposed technique outperforms the statistical technique. Opok *et al.* (2008) developed an autonomous model which can hold both time series model and stochastic models to forecast average net hourly demand and system maximum net hourly demand.

Farhat and Talaat (2010) applied the time series regression approach by the use of historical data. The authors investigated a new approach using curve fitting prediction optimized by genetic algorithms for short-term load forecasting. The time series model extrapolates historical load data to predict the future load. If the historical load data does not represent the conditions, the accuracy of the forecast by the time series model decreases. Modelling of load forecasting includes out of regressive model (p), moving average model (q), ARMA (p, q), ARIMA (p, d, q) model etc. The authors concluded that the model showed the proper selection of input variables and training vectors resulted in very low training and forecasting time.

Fan *et al.* (2010) reported a semi-parametric additive model applied the regression methodology focused on the non-linear relationship between load and various input variables. A separate ANN model had been estimated for each half hourly period. A hyperbolic tangent function was used for hidden neurons and output neurons since it could produce both positive and negative values which helped the speed of training process compared with the logistic function whose output was positive. Tasre *et al.* (2012) exhibited change in load curve pattern and the deviation in dependence of load was taken as exogenous variable. Time series approaches are not widely used for energy industry forecasting, because they do not take in to account other factors such as weather forecast.

2.2.4 Fuzzy Techniques

Fuzzy logic is a form of many valued logic in which the truth values of variables may be any real number between 0 and 1. It is employed to handle the concept of partial truth, where the truth value may range between completely true and completely false. The approach of fuzzy logic imitates the way of decision making in humans that involves all intermediate possibilities between digital values YES and NO.

Daneshdoost *et al.* (1998) conducted a study of short-term forecasting technique which used a fuzzy set-based classification algorithm and a multilayered feed forward ANN. The classification of data was based on the fuzzy set presentation to achieve the smooth transition between the classes of weather condition. He *et al.* (2006) proposed statistical modelling methods like a mathematical combination of previous values of the load and the previous and current values of other variables such as weather data. An artificial intelligence method for getting better performance by dealing with the nonlinearity and other constraints in modelling of short-term load forecasting was proposed. The authors reported that Elman recurrent neural network based on fuzzy classification forecasting model with data classification model was better than that without data classification model and the error was low. Liu and Liu (2006) applied multi-objective genetic algorithm to choose the optimum rules for classifying electrical load. The efficiency and accuracy of short-term load forecasting was improved by using this technique.

Mahor *et al.* (2009) proposed two different methods with a combination of a self-organizing fuzzy neural network (SOFNN) learning method and bi-level optimization model for medium-term and short-term load forecasting by using genetic algorithm (GA) to optimize the number of neurons and fuzzy rules, and a back-propagation algorithm was used to update the weight and membership function parameters. Self-organizing fuzzy neural network applied to the short term load forecasting achieved good forecasting accuracy with mean absolute percentage error (MAPE) of less than 1%. The result showed that the bi-level optimization model achieved better results than SOFNN.

Khosravi *et al.* (2011) applied interval type-2 fuzzy logic systems for the problems of short-term load forecasting by using GA. The models could efficiently handle uncertainties and minimize their effects on forecasted long and short-term load demands.

2.2.5 Support Vector Machine and Expert system Approaches

Support Vector Machine (SVM) is a supervised learning model with learning algorithm that analyzes data used for classification and regression analysis. Since electric load is nonlinear and non-stationary time series having periodicity and randomicity, it is difficult to forecast the load accurately.

If there are large uncertainties in the weather, the forecast algorithm should place smaller weight on the temperature effects and depend primarily on the natural diversity of the load. It is observed that the uncertainty in the weather forecast could be dealt with by using a range forecast rather than a point forecast (Rahman, 1990).

Rahman and Hazim (1993) in their study incorporated the concept of knowledge-based weather segmentations in to this forecasting model that enables to utilize multiple auto regressive exogenous (ARX) models which are linear in nature to correctly identifying and sufficiently modelling the non-linear impact of weather changes on electricity load. The two models (historical load data and K based exogenous variables) were tested in two time periods to produce next day load forecasting and the results were compared to the typical approach.

For instance, Mohandes (2002) applied a method of support vector machines for short-term electrical load forecasting. The author compared its method performance with the autoregressive method. The results indicated that SVMs compare favorably against the auto-regressive method. Chen (2005) also proposed an SVM model to predict daily load demand of a month. Lots of methods are used in support vector machines (Islam, 2011).

Performance of knowledge-based weather segmentations and utilization of multiple auto regression with exogenous variable models were described by Chen *et al.* (2005). The ARX model with three types of variables was used in modelling the factors such as historical electricity load information from previous days or months, exogenous variables including past and forecasted weather variables such as temperature, humidity, wind speed, cloud cover etc. The dummy variables were knowledge based and site dependent.

Zhao and Su (2007) proposed a hybrid method based on short-term load forecasting using Kalman filter and Elman neural network. The hybrid method had high generalization performance and improved the forecasting accuracy with a major drawback that the method was time consuming. Therefore, the neural network method is more appropriate than this method.

Jin *et al.* (2012) described Grey forecasting model and support vector machine and applied to holidays' load forecasting. At first, to forecast the electric load demand data samples in simulated annealing (SA) at half an hour rate grey forecasting model had been used. Then Grey forecasting model and support vector machines were adopted to predict the follow- up residual series with obtained residual series. Cai *et al.* (2011) observed that the forecasting accuracy was improved, especially after using the Support Vector Machine.

Selakov *et al.* (2012) proposed hybrid method based on empirical mode decomposition and support vector mission and reported that both artificial neural network modelling and support vector modelling gave accurate results, but support vector machine had better tendency towards global minimum and produced a smaller forecasting error than the other methods.

Gnana Sheela and S.N. Deepa (2013) reviewed how to fix number of hidden layers in artificial neural network modelling. The hidden neurons can influence the error on the nodes, the minimum error reflects better stability. One of the major challenges in the design of neural network is the fixation of hidden neurons with minimal error and highest accuracy. The authors concluded that the number of hidden neurons providing better framework for designing Elman network.

2.3 LONG-TERM LOAD FORECASTING

The long-term load forecasting aims at balancing of energy requirement vis-à-vis availability for a control period i.e., a year and more. Annual load forecasting is an essential requirement for planning generation from various sources so as to exploit the seasonal availability. As the generation period of a generating station is about 5 years (thermal), the long-term plan should typically cover this period. Forecasting of this type is mainly used to plan the growth of generating capacity and the transmission expansion, which requires a lead time ranging from few months to few years. This is explicitly intended for applications in capacity expansions and long-term capital investment return studies. For any country, the load forecasting depends on the load growth patterns of past years as well as the growth of industrialization and the national economy. Local growth is very much dependent on the community and development. Thus, long-term load forecasting usually covers forecasting horizons from one year to ten years and sometimes up to twenty years.

2.3.1 Artificial Neural Network Approach

Parlos *et al.* (1996) developed an intelligent long-term load forecasting system with categorization of load in different sectors by using ANN and genetic algorithm (GA) for the long-term load forecasting architecture selection and optimization. Due to large uncertainties of weather predictions and gross domestic product, it was very difficult to accurately predict future events over forecasting period considered in long-term load. The ANN method was used by the authors in four cities and the results were compared with four utility generated forecasts.

The annual peak load demand and annual energy demand for a number of years ahead have a vital role in the context of generation, transmission and distribution network planning in a power system. Fu and Nguyen (2003) reported the use of forecasting data based on macro-analysis, in which the total system energy was forecasted, using historical energy data together with socio-economic forecasts. The resultant model represented a probabilistic method for long-term energy forecasting. Using a set of historical energy and socio-economic data related to an actual power system, the authors developed a non-linear relationship between annual energy demand and socio-economic variables with functional-link net and the wavelet networks used in the forecasting models. Long-term temperature predictions are subjected to significant uncertainty.

Ghods and Kalantar (2008) carried out the long-term load forecasting by using parametric methods and artificial intelligence based methods. The parametric load forecasting methods are trend analysis, end-use models and econometric approach. Artificial intelligence-based methods are ANN (recurrent neural network and feed forward back propagation network), wavelet networks and genetic algorithms.

2.3.2 Time Series Regression Approach

Tsekouras *et al.* (2006) presented a new methodology for mid-term load forecasting. Several forecasting methods were implemented by the authors for energy demand forecasting. For short-term load forecasting ARMAX model, regression, ANN's fuzzy logic, expert systems etc., were adopted. SVM had been used for the computation of daily peak demand of the next month and a fuzzy logic model was proposed for mid-term load forecasting. A knowledge based expert system had also been developed for long term load forecasting.

Aslan *et al.* (2011) demonstrated the long-term peak load forecasting by methods of least squares regression and artificial neural network using the load, temperature and population growth data. The authors observed that if longer input data was used the forecasting error could be decreased and artificial neural approach produced better results than different forecasting methods.

García-Ascanio and Maté (2010) introduced a new forecasting approach considering the comparison between Vector Auto Regressive (VAR) forecasting models applied to interval time series (ITS) and the multi-layer perception (MLP) model remodeled to interval data. The two-interval time-series forecasting models were proposed for the accuracy in demand forecasting.

Hong *et al.* (2014) proposed an hourly information (load and weather) to create more accurate and defensible forecast. The authors implemented the case study of North Carolina Electric Membership Corporation (NCEMC) and used the key elements for predictive modeling, scenario analysis and weather normalization. Multiple Linear Regression (MLR) models were used the implementation of long-term probabilistic load forecasting and normalization with hourly information. The authors also proposed an abstract idea of load normalization and demonstrated a simulation approach to normalizing the load against weather.

2.3.3 Fuzzy Logic and Support Vector Machine Techniques

Kandil *et al*. (2002) developed a model which was implemented by using a knowledge based expert system. The developed expert system described two cases which were examined to produce the peak load forecast for normal developing utility and fast developing utility. From this examination, the expert system was very flexible and more accurate in updating the forecasting methods and it could serve as a valuable assistance to system planners in performing their annual load forecasting duties.

Grey forecasting is a method to forecast the system with uncertain factors and the forecasting technique based grey systematic theory. Wang *et al.* (2007) described the grey model algorithm for medium-term and long-term forecasting. For that accumulated generating operation (AGO) of the initial series was required. The authors conducted experiments on a real power system which led to very high performance. In the grey systematic theory, the random variable as grey variable and the stochastic process as the grey process. Grey forecasting need only the correct quantity of data according to actual conditions. The authors followed two methods to provide an improved grey forecasting model, deciding the optimum quantity of initial data and revising the forecasted data through the method of residual revision and filling innovation in proper order. The developed algorithm possesses far superior forecast precision and required less running time than traditional method. Karabulut *et al.* (2008) developed a genetic programming approach on the long-term forecasting of power consumption.

Duan *et al.* (2008) described the long and medium-term load demand which depended on a number of complex factors such as seasonal weather, national economic growth and social habits. Multi-regression analysis (MRA) was used to predict the long and medium-term based on the description of the relationship between the load and some load affecting factors. Disadvantage of the method was that the parameters were invariable just after the forecasting model had been established. Multi-Level Recursive method was applied and the results were unstable due to sequential variance of power system into consideration.

Al-Hamadi *et al.* (2011) described two methods like parametric and artificial intelligence method. Parametric load forecasting method would be categorized under three approaches. They were: regression, time series and grey dynamic methods. The authors concluded that the mean absolute error of the predicted weekly average daily load did not exceed 3.68% of the actual load over a whole year period. Anguita *et al.* (2012) used the support vector machines for regression and time series prediction, approximate support vector regression (SVR) and auto regressive support vector regression (AR-SVR). AR-SVR procedure was most useful when values were predicted outside the time-interval of observation. The results obtained on a real data set, showed that accurate long-term time series prediction could be obtained by long-term energy load forecasting.

A medium-long term loads structure forecasting model had been proposed by Yichun *et al.* (2013) in which the system state equation and grey dynamic model group for various types of electrical load were established, in terms of the system dominant factors and associated factors determined by the grey correlative degree analysis method, and were sold to realize the medium long term structure forecasting of power consumption in terms of Grey Model (GM) (1, N, $x^{(0)}$) model derived from GM (1, N) model. Electric load usage structure statistics was one of the key information's of implementing Demand Side Management (DSM) planning. The system state equations and grey dynamic model group corresponding to power consumption of primary industry, secondary industry, tertiary industry and residential living were made respectively. The value of grey correlation determined the second industry load as the dominant variable in the system. Thus GM (1,1) model for the second industry electricity consumption was setup. It can be concluded that the proposed forecasting model provides the fundamental for planning, demand side management and the analysis on the proportion of various types of power consumption.

2.4 OPTIMIZATION FOR ECONOMIC LOAD DISPATCH

Economic Load Dispatch (ELD) is basically the process of distributing the total load on a system between the various generating stations to achieve the greatest economy of operation. The required load demand highly varies in unpredictable and mostly non-linear with time. ELD is a non-linear constrained optimization problem whose complexity increases when constraints such as valve-point effect and generator's prohibited zones are undertaken (Chowdhury and Rahman, 1990). ELD problem is one of the most important optimization problems and its objective is to minimize the total generation cost of units, subject to the constraints that the sum of the generated power must be equal to the load demand (Wood and Wollenberg, 2005).

The Economic Load Dispatch model leads to remarkable savings in the power system operational cost. It is aimed at minimizing the total fuel cost to obtain the maximum total profit and finding fast computation simulation time for the scheduling programme. Hamdan *et al.* (2004) introduced the concept of cost optimization in unit commitment. This work concentrated the Lagrange Relaxation method which had been proved more efficient in solving large scale problems. The authors described the existing problems in economic load dispatch and the initialization of multipliers was done using interior method. Mathematical formulation and objective function of economic load dispatch were also explained by the authors.

2.4.1 Particle Swarm Optimization Approach

The particle swarm optimization (PSO) is a method applicable to optimize the economic load dispatch. Eberhart and Kennedy (1995b) developed a PSO algorithm based on the behavior of individuals (particles or agents) of a swarm. The PSO as developed by the authors was a very simple concept and the paradigms could be implemented in a few lines of computer code. It required only primitive mathematical operators and was computationally inexpensive in terms of both memory requirement and speed. A number of scientists have created simulations of various interpretations of the movement of organizations in a bird flock or fish school. The original objective of Kennedy and Eberhart (1997) was to mathematically simulate the social behavior of bird flocks and fish schools. The first version of particle swarm optimization was intended to handle only non-linear continuous optimization problems.

The PSO can be used to solve same kinds of problem as genetic algorithm. Eberhart and Kennedy (1995a) applied the PSO algorithm to the training of artificial neutral network weights. Each particle kept track of its co-ordinates in hyperspace which were associated with the best fitness. The value of that fitness was called *pbest*. The global version of the particle swarm optimizer kept track of the overall best value, and its location, obtained thus far by any particle in the population was called *gbest*. The author's paradigm was a promising approach for robot task learning.

Different variants of the PSO algorithm were proposed but the most standard one was the global version of PSO (*gbest* model) introduced by Shi and Eberhart (1998). The authors considered the whole population as a single neighborhood throughout the optimization process. The authors concluded that many researchers in power systems attempted to combine the PSO algorithm with other techniques to form hybrid tools. This hybridization improved the PSO capabilities, accuracy and computation time.

The PSO algorithm had been demonstrated by Gaing (2003) and proposed a nonlinear characteristic of generator such as ramp rate limits and prohibited operating zone for actual power system operation. The author found that it had superior features, including high quality solutions, stable convergence characteristics and good computation efficiency. The results of the authors showed that, the proposed PSO method could avoid the defects of premature convergence of genetic algorithm method and could obtain higher quality solution with better computation efficiency and convergence property than the other methods.

The evolutionary programming has been used as one of the techniques to solve the problem of economic dispatch in power system. Alternative techniques of evolutionary programming known as meta-evolutionary programming, which was basically a standard evolutionary programming with Log-normal Gaussian mutation. Rahimullah *et al.* (2003) observed that for economic dispatch excluding losses, fast evolutionary programming was outperformed Gaussian or normal mutation used in general evolutionary programming. For economic dispatch including losses, R-meta evolutionary programming performed better than other types of evolutionary programming.

Park *et al.* (2005) suggested a Modified PSO(MPSO) mechanism to deal with the equality and inequality constraints in the economic dispatch problems. The authors found that the MPSO had provided the global solution satisfying the constraints with a very high probability for the economic dispatch problems with smooth cost functions. In the case of non-smooth cost function due to the valve points effects, the MPSO had also provided the global solution with a high probability and had shown the superiority over the conventional method i.e., the Hopfield neural network and the evolutionary programming approach, while providing very similar results with the modified Hopfield neural network.

Adhinarayanan and Sydulu (2006) presented a new approach to economic dispatch problems with cubic fuel cost functions based on the particle swarm optimization algorithm and its efficiency was tested with smooth cost functions. This method had been tested on 3 generator systems with smooth cost functions and 3 generator systems, 5 generator systems, and 26 generator systems with cubic fuel cost function. PSO showed better results than GA method and could obtain high probability solution with better computation efficiency.

Transient stability constrained economic power generation is a nonlinear constrained problem subject to load flow equation and power system capacity requirements. Hoballah and Erlich (2009) presented a methodology for continuously checking the transient stability conditions of generators to ensure power system transient stability with minimizing the additional cost for increased generation and the opportunity cost for reduced power in feeder. The combined PSO-ANN method proposed by the authors was successful to improve system transient stability with minimum cost duration rescheduling process.

A comprehensive coverage of different PSO applications in solving optimization problem in the area of electric power systems was found in the study of Al-Rashidi and El-Hawary (2009). The new self-adaptive inertia weight particle swarm optimization with special function had been applied for hydroelectric generation scheduling of real operated cascaded hydroelectric system by Mahor *et al.* (2009). A new self-adaptive inertia weight PSO technique was adopted by the authors to solve the scheduling problem and results were critically compared with the results from linear differential inertia weight (LDIW) PSO method. The new self-adaptive inertia weight PSO provided better optimization than LDIW-PSO method.

Economic Dispatch problems with quadratic cost functions are solved by gradient-based optimization methods. Jaini *et al.* (2010) pointed out that the advances in computation and search for better solution of complex problems had led to use stochastic optimization techniques such as ant colony optimization, evolutionary algorithm, particle swarm optimization, differential evolution etc. for solving economic dispatch problem.

Parassuram *et al.* (2011) applied a new hybrid evolutionary algorithm to solve economic dispatch problem with the valve-point effect. This hybrid PSO method consists of a strong co-operation of differential evolution (DE) and PSO, since it maintained the integration of the two techniques for the entire run of simulation. The authors concluded that the hybrid PSO method was capable of dealing directly with load demand at various intervals of time in the scheduled horizon. The hybrid PSO had provided the global solution in the three-unit test system and the better solution than differential evolution, genetic algorithm and PSO.

Chakraborty *et al.* (2011) applied the quantum mechanics inspired PSO in continuous optimization problem of economic load dispatch. The objective function of the method included valve point effects, generators ramp rate and prohibited zones were to minimize the fuel cost of generators using a hybrid quantum inspired PSO. A complex and highly efficient initial solution generator was applied on Hybrid Quantum PSO that led to global best value in affordable time. The authors evaluated that this method could also be applied in other power system optimization problems such as unit commitment, optimal power flow, voltage control, optimum capacitor placement, feeder balancing and so on.

PSO is an evolutionary computation technique similar to genetic algorithm. Wai *et al.* (2012) reported that load forecasting model via only historical load data were designed to simplify the forecasting structure and reduce the equipment cost for the data collection. The forecasting structure could be developed and the corresponding computation time shortened especially in PSO structure. From the test results, the authors found that the mechanism of evolutionary program was more efficient than genetic algorithm in computation time, and it could generate a high-quality solution with a shorter calculation compared to other stochastic algorithms. Dasgupta and Banerjee (2014a) proposed different algorithm like particle swarm optimization with constriction factor approach, PSO with inertia weight factor approach and PSO with constriction factor and inertia weight approach to solve economic load dispatch problem with 15 thermal units with generator constraints. From the test results, the PSO with constriction factor approach gave the best global optimum solution with less computation time.

2.4.2 Genetic Algorithm Method

Genetic algorithm (GA), a heuristic method has been successfully used to solve power optimization problems. The genetic algorithm method is usually faster than simulated annealing because the genetic algorithm has parallel search techniques, which emulate natural genetic operations.

The genetic algorithm is essentially a search algorithm based on the mechanics of nature (e.g., natural selection, survival of the fittest) and natural genetics. Walters *et al.* (1993) used genetic based algorithm to solve an economic dispatch problem for valve point discontinuities. The genetic algorithm evaluated encoding of the original parameters instead of the actual parameters. The parameter set was reduced to a series of representative symbols from an arbitrary yet effective alphabet and solutions were evaluated based on certain symbol structures. The results revealed that the genetic algorithm was a powerful optimization tool that could be used to solve economic dispatch. The advantage of the GA lay in its ability to handle any type of unit characteristic data, whether smooth or not. However, scaling parameter selection might present a major obstacle on solving more complex problems.

Sewtohul *et al.* (2004) described four genetic algorithms for economic dispatch problem with valve point discontinuities. They were simple genetic algorithm (SGA), SGA with generation apart elitism, SGA with atavism and SGA with atavism and generation apart elitism or atavistic genetic algorithm (AGA). The higher order non-linearity and the discontinuity of the cost function are the consequences of the valve-point effect. The authors observed that when the valve point loading and ramping characteristics of the generators were taken into account, AGA out-performs SGA,

SGA with generation apart elitism, SGA with atavism, Tabu search (Parassuram *et al.,* 2011) and conventional Lagrange multiplier method.

The input-output characteristics of a generator are approximated by using quadratic or piecewise quadratic functions, under the assumption that the incremental cost curve of the units are monotonically increasing piecewise linear function. Pereira-Neto *et al.* (2005) proposed a simple and efficient evolutionary strategy optimization (ESO) method to solve the economic dispatch problem with nonconvex and non-smooth function to describe the cost due to valve point loading. The study also considered non-linear generator characteristics, such as ramp-rate limits and prohibited operating zones in the power system operation. The results obtained showed that the ES was an efficient and robust tool to solve, with comparative ease, this kind of power system problem.

The effectiveness of the improved genetic algorithm method was the objective of the study by Tofighi *et al.* (2011). The authors conducted the numerical studies performed for two test systems consisting of 13 and 40 thermal units whose incremental fuel cost function was taken into account the valve-point loading effects. The valve point effects resulted in the ripples in the fuel cost function and there by the number of local optima were increased. The practical ED problem was represented as a non-smooth optimization problem with equality and inequality constraints, which could be solved by the traditional mathematical methods. In this study, the binary representation was applied to power optimization problems and the real valued representation scheme was used for solution. The results obtained through the IGA method was compared with fast evolutionary programming (FEP), MFEP, IFEP, IGA-MU and DEC-SQP methods. The authors concluded that the improved genetic algorithm incorporated the improved evolutionary direction operator and the gene swap operator to enhance its search capacity, which led to a higher probability of getting the global or near global solution.

Generally, the economic dispatch of a power system can be categorized into Static Economic Dispatch (SED) and Dynamic Economic Dispatch (DED). Hybrid evolutionary programming and sequential quadratic programming methods have been proposed to solve the non-convex DED problems. A hybrid immune genetic algorithm was proposed to solve the nonconvex DED problem with constraints in the study of Mohammadi-Ivatloo *et al.* (2013). The feasibility and efficiency of the immune GA method was demonstrated on five, ten and thirty unit test systems. The numerical results revealed that the dispatch solution obtained by the proposed Immune Genetic Algorithm (IGA) approach led to a smaller operating cost than those found by other methods, which showed the capability of the algorithm to determine the global or near global solutions for the DED problems. Gaing and Ou (2009) described the fast-evolutionary programming (FEP) with swarm direction in FEP compared with FEP and Improved FEP in terms of solution quality, convergence speed and computation efficiency.

2.5 GIST OF OBSERVATIONS

Many researchers have identified the economic load dispatch problem as the most important to tackle the challenges of reducing the generation cost. Different methods were used by various researchers for optimization such as conventional methods and heuristic methods. Among these methods, PSO is an effective modern heuristic technique for economic load dispatch. It is found that the ANN method is more suitable and effective than the other methods of load forecasting.

Table 2.1 shows the summary of major observations of the literature review.

Table 2.1 Summary of the literature review

S. No	Title of Paper		Advantages	Disadvantage
1	Park, Dong C., M. A. El-Sharkawi, R. J. Marks, L. E. Atlas, and M. J. Damborg. "Electric load forecasting using an artificial neural network." *IEEE transactions on Power Systems* 6, no. 2 (1991): 442-449.	Park *et al.,* reported an algorithm of the combination of ANN and Time series model	ANN is suitable to interpolate among the load and temperature pattern data of training sets to provide future load pattern.	Higher error with test data and they have not considered features such as load on weekdays and weekend days.
2	Lee, K. Y., Y. T. Cha, and J. H. Park. "Short-term load forecasting using an artificial neural network." *IEEE Transactions on Power Systems* 7, no. 1 (1992): 124-132.	Lee *et al*., proposed non-linear model and weights are estimated using backpropagation neural network.	Dynamic approach (forecast 24 hour load sequentially using previous time load) performs better than statistical approach (forecast 24 hour load simultaneously).	Parameters of slope and threshold of the sigmoid function was not defined. Weather variables were not used.
3	Li, Shuhui, Donald C. Wunsch, Edgar O'Hair, and Michael G. Giesselmann. "Comparative analysis of regression and artificial neural network models for wind turbine power curve estimation." *Journal of Solar Energy Engineering* 123, no. 4 (2001): 327-332.	Li *et al.,* have discussed about comparative analysis of regression and ANN for wind turbine model	The selection of an appropriate function for regression model is extremely difficult, hence neural network model showed better performance than regression model.	They have not considered training of neural network with more data for different seasons of the year which may be needed for better network performance.
4	Campbell, Piers RJ, and Ken Adamson. "Methodologies for load forecasting." In *Intelligent Systems, 2006 3rd International IEEE* Conference *on*, pp. 800-806. IEEE, 2006.	Campbell *et al.,* suggested that methods like similar day approach, neural networks, expert system, fuzzy logic and statistical learning algorithms could be used for short term load forecasting.	In time series method special holiday encoding considered and its previous days load were used.	More amount of historical data is required and less accuracy.
5	Selakov, A., S. Ilić, S. Vukmirović, F. Kulić, A. Erdeljan, Z. Gorecan, and Z. Gorečan. "A comparative analysis of SVM and ANN based hybrid model for short term load forecasting." In Transmission and Distribution Conference and Exposition (T&D), 2012 IEEE PES, pp. 1-5. IEEE, 2012.	Selakov et al., (2012) reported that support vector machine had better tendency towards global minimum and produced a smaller forecasting error than the other methods.	Proposed hybrid method based on empirical mode decomposition and support vector mission Both ANN and support vector model	More time consuming

6	Norhamimi, Ahmed, M. M., and I. Hassan. "Costs optimization for unit commitment and economic load dispatch in large scale power systems." In *Power and Energy Conference, 2004. PECon 2004. Proceedings. National*, pp. 190-194. IEEE, 2004.	Lagrangian Relaxation technique an bundling methods were applied for cost optimisation economic load dispatch in large power scale.	Lagrangian Relaxation method is the most successful apporoach for ELD and UC. In LR, UC and ELD decomposed into a master problem and sub problem and solve repeatedly until an uptimal solution is obtained.	Computational and dimensional requirements grow rapidly with number of generating units to be committed.
7	Gaing, Zwe-Lee. "Particle swarm optimization to solving the economic dispatch considering the generator constraints." *IEEE transactions on power systems* 18, no. 3 (2003): 1187-1195.	Proposed non-linear characteristics of generator such as ramp rate limits and prohibited operating zone for actual power system operation.	High quality solutions, stable convergence characteristics and good computation efficiency	Nil
8	Tofighi, Morteza, Reza Maddahi, and Mohammad Sadeqzadeh. "An improved genetic algorithm based economic dispatch with non-smooth fuel cost function." In *Electrical Engineering and Informatics (ICEEI), 2011 International Conference on*, pp. 1-6. IEEE, 2011.	The effectiveness of the improved genetic algorithm method was the objective of the study by Morteza Tofighi *et al.*	The improved genetic algorithm incorporated the improved evolutionary direction operator and the gene swap operator to enhance its search capacity	Nil

2.6 CONCLUSION

Several researchers have developed different methods of short term, mid-term and long term load forecasting and found the effectiveness of artificial neural network approach. The ANN method has been applying for short term, mid-term and long-term load forecasting of power system. A notable development was visible in the research of Lee *et al.* by grouping the load pattern as week days and weekend days in short term load forecasting and thereby the percentage error was reduced to a minimum. Other methods of short-term load forecasting like multiple regressions, time series etc., support vector regression, fuzzy logic and expert system techniques used by various researchers have been reviewed in this chapter.

Application of scientific techniques in load forecasting and optimization of generation cost have not so far been reported from Kerala power system. The main objective of the present research work is to use artificial neural network method for load forecasting and genetic algorithm and particle swarm optimization method for cost optimization.

CHAPTER 3

KERALA POWER SYSTEM: STATE-OF-THE ART AND THE APPLICATION OF STATISTICAL METHODS FOR DEMAND FORECASTING

3.1 INTRODUCTION

The demand for electricity is closely linked to economic growth and depends on the industrial development as well as the increase in population. The electric power demand in Kerala has been steadily increasing and the load factor of total power system has been decreasing. It is very significant to have sufficient advance knowledge of the various aspects of electrical load for an efficient administration of electrical utility system. This is the concept of load forecasting that helps to make important decisions including decisions on purchasing and generating electric power, load switching and infrastructure development (Kodogiannis and Anagnostakis, 2002). Thus, load forecasting becomes an essential tool for the operation, planning and sustainability of a good power system.

3.2 KERALA POWER SYSTEM: STATE-OF-THE ART

The Kerala power map is having its own characteristics. Kerala had achieved a status of a power surplus state till 1980s. It sold power to the neighboring states at very cheap rates for nearly two decades during 1969-1987. The electric current produced from hydroelectric process costs only Rs. 2 per unit. This boosted the setting up of power intensive industrial units. However, from 1990 onwards the situation drastically changed with power shortages of varying magnitudes. The drastic drop in rainfall in the south monsoon season, caused a serious supply shortage for power in the State. This, in turn, forced the State to introduce one-hour load shedding of households and power cut of industries (Economic Review, 1997).

The State had to seek different alternatives including power purchase from outside sources during the peak time demand. The current obtained from thermal stations costs more than Rs.10 per unit. The challenges faced by the State during that time were the following: Unreliability of monsoon, high dependence on costlier power, high peak-off peak ratio, increasing domestic consumption, High-tension - Low-tension (HT-LT) ratio, lack of energy resources, high levels of Transmission and Distribution loss including transmission constraints of import power from one side of the State to another and exposure to global oil prices. The cost of power procurement alone works out at present 60% of the total revenue requirement of Kerala State Electricity Board Limited (KSEB Ltd) depending on the availability of monsoon. These aspects necessitate to formulate an optimization strategy in the management of power system. The cost of power depends on source of power. Hence any optimization strategy in the management of power system involves scheduling of power from various sources. As the scheduling involves many technical and commercial considerations and constraints, the efficiency in scheduling depends on the accuracy of load forecast. The load forecasting for Kerala power systems has come in to being during the period from 2007-08 to 2011-12. Therefore, the peak load forecasting is usually done for the service area for power purchase and facility dispatch for a week ahead (Economic Review, 2012).

3.2.1 Energy Sources in Kerala: Availability and Development

The energy sources in Kerala consists of hydel, thermal, wind and solar. Hydel is the most reliable and dependable source. The KSEB Ltd has been entrusted with the responsibilities of generation, transmission and supply of electricity in the State and has been functioning as a catalyst for the total development of the State. The beginning of electricity generation in Kerala was in 1940 under the Department of Electricity at Pallivasal. This hydro-electric project had an installed capacity of 37.5 MW. The Sabarigiri Hydro Electric Project commissioned in 1966 had the installed capacity of 300 MW. Another 6 more projects were implemented during the same period and thus total installed capacity had gone up to 1011.5 MW by 1976 (Economic Review, 1976). More hydroelectric projects were commissioned up to 1980s and power was surplus in the State during 1969-1987. After 1988, the Kerala State faced a reversal of the situation with power shortages of varying magnitudes, depending on the intensity and vagaries of monsoon. This necessitated imposing of power cuts on the industrial sector and heavily relying on imported power, mainly its share from the Central Sector (Power Plants of National Thermal Power Corporation) and to some extent assistance from neighboring states (Economic Review, 1987). Thus, the KSEB Ltd for the first time had to face many challenges of the purchase of power from outside which generated much financial problems.

The State had to strategically increase the installed capacity and it was increased in 1990 up to 1487 MW and again increased to 1505.5 MW in 1996 and further increased by 58.4% from 1505.5 MW to 2383.5 MW in 1999. The commissioning of Bhramapuram Diesel Power Plant was in 1999. From 2000 to 2008 the installed capacity hiked from 2383.5 to 2662.25 MW. In this total installed capacity, the major share of 1888.6 MW came from 24 hydel stations.

The installed capacity as on 31st March 2008 was 2662.25 MW. It was only an increase of 0.188% from 2007 capacity. Total energy availability was 16584.35 MU and the energy requirement was 15630.45 MU and therefore the surplus energy was 953.90 MU. The nature provided a good monsoon which helped the Kerala State Electricity Board to generate more hydel power and manage the power supply situation with quantum of cheaper hydro power. This helped the Board to earn substantial amount of revenue by utilizing the features of the Availability Based Tariff (ABT) by generating more power during day peak periods thereby availing higher tariff under unscheduled interchange with strategic decision. The sale of energy has increased corresponding to the increase of total consumers.

The installed capacity as on 31st March 2009 was 2694.75 MW including Independent Power Project (IPP) and Captive Power Project (CPP). The State of Kerala was at that time having the highest proportion of liquid fuel based installed capacity in the country with its 771 MW liquid fuel based generators. This situation exposed the State and KSEB Ltd to the speculative fluctuations of global oil prices. For procuring only 6% of the energy requirement from liquid fuel power stations, KSEB Ltd had been spending more than 25% of its total power purchase cost.

Out of the total installed capacity of 2857.59 MW during 2011, the major share of 2040.8 MW was from 24 hydel stations i.e., 783.11 MW was from the thermal projects including National Thermal Power Corporation (NTPC) at Kayamkulam.

Kanjikode Wind Farm had an installed capacity of 2.03 MW and wind energy from IPP was 31.65 MW. Thus, the total energy availability on 31st March 2011 was 15996.07 MU. But the requirement was 17739.51 MU and thus there arose a negative surplus of -1743.44 MU (Economic Review, 2011).

There was only 15.5 MW additional capacity during 2014-2015 in hydel sector. Out of the total installed capacity of 2836 MW during 2014-15, the contribution of the State sector was 2186 MW (77%), the Central sector 360 MW (13%) and Private sector 290 MW (10%). During this period the generation of power from KSEB Ltd's own plants provided 34% (7342 MU) of the total energy requirement. Significantly, 18795.44 MU of energy was also sold, including sales outside the State during the year 2014-2015 (Economic Review, 2015). In this sale of energy, 18426 MU valued at Rs.1074485 lakh was sold internally that showed an increase of 972 MU as compared to the previous year's 17454 MU. It was estimated that the annual consumption and maximum demand would be 26584 MU and 24669 MU respectively by the end of 12th Plan period, i.e., 2017.

During 2015-2016, the installed capacity of power in the State was increased to 2880.20 MW (as on March 2016). Out of this, the major share of 2104.3 MW (73.06 percent) was from hydel, 718.46 MU from thermal, 43.27 MW from wind and 14.15 from solar (Economic Review, 2016).

During 2016-17 the total additional capacity added from all sources was 55.03 MW. Total installed capacity of power in the State as on March 2017 is 2,961.11 MW. Of which, hydel contributed the major share of 2,107.96MW (71.19 %); while 718.46 MW was contributed by thermal projects, 59.27 MW from wind and 75.42 MW from solar (Economic Review 2017). During 2017-18 the total installed capacity in Kerala was 2791.25 MW. Of which KSEB Ltd.'s contribution was 2215.24 MW and others 576.01 MW. Table 3.1 shows this position as on March 31, 2018.

Table 3.1 Installed capacity as on 31.03.2018

Source	**Installed Capacity (MW)**
KSEB Ltd	
Hydro Electric Power Plants	2046
Thermal Power Plants	159.96
Wind Plants	2.025
Solar	7.25
Sub Total	**2215.235**
Captive (Hydro, Solar and Thermal)	64.18
IPP (Thermal, Hydro, Wind and Solar)	501.83
Co-generation (Thermal)	10.00
Sub Total	**576.01**
Total MW in Kerala	**2791.2450**

The availability of energy from Central Generating Stations was 20.99 MU and purchase was 8.3512 MU and the energy from hydro was 21.04 MU. Thus, as Table 3.2 shows, the total energy consumption for a day as on 20th Aug 2018 was 50.3843 MU.

Table 3.2 Energy consumption for a day as on 20.08.18

Energy	MU
Availability of CGS	20.990
Purchase	8.3512
Hydro	21.04
Total	**50.3843**

Source: State Load Dispatch Centre, KSEB Ltd., Kalamassery

3.2.2 Peak Demand and Availability

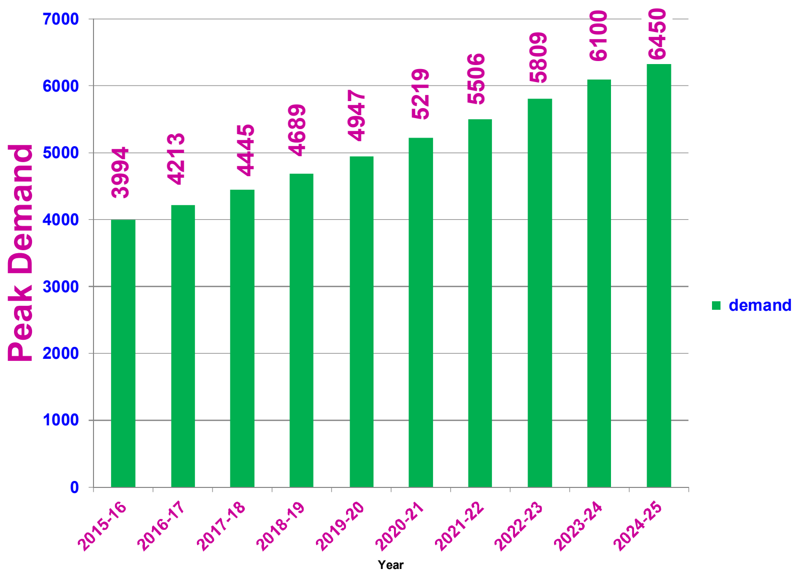
The power requirement in Kerala is being increased every year. During 2007-08 periods, the peak demand reached to 2745 MW and the morning demand was estimated at 2034 MW. The maximum daily consumption during the year was 47.60 MU and the maximum monthly consumption was 1336 MW. Usually there is an increase in energy demand up to 64 MW per day during the months of February to March every year due to many reasons. They are: Energy demand of all the Southern States may rise during the summer months and further there may be difficulty in getting open access for sourcing power through traders. The peak demand and energy demand in the State shows an excessive growth rate since the period 2011-2012 and this has been continuing. During 2011-2012, the peak demand reached up to 3348 MW and there was a wide gulf between the availability and requirement due to various unforeseeable factors (KSEB Ltd., Handbook, 2011-2012). The increase in energy demand in June and July 2013 is 13% and 12% respectively. But in May, October, November and December the only increase was up to 4% with load shedding or local restriction. In April, August and September, the energy demand had been increased 8 to 8.75% over 2011-2012. With the outgoing load shedding and other regulations on energy usage, the increase in energy demand expected for the remaining months of the year over actual demand during the previous year 2011-12 was about 5%. The peak demand calculated for 10 years by KSEB Ltd from 2015-16 to 2024-25 (in MW) is shown in Table 3.3.

Table 3.3 Peak Power Requirement Calculated by KSEB Ltd for 10 years from 2015-16 to 2024-25 (in MW)

Year	Peak Demand in MW	Internal Power Availability in MW	Peak Import Requirement in MW
2015-2016	4004	1650	2354
2016-2017	4213	1700	2513
2017-2018	4445	1800	2645
2018-2019	4689	1850	2839
2019-2020	4947	1900	3047
2020-2021	5219	1950	3269
2021-2022	5506	2000	3506
2022-2023	5809	2100	3709
2023-2024	6100	2300	3800
2024-2025	6450	2350	4100

Source: State Load Dispatch Centre, KSEB Ltd., Kalamassery

While the peak demand in 2015-16 was 4004 MW, it reaches up to 6450 MW in 2024-25. Thus, there is an increase in peak demand from 209 MW in 2015-16 to 350 MW in 2024-25. Similarly, the peak import requirement is also increasing from 2354 MW to 4100 MW respectively. The graphical representation of the peak power requirement given in Table 3.3 is shown in Figure 3.1.



Source: State Load Dispatch Centre, KSEB Ltd., Kalamassery

Figure 3.1 Peak demand for 10 years

The energy demand and peak demand in the Kerala State had been showing an unprecedented increase during the year 2012-13. The energy demand from June to September 2012 shows an excessive increase of 8 to 13% over the actual demand for the year 2011-12. The KSEB Ltd had imposed ½ an hour cyclic load shedding through 11KV feeders from 27thSeptember 2012 and 15th December 2012 to 31stMay 2013. Through this power restrictions and load shedding imposed in the state, the increase in energy demand expected for the remaining months up to May 2013 was about 5% over the energy demand of the previous year.

With the available storage as on 28th December 2012 and also expecting average monsoon for remaining months of the water year 2012-2013, the average hydro generation possible for the remaining months worked out to be about 11.90 MU per day only. With the 40% reduction in inflo, the hydro availability was limited to 10.29 MU per day only for the remaining months of the current water year up to May

2013. Further, the actual generation from hydel plants depended on the availability of water and the daily generation would have to be regulated based on the energy and peak demand, availability of power from CGS, traders, energy exchange and short-term market etc.

About 55% of the peak requirement of electricity was met from hydel plants in the year 2013-2014 (Annual Revenue Requirement (ARR), KSEB Ltd, 2013-2014). The energy availability from hydel plants are being projected on the expectation of normal monsoon. If there is any failure of monsoon, it will result in the increase of power purchase and this will severely affect the financial stability of KSEB Ltd. Failure of monsoon during 2012-2013 alone has thus resulted in an additional expense of Rs. 2500 crores on the cost of power purchase.

To meet the increase in energy demand, Kerala State Electricity Board has been heavily depending on the short-term market and energy exchanges, because new major hydel projects have not yet been materialized in the state, due to various reasons. At present about 15 to 20% of the energy requirement of the state is being met from short-term market i.e., high dependence on costlier power.

About 51% of the total energy consumption is from the subsidized categories like domestic and agricultural categories. But considering the socio-economic reasons, providing electricity to consumers at subsidized rates may have to continue further for few many years. Due to high consumption of the domestic and other LT categories, the peak demand in the state is about 50% higher than that of off-peak periods. This has resulted in power procurement at excessive rates during peak hours. HT-LT ratio in the state is 1:4. This contributed more technical losses in the LT distribution system. Lack of energy resources is another major problem in the state. The major energy resource available in the state suitable for commercial production of electricity is hydel source, the development of which is greatly impeded after the regulation of Forest Conservation Act, 1980.

The annual energy requirement for the year 2013-14 was expected to be 21656.70 MU and the maximum peak demand was to be 3515 MW. The total cost of power purchase from Central Generating Stations for the year 2013-14 was fixed as Rs.1637.86 crores and variable cost was Rs.1381.86 crores. The net energy input to KSEB Ltd was around 9816.35 MU.

In Kerala, electricity energy consumption increased to 24068.74 MU in 2016-17 from 19,325 MU in 2015-16. The consumption was further increased to 25619.75 MU in 2017-18. But the peak demand in 2018(for instance, August 20) is 2886 MW (KSEB Ltd website).

3.2.3 Cost of Generation and Power Purchase

The electricity demand in the state could not be met from the energy available from hydel and CGS. The energy rate from liquid fuel stations within the state was much costlier. It was about Rs.11.50 per unit during 2013-14. Hence in order to meet the energy demand and also to avoid the energy schedule from high cost liquid fuel stations, the KSEB Ltd had to procure energy through traders and energy exchanges from various generating stations located outside Kerala at most competitive rates.

Due to transmission constraints and other reasons, there were some limitations on the import of energy from generating sources located outside the state through traders and energy exchanges. 1800 MW was imported through the inter-state feeders of Kerala State Electricity Board including the share from Central Generating Station.

KSEB Ltd has entered into Power Purchase Agreements (PPA) with various Central Generating Stations of NTPC, Neyveli Lignite Corporation (NLC) etc. This includes purchase of 235.38 MW of power from nuclear power stations and 1245.77 MW of power from various thermal stations for 2016-17. As a measure to encourage non-conventional sources of energy, KSEB Ltd has executed PPAs for purchase of power from wind energy projects, Agali (18.60 MW) and Ramakkalmedu (14.25 MW) and from Small Hydro Projects Meenvallam (3 MW), Iruttukkanam (3 MW), Karikkayam (10.5 MW) Ullunkal (7 MW), Iruttukanam (4.5 MW) and Mankulam Mini Hydro (0.11 MW). Power is also being purchased from co-generation plant of MPS steel (10 MW).

The cost of generation and power purchase is increased on account of the reduction in hydel availability and the consequent increase in demand and excessive energy prices of short-term markets, transmission constraints on importing power from outside the state, increase in cost of liquid fuel stations etc. The efforts of the state to overcome the primary energy resource deficit during 2011-12 had resulted in heavy dependence on crude oil products such as Naphtha and LSHS (Low Sulphur High Stock). Thus, Kerala has become the State having the highest proportion of liquid fuel based installed capacity in the country with its 771 MW liquid fuel based generators. This is exposing the State and the KSEB Ltd to the speculative fluctuations of global oil prices. For producing just 6% of the energy requirement from liquid fuel power stations, KSEB Ltd has been spending more than 25% of its total power purchase cost. There are some constraints to import power through the interstate feeders and it is limited to 1800 MW only including the Central share from Central Generating Station.

Similarly, during the period from December 2012 to May 2013, the KSEB Ltd imposed power restrictions on electricity usage due to the critical power situation of the state and also considering corridor constraints for procuring power from outside the state and lack of adequate fund for additional generation and power purchase from liquid fuel stations. Thus, the availability of hydel power had been considerably reduced and electricity demand in the state had been continuing as that in the summer months. The energy prices in power exchanges are likely to increase during the summer months in comparison to the present rates. The energy demand of all the southern states may rise during the summer months and further there may be difficulty in getting open access for sourcing power through traders etc. Due to the failure of monsoon in Kerala, the energy demand and peak demand of the state during the monsoon months had remained at high levels as in summer months. The cost of generation and power purchase was increased by Rs.1193.22 crores for the remaining months of the year December 2012 to March 2013 for meeting the energy demand without any regulation on power usages other than the ongoing half an hour cyclic load shedding. During the months from April 2012 to November 2012, Kerala State Electricity Board had procured 2631 MW from short term markets at an average rate of Rs.5.22 per unit. This was due to the failure of monsoon and consequent increase of demands by more than double from that of the previous year. Thus, optimization of economic dispatch had been resorted to during that period.

Water is the only commercially viable source for power generation within the state to ensure reliability of supply as well as energy security capacity addition in Kerala. The need for equipping Kerala Power System to meet the demands of the excepted explosive growth in the industrial sector is well recognized. The expected growth in modern areas like IT sector requires reliable and increased quality power system. In the state, KSEB Ltd is the only one organization to supply the power to different categories of consumers.

The cost of hydro-power generation is the expenses for operation and maintenances of the existing stations of KSEB Ltd that includes the expanses for employees, repairs and maintenances of generating stations and administrative and general expenses. For instance, the total operation and maintenances expenses during 2015-16 were 68.08crores and reached to 72.07 crores in 2016-17 and 76.0 were 68.08crores and reached to 72.07 crores in 2016-17 and 76.8 crores in 2017-18. The generation businesses of KSEB Ltd including other expenses for the year 2016-17 was 672.61 crores and for the year 2017-18 was 677.48 crores. Moreover, the cost of own generation is also a part of Annual Revenue Requirement (ARR) of distribution. Thus, the total ARR of the distribution contains the cost of own generation, intra-state transmission charges, power purchase, interest and finance charges, depreciation, operation and maintenances expenses, Return on Equity. Thus, the total amount approved for the ARR of generation and distribution by the order of the State Electricity Regulatory Commission 2017, is 1148.82crores for the year 2017-18.

3.2.4 Strategies of Optimization in Power Purchase

KSEB Ltd has been taking some efforts to optimize the power purchase through the following methods:

1. Scheduling the power strictly based on merit order;
2. Taking efforts to avail power through Unscheduled Interchange at competitive rates;
3. Power procurement done through energy exchanges;
4. Taking efforts to procure power through traders at most competitive rate; and
5. Taking efforts to reduce the power procurement from liquid fuel stations.

Anticipating excessive energy demand during the summer months, due to various factors, the Board plans to conserve as much as water in the storage reservoirs during monsoon months for the use of summer months. The Board examines in detail the option of banking the relatively cheaper power available during monsoon months for the use of summer months, by way of swap sale. For instance, the KSEB Ltd had succeeded in supplying 150 MW on firm basis for the period from 1st October 2010 to 15th October 2010 with a condition to return 105% of the quantum supplied by KSEB Ltd from 1st March 2011 to 31st March 2011 at uniform quantity on firm basis.

Advance tie-up with traders is made for the use of summer months so that the open access could be booked in advance and thus the transmission constraints could be avoided to a great extent. The Board can avail energy at competitive rates from short term market.

The energy availability through unscheduled interchange and energy exchanges depended on day to day as well as time to time system status including that of regional grid. The energy from these sources might be unavailable during summer months due to the following reasons:

1. Unscheduled Interchange (UI) drawal: - The frequency of the summer months usually below 49.50 Hz and hence severe penalty will be liable for over drawing from the grid during low frequency domain. The UI rate for the over drawal when the frequency between 49.50 Hz to 49.20 Hz was Rs.12.22 per unit and the same when frequency below 49.0 Hz was Rs.17.46 per unit. Also, Central Electricity Regulatory Commission has restricted UI drawal as 12% of the scheduled drawal or 150 MW during any time block when the frequency was less than 49.70 Hz.

2. Unpredictable energy exchange: - The rate at energy exchange was liable to change rapidly and unpredictably. The energy rates of the exchanges went even up to Rs.15.00 per unit during summer months. There were severe transmission constraints in the southern grid. Considering the above reasons, KSEB Ltd had taken steps to make firm tie-up for power procurement through traders in advance, so that the traders could book their open access facility in advance. The energy rate in the short term trader market was also highly unpredictable (Economic Review, 2011).

To overcome the peak demand of electricity the Board had taken several steps. The peak demand in the State, for instance, was about 50% higher than that during off-peak hours during 2010-2011. This forced much investment in the power system to meet the peak demand and purchase of thermal energy from outside the state. With the reduction in availability of power from central generating stations and non-materialization of major central sector projects in time, the Board was then depending on the volatile short-term market to fully meet the power demand in Kerala. The increase in cost of generation in all thermal projects due to dependence on imported coal as well as phenomenal rise in price of crude oil was also adversely affected the finances of the Board. If there is any failure of monsoon, power purchase becomes essential so that it will severely affect the financial position of KSEB Ltd. That is, 10% shortfall in monsoon will create an additional financial impact of more than 400 crores on KSEB Ltd.

To meet the increase in energy demand, KSEB Ltd had been depending heavily on the thermal power. Thus, the cost of power purchase increased. In 2005-2007, for instance, the cost of thermal power purchased was around Rs.1741.7 crores, but the total aggregate revenue requirement was 38.21%. In 2010-2011 this was increased as 4044.58 and the % of ARR was 57.40%.

In 2009-10, the average power purchase price was of Rs.3.50 per unit due to the saving on cost of power purchase over the reduction of transmission and distribution losses. The transmission and distribution losses in the Kerala power system during 2001-2002 were 30.76%, while it was able to reduce as 17.71% during 2009-10, a reduction of 13.05% over the last eight years. Otherwise, the KSEB Ltd had to reduce the power purchase by 3199.90 MU by way of reduction in transmission and distribution loss and the savings in cost of power purchase. On this account alone it was workout as Rs.119.97 crore for the year 2009-10.

3.2.5 The Existing Practice of Demand forecasting in KSEB Ltd.

The KSEB Ltd is following a conventional method of load demand forecasting, i.e., without adopting any scientific tools. Before calculating the demand, the total availability of power is estimated from the State and Central Generating Stations. The

Southern Region Load Dispatch Center (SRLDC) Bangalore website shows the share from the Central Generating Stations, long term contract and quantum of power exchange. Usually, for taking the load demand a ten-year hydro-schedule is prepared and informed by State Load Dispatch Center (SLDC) Kalamassery to all hydro-generating stations in the State. At the beginning of summer season, there must be a prescribed level of storage of water in reservoirs for the use of power generation during the summer season. Therefore, conservation of water during the summer season (March–May) in group one reservoirs (Idukki, Sbarigiri, Idamalayar, Sholayar and Pallivasal) is necessary. The use of water for generation of electricity must be restricted to the prescribed unit of power. But in the case of disfilling reservoirs such as Lower Periyar, Neriyanamgalam etc. 100% of electricity is generated during the rainy season. If there is permit work for maintenance of any of the generators, the availability of power will be decreasing. For instance, the outage of feeders or outages of generating units.

Any mismatch in the availability and demand will be reflected as shortage. This is shown as a negative aspect in the forecasting. This decrease is balanced by obtaining power from Central Generating Stations or URS.

Usually the peak demand starts from 6pm and continues up to 9pm in summer season. There is a shifting of peak demand depending on summer days or monsoon days. The demand is calculated during working days from Monday to Friday. The demand is varied slightly from Monday to Tuesday and it will reach at the peak on Wednesday and it will decrease slightly from Thursday to Friday. For the purpose of forecasting the electricity demand, the demand of similar day of the previous week is taken for the forthcoming day. That is, the previous Wednesday's demand is taken for calculating the demand of the next Wednesday. Similarly, the previous year's position including the month and day is also examined. But this calculation is subject to the prevalence of intermittent rainfall. The rainfall may upset a clear-cut calculation of demand.

3.2.6 Projected Energy Consumption for the Next 10 Years for Kerala

The 19th Electric Power Survey Committee constituted by the Government of India on June 11, 2015 is a significant milestone towards forecasting electricity demand on an all India basis. The Committee's function is to forecast state wise, region wise and all India wise electricity demand on short, medium and long term. This planning exercise is instrumental to base subsequent planning activities in the country.

Table 3.4 Projected Energy Consumption for the Next 10 years for Kerala: Category wise (in MU)

Particulars	2017-18	2020-21	2023-24	2026-27	Increase over 2017-18 (in per cent)
Domestic	11,123	13,098	15,293	17,805	60
Commercial	3,689	4,497	5,399	6,414	74
Industrial	4,344	4,715	5,086	5,450	25
Agricultural	313	339	365	391	25
Bulk Supply	1,380	1,601	1,839	2,086	51
Public lighting	428	513	605	703	64
Public Water Works	392	437	484	534	36
Railway Traction	231	260	292	335	45
Total	21,900	25,460	29,363	33,718	54

Source: 19th Electric Power Survey by Central Electricity Authority

The above Table 3.4 shows the projected energy consumption of the State for the next 10 years. As per the 19th Electric Power Survey by Central Electricity Authority, there will be an increase of 74 per cent in commercial consumption and 60 per cent increase in domestic consumption of Energy in the State by 2026-27.

3.3 APPLICATION OF STATISTICAL METHODS FOR DEMAND FORECASTING

In the process of system planning, control and management of power distribution, the long term and short-term peak load demand projections has a pivotal role to play. The short-term forecasts vary usually from few hours ahead to a few weeks. It can help to estimate load flows and to make decisions that can prevent overloading. Timely implementation of such decisions leads to the improvement of network reliability and to the reduced occurrence of equipment failures and blackouts (Campbell *et al.*, 2006). A number of mathematical methods and ideas have been proposed for load forecasting. Different forecasting methods are used for short-term load forecasting which include statistical techniques like time series, multiple regressions and soft computing strategies such as neural networks, fuzzy logic, support vector machines and expert systems. In this chapter two statistical method viz: time series and multiple linear regression used for load forecasting are analyzed. The next chapter contains the soft computing strategies such as artificial neural network and support vector regression and their application in Kerala Power System.

3.3.1 Time Series Method

Time series regression is a statistical method for predicting a future response based on the response history (known as autoregressive dynamics) and the transfer of dynamics from relevant predictors. Time series regression can help to understand and predict the behavior of dynamic systems from experimental or observational data. Time series regression is commonly used for modelling and forecasting of economic, financial, and biological systems. One of the most easily and commonly used model for the load forecasting is the time series method (Box and Jenkins 1976; Park *et al*., 1991b). To start a time series analysis by building a design matrix (α, β_t), which can include current and past observations of predictors ordered by time (t). Most commonly used classical time series methods are Auto Regressive Moving Average (ARMA), Auto Regressive Integrated Moving Average (ARIMA), Auto Regressive Moving Average with Exogenous variables (ARMAX) and Auto Regressive Integrated Moving Average with Exogenous variables (ARIMAX). ARMA models are usually used for stationary processes while ARIMA is an extension of ARMA to non-stationary processes (Aquino *et al*., 2007). ARMA and ARIMA use the time and load as the only input parameters. Short-term demand forecast modeling by time series has been done and the error has been estimated as detailed in next section.

3.3.1.1 Time series based short-term load forecasting

By using the time series method, the short-term and mid-term load forecasting for the Kerala power system has been done. The data collected from the System Operation, Kerala State Electricity Board Ltd., (KSEB Ltd.) Kalamassery and India Meteorological Department, Government of India, Thiruvananthapuram. In time series analysis, the partial auto-correlation function (PACF) gives the partial correlation of a time series with its own lagged values, controlling for the values of the time series at all shorter lags. It contrasts with the autocorrelation function, which does not control other lags. The idea of the time series signal is based on a load pattern with known seasonal, weekly and daily periodicities. These periodicities give a rough prediction of the load at the given season, day of the week and time of the day. The difference between the prediction and actual load can be considered as a stochastic process (González-Romera et al., 2007). The techniques used for this random signal include the Kalman filtering, Box-Jenkins method and Auto Regressive Moving Average models (Park *et al*., 1991b). Time series methods are based on the assumption that the data have an internal structure, such as auto correlation, trend or seasonal variation. The time series methods ARMA (Auto Regressive Moving Average) and ARIMA (Auto Regressive Integrated Moving Average) use the time and load as the only input parameters. Sometimes the parameters may depend on weather. In that case, weather can be considered as an exogenous variable and create a model with ARIMAX specification. Among the classical time series model, this is built upon fitting a time series to the original data (Opok *et al*., 2008). It takes the form as:

$$Y_t = \alpha + \beta_t + U_t \tag{3.1}$$

$$Y_t = F_{(t)} + U_t \tag{3.2}$$

Y_t is the demand at time t, $F_{(t)}$ is a function of time that defines the peculiarity of the function used for the time series model and U_t is the error term. This function plays an important role in data analysis aimed at identifying the extent of the lag in an autoregressive model. The use of this function was introduced as part of the Box–Jenkins approach to time series modeling, where by plotting the partial auto correlative functions one could determine the appropriate lags **p** in an AR (**p**) model or in an extended ARIMA (**p**, **d**, **q**) model. t, t-1, t-2... t-k is the previous value or lagged value. t, t+1, t+2... t+k is the future value called as lead value. Time series is a collection of random variables arranged in the order of time. Y_t is stochastic variable. Y_t, Y_{t-1}, Y_{t-2}...Y_{t-k} is the lagged stochastic variable. The model of auto regressive process is as follows:

$$Y_t = \alpha + \beta y_{t_{-1}} + U_t \quad (3.3)$$

Y_{t-1} is one lag and therefore auto regressive of order 1, i.e., AR (1).

$$Y_t = \alpha + \beta\ _1 y_{t_{-1}} + \beta_2 y_{t_{-2}} + U_t \text{ auto regressive of order 2, i.e., AR (2)} \quad (3.4)$$

$$Y_t = \alpha + \beta\ _1 y_{t_{-1}} + \beta_2 y_{t_{-2}} + U_t + \ldots + \beta_p Y_{t-p} + U_t \text{ auto regressive of order p} \quad (3.5)$$

β is the auto regression coefficient.

A moving average (MA) model specifies that the output variable depends linearly on the current and previous (past) values of a stochastic term. Hence, it can be specified as follows.

$$Y_t = U_t + \gamma_1 U_{t-1} \ldots\ldots\ldots MA(1) \quad (3.6)$$

$$Y_t = U_t + \gamma\ _2 U_{t-2} \ldots\ldots MA(2) \quad (3.7)$$

$$Y_t = U_t + \gamma\ _1 U_{t-1} + \gamma\ _2 U_{t-2} + \ldots + \gamma\ _q U_{t-q} \ldots\ldots MA(q) \quad (3.8)$$

A combination of Auto Regressive model and moving average model known as Box-Jenkins model or ARMA model (Campbell and Adamson 2006). The model of ARMA is:

$$Y_t = \alpha + \phi y_{t-1} + \varepsilon_t + \theta \varepsilon_{t-1} \ldots \text{ ARMA (1, 1)} \quad (3.9)$$

For modelling ARMA, a trial and error method is to be adopted. $\phi$is the root and ε_t is a random variable. ARIMA model is the Box- Jenkins model with integrated process. The form of ARIMA model is:

$$Y_t = y_{t-1} + \varepsilon_{t.I} \text{ (I)} \tag{3.10}$$

This is a non-stationary series.

$Y_t \sim \mathrm{I}(1)$

$\Delta_{yt} \sim \mathrm{I}(0)$

$Y_t \sim \mathrm{I}(2) - 2$ unit root, i.e. two different roots.

$\Delta_{2yt} \sim \mathrm{I}\ (0)$ differentiate two times to make it stationary.

$Y_t \sim \mathrm{I}(\mathrm{d})$ ARIMA (1, d, 1)

$\Delta_{dyt} \sim \mathrm{I}(0)$. This is a stationary series. ARIMA (1, 1) or $Y_t \sim \mathrm{I}$ (d), ARIMA (p, d, q).

From these mathematical modeling and by using the data collected from the Load Dispatch Centre, KSEB Ltd., Kalamassery, the following plots of results are obtained. They are: sequence plot for actual data, sequence plot for actual and forecasted values and in-sample predictions.

Case-1: One day prediction with one-year data

Figure 3.2 shows the sequence plot of the hourly demand data used for one year from 01-04-2013 to 31-03-2014. An increasing trend is seen in the plot and is not stationary.

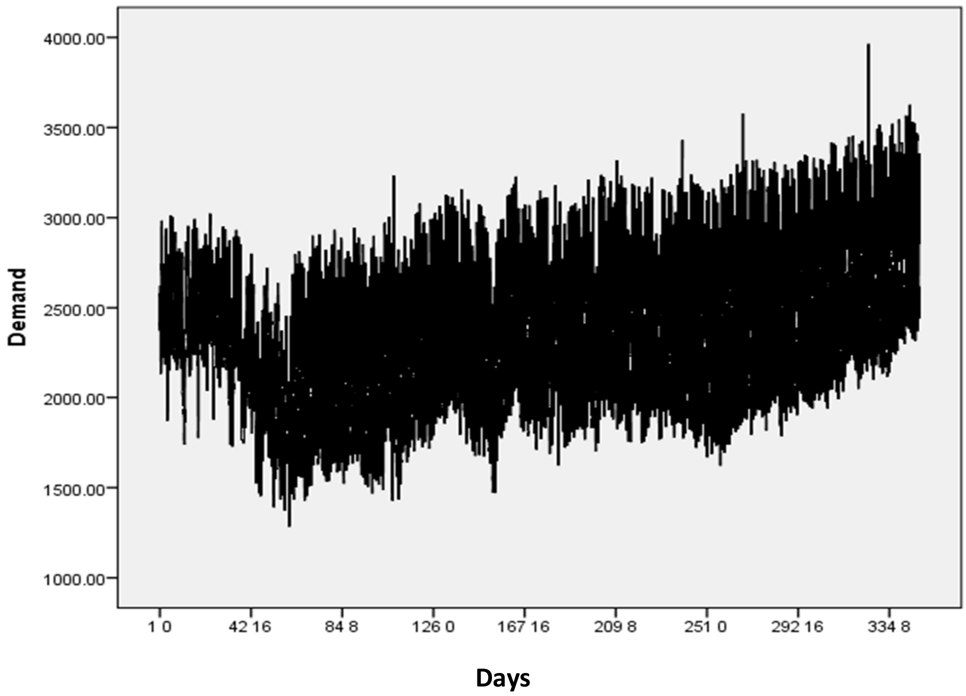


Figure 3.2: Sequence Plot for Actual Data

To make the data stationary, a first difference transformation was made and the plot is shown in Figure 3.3. This figure shows the sequence plot of the transformed data for one year (01-04-2013 to 31-03-2014). Now the data is stationary.

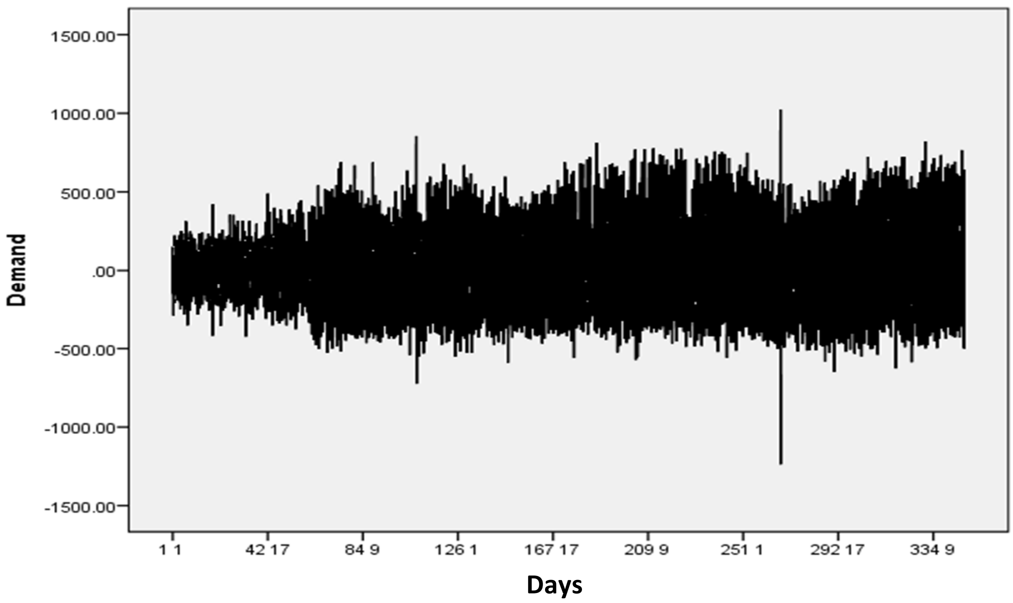


Figure 3.3: Sequence Plot for Transformed Data with First Difference.

The Figures 3.4 shows that the autocorrelation function for transformed data with first difference of the residuals. The upper and lower control limit is shown in this figure also.

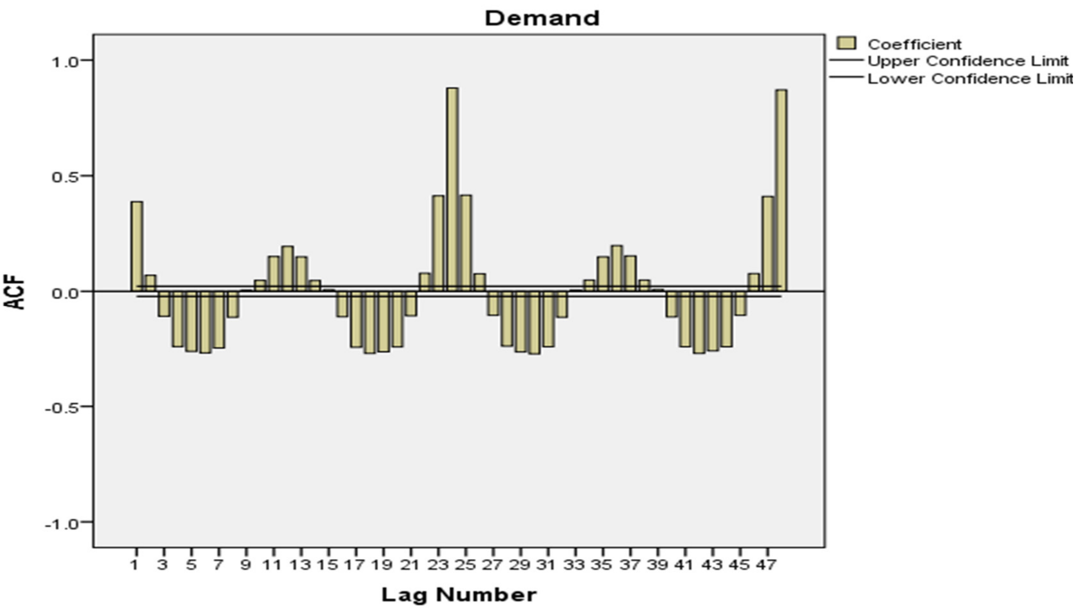


Figure 3.4: Autocorrelation Function for Transformed Data with First Difference

The Figure 3.5 shows the partial autocorrelation function for the transformed data with first difference. The partial auto correlation of an AR(P) model is zero at lag (p+1) lag and greater.

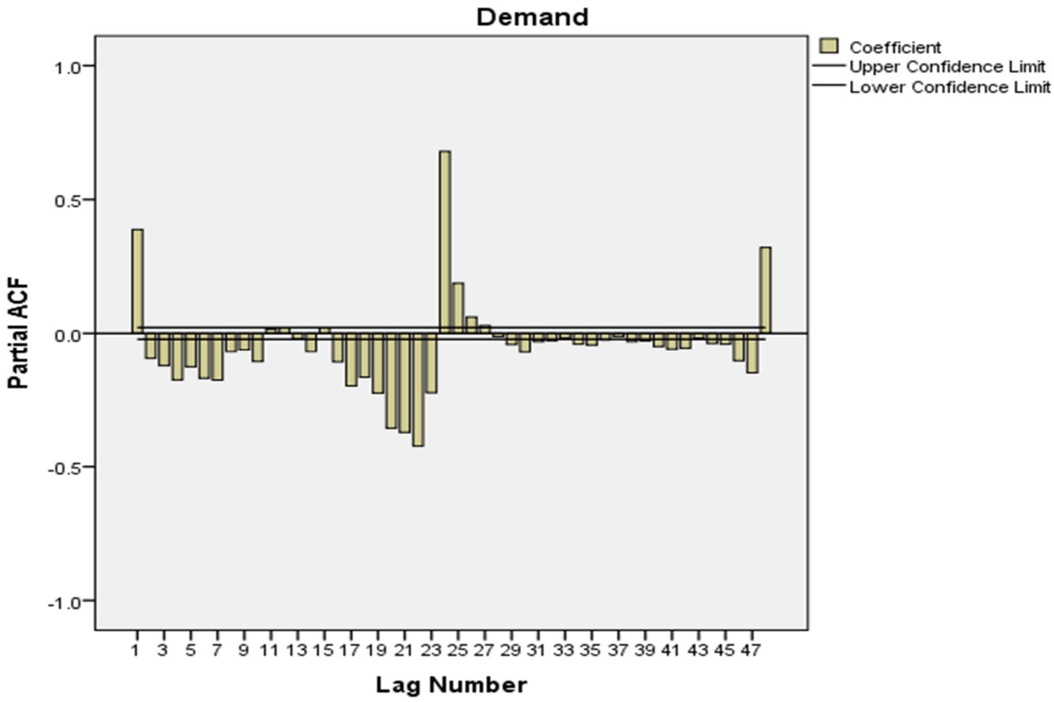


Figure 3.5: Partial Autocorrelation Function for Transformed Data with First Difference

The plots indicate that an AR model be appropriate then the sample partial auto correlation plot is identified the order.

Figure 3.6 shows the residuals of autocorrelation function and partial autocorrelation function for the transformed data. It can see that the residuals are not correlated as every point lie within the limits, the model is acceptable.

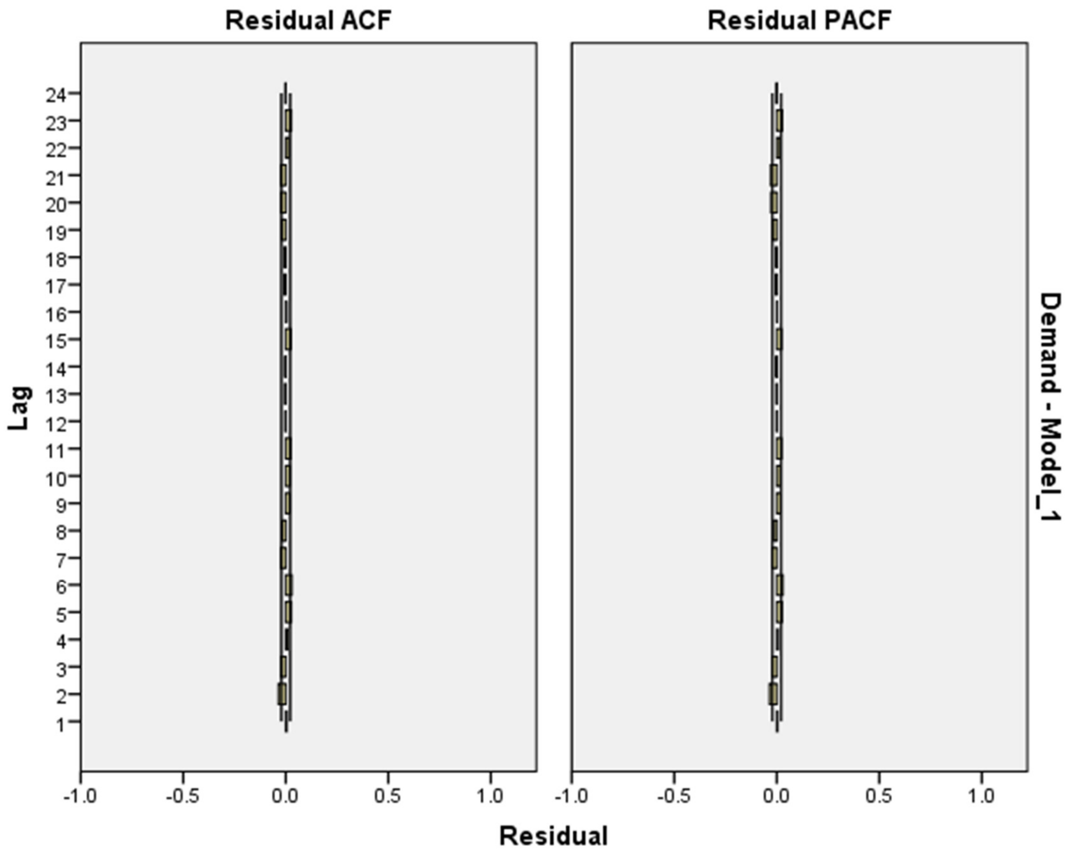


Figure 3.6: Residual Autocorrelation Function and Partial Autocorrelation Function.

The time series model ARIMA (1, 1, 2) (1, 1, 1) is now fitted for the above data, then the time plot of the model with actual observations and forecasted observations is obtained as follows. The fitness values of the model are shown in Figure 3.7 as in blue color. The observed values and forecasted values of the model are shown in red and dark blue colours respectively.

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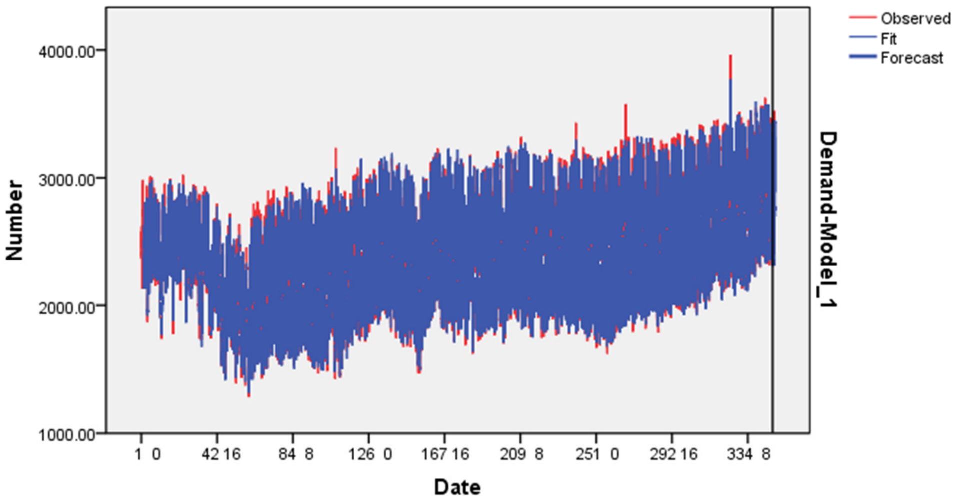


Figure 3.7: Sequence Plot of Actual and Forecasted Values

For checking the effectiveness of the model in forecasting future values, an in-sample forecasting of last 21 days was done. For this, the data up to 30-03-2014 was taken, to forecast the 24-hour demand observations for 31-03-2014 by using the model that developed and compared the values with actual data.

Figure 3.8 shows the actual values, predicted values, upper control limits and lower control limits of the above model.

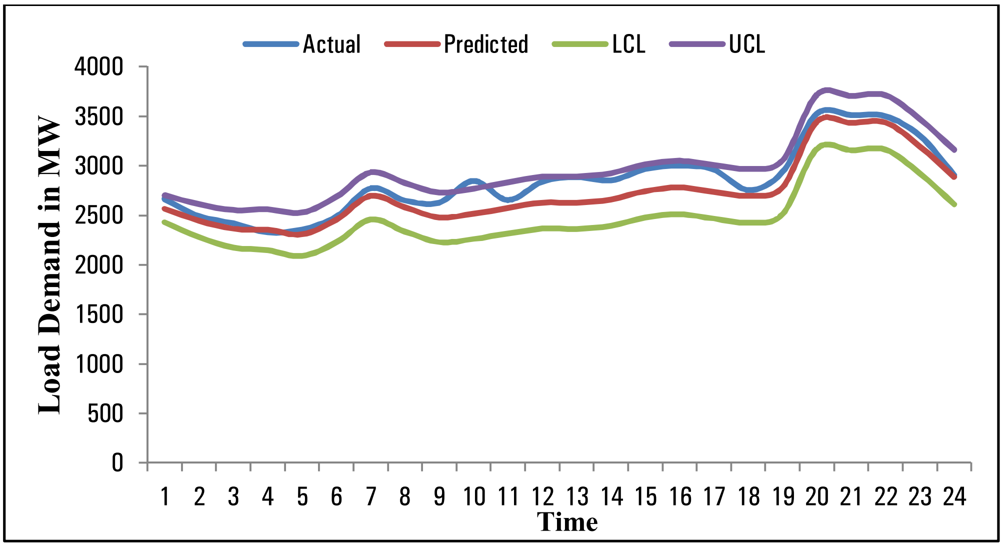


Figure 3.8: Predicted Observations and the Control Limits (In-sample Prediction)

From the Figure 3.8 and Table 3.5, it can be inferred that forecasted and observed values are almost same. That is, the model is effective in forecasting. Now the remaining data points are augmented to analyze the complete sample. Analysis of the complete data yields the same model as before.

Table 3.5: Predicted Observations and the Control Limits (In-sample Prediction)

	Actual	Predicted	LCL	UCL	% Error
Hour1	2664.58	2566.39	2431.17	2701.61	3.68
Hour2	2491.13	2445.49	2278.72	2612.27	1.83
Hour3	2418.64	2364.85	2175.69	2554.00	2.22
Hour4	2328.47	2353.55	2147.54	2559.56	1.07
Hour5	2356.22	2308.05	2088.94	2527.16	2.04
Hour6	2487.24	2456.05	2226.56	2685.55	1.25
Hour7	2772.16	2696.14	2458.31	2933.98	2.74
Hour8	2649.55	2581.07	2336.48	2825.66	2.58
Hour9	2627.60	2478.87	2228.76	2728.98	5.66
Hour10	**2848.27**	**2515.77**	**2261.13**	**2770.41**	**11.67**
Hour11	2654.17	2575.30	2316.93	2833.67	2.97
Hour12	2840.15	2627.13	2365.67	2888.58	7.50
Hour13	2885.05	2628.38	2364.37	2892.40	8.89
Hour14	2852.69	2660.24	2394.10	2926.38	6.74
Hour15	2965.93	2744.97	2477.06	3012.88	7.44
Hour16	3002.40	2780.56	2511.17	3049.95	7.38
Hour17	2960.90	2738.38	2467.75	3009.00	7.51
Hour18	2755.36	2699.33	2427.68	2970.99	2.03
Hour19	2937.37	2784.24	2511.72	3056.76	5.21
Hour20	3524.42	3445.31	3172.06	3718.56	2.24
Hour21	3513.46	3431.63	3157.77	3705.49	2.32
Hour22	3498.45	3437.24	3162.86	3711.61	1.74
Hour23	3305.77	3196.51	2921.71	3471.32	3.30
Hour24	2909.59	2886.31	2611.14	3161.48	0.80

In all models diagnostic checking procedures are done. Thus, by making use of the above model up to 31-03-2014, it can be forecasted the daily absenteeism for the next 24 hours, and the values are obtained and are given in the Table 3.5.

Case 2- One month ahead prediction with two years data (2014 April- 2016 March).

This case is analyzed using R-Studio. First, the stationarity of the time series plot is to be checked, i.e., demand versus time. This is the auto correlation and partial auto correlation function is shown in Figure (3.9). Clearly, this is not a stationary process, because there is no lagging even after 100 lags. Therefore, to confirm the non-stationarity, the Statistical Package for Social Sciences (SPSS) test is necessary. The SPSS test is a test for stationarity. If the value of $p < 0.05$, it is not stationary. To convert non-stationary process in to stationary, differentiation is to be done. After this, many of the time series points become stationary. In this study differentiation is done only once and after that the process became stationary. ARIMA is the function in which it gives best suited model for the given data. When ARIMA is executed it became ARIMA 312 where, $p = 3$, $d = 1$, and $q = 2$. Thus, ARIMA is fitted for demand with order 312 and this method is having the maximum magnitude. Figure 3.9 shows the stationarity and there are still non-stationary points, again it is necessary to do differentiation.

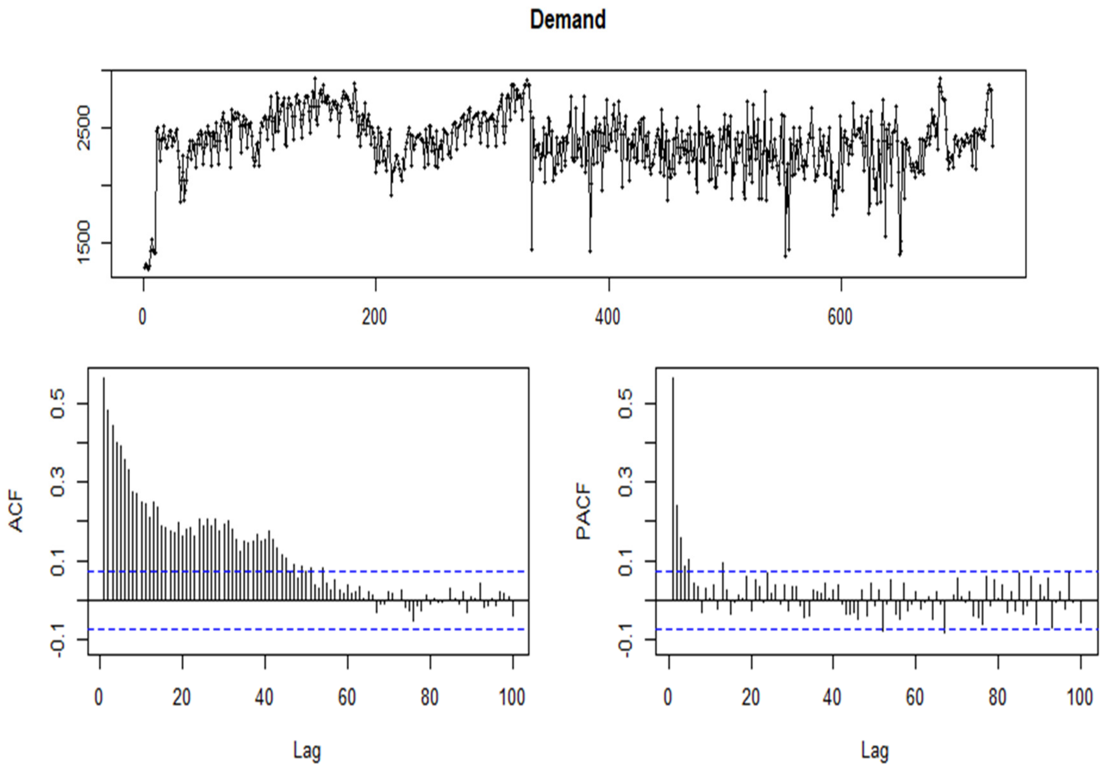


Figure 3.9: Autocorrelation and Partial Autocorrelation Function for Transformed Data with First Difference of 2016 April.

Next, the residuals are taken because the goodness of it is to be checked, i.e. there is a need to satisfy the assumptions. The assumptions are that the errors should be independent and they should follow normal distribution. Here, by using maximum likelihood estimation and for that errors should be normally distributed and independent. Therefore, for checking the independence the Box-Jenkins test is used. If $p > 0.05$ the errors are independent. The value obtained is 0.12 which is greater than 0.05. The normality is to be checked whether the value is less than 0.005. Here, it is less than 0.005, hence follows, a normal distribution. This is the histogram of the residuals. Thus 3 values are predicted. They are April 01,2016, April 02,2016 and April 03,2016.

Table 3.6 shows the actual and predicted values, MAE, MPE, MAPE, MSE and RMSE for April 01, 2016. By using the Equation (3.17) – (3.20), the values of MAE, MPE, MAPE, MSE and RMSE are calculated.

Table 3.6 Calculation of Prediction error parameters

Time Series 2016 April						
Actual	Predicted	MAPE	MAE	MSE	RMSE	MPE
2274.4	2565.715	12.80843	291.315	84864.43	2828.814	-12.8084
2886.717	2592.944	10.17672	293.773	86302.58	2876.753	10.17672
2937.553	2589.323	11.85442	348.23	121264.1	4042.138	11.85442
2810.311	2600.458	7.467252	209.853	44038.28	1467.943	7.467252
2823.486	2598.523	7.967562	224.963	50608.35	1686.945	7.967562
2590.666	2599.804	0.352728	9.138	83.50304	2.783435	-0.35273
2591.735	2599.728	0.308403	7.993	63.88805	2.129602	-0.3084
2536.566	2599.789	2.492464	63.223	3997.148	133.2383	-2.49246
2643.144	2599.812	1.639411	43.332	1877.662	62.58874	1.639411
2432.983	2599.81	6.856891	166.827	27831.25	927.7083	-6.85689
2581.258	2599.814	0.718874	18.556	344.3251	11.4775	-0.71887
2603.029	2599.814	0.12351	3.215	10.33623	0.344541	0.12351
2348.91	2599.814	10.68172	250.904	62952.82	2098.427	-10.6817
2425.405	2599.814	7.190923	174.409	30418.5	1013.95	-7.19092
2342.721	2599.814	10.97412	257.093	66096.81	2203.227	-10.9741
2527.985	2599.814	2.841354	71.829	5159.405	171.9802	-2.84135
2595.357	2599.814	0.17173	4.457	19.86485	0.662162	-0.17173
2453.458	2599.814	5.965295	146.356	21420.08	714.0026	-5.96529
2610.019	2599.814	0.390993	10.205	104.142	3.471401	0.390993
2488.72	2599.814	4.463901	111.094	12341.88	411.3959	-4.4639
2714.653	2599.814	4.230338	114.839	13188	439.5999	4.230338
2760.92	2599.814	5.835229	161.106	25955.14	865.1714	5.835229
2766.721	2599.814	6.032659	166.9068	27857.89	928.5963	6.032659
2698.294	2599.814	3.649697	98.47954	9698.22	323.274	3.649697
2733.042	2599.814	4.87471	133.2279	17749.67	591.6556	4.87471
2750.788	2599.814	5.488402	150.9743	22793.25	759.775	5.488402
2446.721	2599.814	6.257048	153.0925	23437.33	781.2442	-6.25705
2638.99	2599.814	1.484523	39.17642	1534.792	51.15972	1.484523
2745.251	2599.814	5.297783	145.4375	21152.05	705.0685	5.297783
2665.297	2599.814	2.456885	65.48329	4288.061	142.9354	2.456885
	Total:	151.054	3935.488	787453.8	26248.46	-473.665
	Average:	5.035133	131.1829	26248.46	162.0138	-15.7888

The percentage error of the above two cases shows almost same as maximum of 11.67% and 11.85% respectively. The tables for prediction error parameters for the year 2014 and 2015 are given in Appendix - I. The values of MAE, MPE, MAPE, MSE and RMSE are tabulated in the next section 3.3.3

3.3.2 Multiple Regressions Method

In statistical approach, the regression analysis is a statistical process for estimating the relationships among variables. It includes many techniques for modeling and analyzing several variables. The choice of variables depends on the availability of data, its quality and their correlations. There will be a strong relationship between a dependent variable and one or more independent variables (Akole and Tyagi, 2009). Many techniques for carrying out regression analysis have been developed such as linear and ordinary least squares regression techniques. For electric load forecasting regression methods are usually used to model the relationship of load consumption and other factors such as weather, day type and customer class. Since temperature is the most important information of all-weather variables and it is used in the regression approach. In regression based models, the prediction error is minimized to zero by using the least squares algorithm.

The simple linear regression model is based on the linear relationship of dependent variable Y and independent variable X is on the line or exact or deterministic (Rothe *et al*., 2009). That is the point exactly on the line,

$$Y = a + b\,x \ldots\ldots\ldots \tag{3.11}$$

This equation is for a straight-line which intercepts Y axis at 'a' with slope of 'b'. In order to attain zero error, by using the least squares error method; the equations can be written as:

$$\sum_{i=1}^{n} \mathrm{Y_i} = \mathrm{an} + \mathrm{b} \sum_{i=1}^{n} \mathrm{X_i} \ldots\ldots \qquad (3.12)$$

$$\sum_{i=1}^{n} \mathrm{X_i}\,\mathrm{Y_i} = \mathrm{a}\sum_{i=1}^{n} \mathrm{X_i} + \mathrm{b} \sum_{i=1}^{n} \mathrm{X_i}^2 \ldots \qquad (3.13)$$

The variables x, y and n are representing the peak load, the year and the number of years which are based on the forecasting (Aslan *et al.*, 2011). The coefficients of 'a' and 'b' are calculated from the above equations and replaced in Equation (3.13) for the load forecasting. Multiple regressions are a statistical data analysis technique. Whenever a quantitative variable is used, the dependent variable is to be taken as a function of, or in relationship to and or any factor of interest. The multiple regression say, y is a function of more than one predictor variable, the matrix equations that express the relationships among the variables must be expanded to accommodate the additional data. This conventional multiple regression model involves the multiple regression between the load demand and various other factors that can be influenced on the load demand.

The multiple regression models can be written as:

$$\mathrm{Y_i} = \alpha_0 + \sum_{i=1}^{n} \alpha_{\mathrm{k}}\, x_{\mathrm{ki}} + \mathrm{u_i} \qquad (3.14)$$

i = 1, 2, 3....n, size of the i^{th} observation, k is the number of independent variables, Y is the dependent variable, x is the independent variables (regressed), α_0 = intercept,

α_k = regression coefficient and u = stochastic disturbance term. For estimation of regression coefficients, ordinary least square method is used.

3.3.2.1 Multiple Regression Based Load Forecasting

In this study, multiple regression method is applied for short term and mid-term load forecasting. The Y matrix is taken as the response of the demand matrix and the cross one matrix is taken as design matrix. The regressor, the independent variables, are rainfall, temperature and humidity. Then it is fitted with detailed model with Y matrix with respect to X matrix. The model is:

$$Y = \beta_0 + \beta_1 * X_1 + \beta_2 * X_2 + \beta_3 * X_3 \quad (3.15)$$

Where Y is the demand in MW, β is the regression coefficients, X_1, X_2 and X_3 are the independent variables.

$$\text{Demand} = \beta_0 + \beta_1 * \text{rainfall} + \beta_2 * \text{temperature} + \beta_3 * \text{humidity}. \quad (3.16)$$

The data collected from KSEB and IMD has been used to find out the forecasted load of the year 2015 (one day prediction with one year data) by using the multiple linear regression model in R-Studio.

From the result, R value of demand = 1636 -1.6816* original value of rainfall+ 26.916* original value of temperature.

The negative sign indicates the demand decreases when rainfall increases, whereas the temperature increases demand also increases and the value is positive. But when humidity increases the demand will decrease, so the p - value of β_3 is ≥ 0.05, i.e. which is not significant in the model. Hence, the humidity is removed from the model and only the rain fall and temperature are used. Therefore, firstly all the three variables are used and the values are β_0 = 1636.9425, β_1 = -1.6816, and β_2 = 26.9164. The p- value of this model is greater than 0.05 and thus β_3 is removed.

This is the same as 26.9164, only the intercept part and also that it should be independent. From the data it is not seen that it is not dependent, because the correlation is only 0.35 between rainfall and temperature and is not very high. If it is somewhere above 0.6 or 0.7, it can be shown that it is dependent. Here it is only in the value 0.35, the principal component analysis need not be considered and therefore simple multiple linear regression is taken.

Predicted value.

For April 01, 2014

$$\text{Predicted load, } Y = 1636.9425+(-1.6816\times 0.4)+26.9164\times 28$$
$$= 1636.9425-0.67264+753.6592$$
$$= 2389.929 \text{ MW}$$
$$\text{Percentage error} = 2369.869-2389.929\ /2369.869\times 100$$
$$= -0.84646\%$$

A similar approach is used to predict the load demand and percentage error for different period viz: 2014, 2015 and 2016.

For April 01, 2015

Actual demand	=	2335.98MW, Rain fall = 0,
Predicted load, Y	=	1636.9425 + (-16816×0) + 26.9164×29.861
	=	2440.6932MW
Percentage error	=	2335.98 - 2440.632 /2335.98×100
	=	-4.48262399%

For April 01 2016

Actual demand	=	2274.4MW, Rain fall = 0,
Predicted load, Y	=	1636.9425 + (-16816×0) + 26.9164×30.2
	=	2449.8178MW
Percentage error	=	2274.4 - 2449.8178 /2274.4×100
	=	-7.7127 %

The calculated values of the prediction error parameters (MAE, MPE, MAPE, MSE and RMSE for the year 2014, 2015 and 2016 are given in Appendix – II.

3.4. EVALUATION OF FORECASTED ERRORS OF TIME SERIES AND MULTIPLE REGRESSIONS: A COMPARISON

If statistical models are used for forecasting, error can be evaluated statistically. Forecast errors have two components, model error and assumption error. These errors can be assessed as soon as the forecast is completed and before the actual data is known. In calculating a forecast error, the variance is calculated first and to obtain forecast error by taking the square root. Model error is inherent in the model itself. Its magnitude depends on the model's variance, variance of the estimated coefficients and the changes in the values of independent variables. A good forecasting model should have small variance.

The assessment of the time series and multiple regression models' prediction performance was done by quantifying the prediction obtained on an independent data set. The mean absolute error (MAE), the mean absolute percentage error (MAPE), and route mean square error (RMSE) were used to represent the performance of the above two models.

MAE = MAD = $\frac{1}{n} \times \sum_{t=1}^{n} e_t$ where, $e_t = \left|L_{rt-}L_{ft}\right|$

$$\text{Therefore MAE} = \frac{1}{n} \times \sum_{t=1}^{n} \left|L_{rt-}L_{ft}\right| \tag{3.17}$$

L_{ft} is the forecasted load for a period t, L_{rt} is the actual load of period t.

n is the number of total data or number of periods of evaluation and e_t is the absolute error.

$$\text{MSE} = \frac{1}{n}\sum_{t=1}^{n} e_{t^2} = \frac{1}{n}\sum_{t=1}^{n}\left|L_{rt-}L_{ft}\right|^2 \tag{3.18}$$

$$\text{Root Mean Squared error, RMSE} = \sqrt{MSE} = \left[\frac{1}{n}\sum_{t=1}^{n}\left|L_{rt-}L_{ft}\right|^2\right]^{1/2} \tag{3.19}$$

$$\text{Mean absolute percentage error, MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{e_t}{L_{rt}}\right| \times 100$$

$$= \frac{1}{n}\sum_{t=1}^{n}\left|\frac{L_{rt-}L_{ft}}{L_{rt}}\right| \times 100 \tag{3.20}$$

Mean square error (MSE) is computed first squaring the individual errors, which give all positive values and then taking the average value of all data points. This approach gives more importance to large errors in the mean squared error computation than small errors. Mean absolute percentage error (MAPE) is another measure of prediction accuracy in which find the absolute percentage error for each forecast and computing the average of these values. The advantage of MAPE is that it allows comparison among different series which are not possible with MSE. If absolute errors are used in place of the absolute percentage errors, the mean absolute deviation (MAD) is obtained. Another measure of prediction error is the mean percentage error (MPE).

Accuracy is a relative term i.e., 1% error may be too large for one case, where as 5% error is acceptable in another case. In the case of Kerala power system, the actual load is less than the forecasted load in most of the cases. The MAPE is varied from 17.57to 5.0531 for the year 2014 to 2016. For reducing the forecast error on an annual basis is to develop hourly or weekly or monthly or one day ahead models for forecasting to take advantage of the least square's estimation properly.

When prediction is carried out over several periods, a series of error values are obtained for each time period. If absolute errors are used in place of the absolute percentage errors, the mean absolute deviation (MAD) is obtained. Another measure of prediction error is the mean percentage error (MPE).

From the two methods (TS and MLR) percentage error has been calculated and also MAPE, MPE, MSE and MAE are calculated and compared for each method. The calculated values of MAE/MAD, MAPE, MPE, MSE and RMSE are shown in Tables 3.7 and 3.8.

Table 3.7: Values of Prediction Error in Time Series Method

Time series method					
Year	MAE/MAD	MAPE	MSE	RMSE	MPE
2016	131.1829	5.0351	26248.46	131.1829	0.22955
2015	374.65	17.5718	203619	374.652	-16.5529
2014	364.899	15.9072	177095	364.899	-15.7888

From the comparison, average value of the percentage error of the TS method shows lower values for the year 2014 and 2015 than the MLR method. In the case of next year, the error slightly higher in TS method as compared to MLR method. The forecasted load is higher than that of the actual load.

Table 3.8: Values of Prediction Error in Multiple Linear Regression Method

Multiple Linear Regression method					
Year	MAE/MAD	MAPE	MSE	RMSE	MPE
2016	232.1657	8.5548	72910.24	232.1657	-5.06388
2015	195.2435	9.142	69230.85	195.2435	-3.72727
2014	120.2385	5.26270	23596.05	120.2385	-3.18771

3.5 CONCLUSION

The total available power in Kerala on daily basis is 2400 MW. In this, the internal generation is 1750MW and the power purchased is 650 MW. The annual and daily consumption as on 31st March 2018 is 23784MU and 65.1616 MU. There is an increase of 17.48 MU per daily consumption. The maximum peak demand during the period of 12 years from 2004-05 to 2015-16 is 4079 MW. The total expected energy consumption for 2026-27 is 33718 MU as per the 19th Electric Power Survey of Central Electricity Authority. Through Power Purchase Agreements, the KSEB Ltd has been taking efforts of filling up the deficiency of power.

The statistical methods used in load forecasting such as time series method and multiple regression techniques are also analyzed in this chapter. The time series method is used for a particular day depending on climatic conditions and a certain period of day with a unique pattern of load dynamics. Data available from KSEB were used in this work for testing and demonstrating the performance of the time series models and multiple linear regression for the STLF and Mid-term load forecasting. It is found that, the actual load is less than the predicted load in most of the cases. The calculated values of MAE, MSE, MAPE, RMSE and MPE shows that the error in time series model is slightly higher than that of multiple linear regression model for the year 2014 and 2015. The value of MAE and MAPE of MLR on April 2016 is 232.1657 and 8.4458 and that of time series model is 131.1829 and 5.0351 respectively. Average value of MSE and RMSE of MLR and TS model is 72910.24, 232.1657 and 26248.0, 131.1829 respectively.

CHAPTER 4

DEMAND FORECASTING OF KERALA POWER SYSTEM THROUGH ARTIFICIAL INTELLIGENCE TECHNIQUES

4.1 INTRODUCTION

Kerala power system has a high content of hydel component. As much as 55% of the peak demand can be met from hydel sources. However, almost 80% of total annual inflow is received in a period and hence the utilization of hydel is very critical in optimizing the total power purchase cost (Economic Review, 2007). As hydel machines have least constraints attached to start-stops, loading and number of hours of operation, an accurate load forecast is essential for proper planning of economic operation. Due to the complexity, it is difficult to find suitable data that can be used in demand forecasting. Such problem is particularly acute in fast growing companies, a situation compounded by factors such as inadequacy of support data base, unparallel experience of fast growth and unavailability of forecasting techniques capable of addressing adequately this particular problem. The situation is made more difficult when the data are scattered and not integrated with energy planning.

Long term load demand depends on a number of complex factors such as weather, national economic growth and social habits. It is difficult to forecast load demand accurately over a planning period of thirty years long. There are a large number of influential factors that characterize and directly or indirectly affect the underlying forecasting process. All of them are uncertain and uncontrollable (Zhang and Ye, 2011). Therefore, long term load forecast for a period of above 10 to 30 years by its nature is inherently inaccurate.

Artificial Intelligence method including short-term, mid-term and long term load forecasting by artificial neural network (ANN) and SVR are used in the present research work for forecasting the demand. In this chapter, application of neural network for short term, mid-term and LTLF is made.

4.2 ARTIFICIAL NEURAL NETWORK

An artificial neural network is an information processing paradigm that is based upon the design of human brain and central nervous system (Freeman and Skapura, 1991). A neural network is a machine that is designed to model the way in which the brain performs a particular task i.e., each neuron receives input from neighbours or external source and use this to compute an output signal which is propagated to other units. Neural networks are essentially non-linear circuits that have the demonstrated capability to do non-linear curve fitting (Sforna and Proverbio, 1995). The basic elements of the neural networks consist of several layers of processing units called neurons or nodes. Each neuron has own memory and ability to solve specific problems. The output units, which send data out of any neural network, are some linear or non-linear mathematical function of its inputs. The inputs and hidden units, with input and output signals remain within the neural network. The input may be the outputs of other network elements as well as actual network inputs (Hodzic *et al.,* 2006).

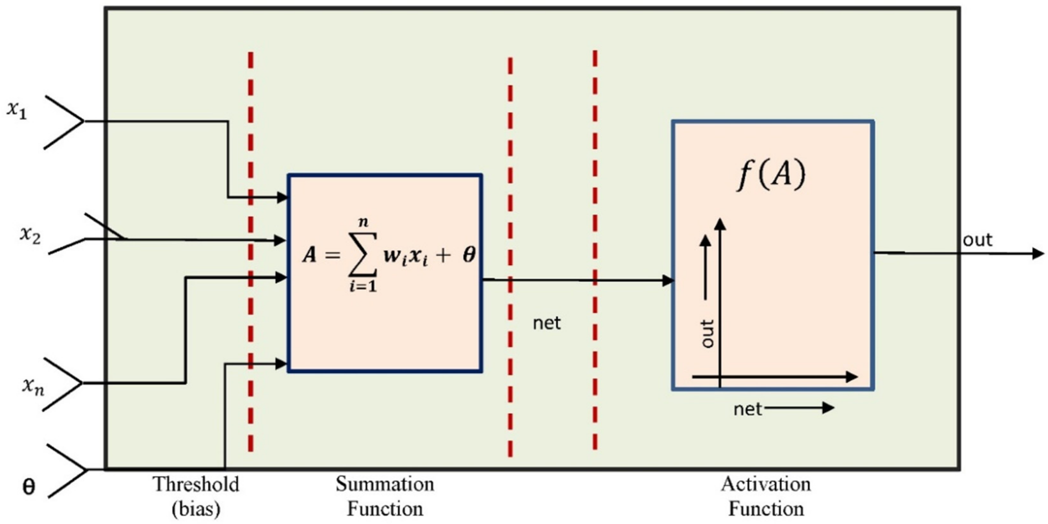
The data flow from input to output units is strictly feed-forward. The data processing can extend over multiple units, but no feedback connections are present. New inputs are presented to the input unit where they filter into and are processed by the middle layers through training. However, at this point the output is retained and no back propagation is occurred. The output of a forward propagation is a predicted model for the data which can be used for further analysis and interpretation.

4.2.1 Structure of Artificial Neural Network

ANN consists of a pool of simple processing units which communicate by sending signals to each other over a large number of weighted connections. The processing units are neurons or cells. Each unit performs a relatively simple job to receive input from neighbors or external sources and use this to compute an output signal which is propagated to other units. Apart from this processing, a second task is the adjustment of the weights. The system is inherently parallel in the sense that many units can carry out their computations at the same time. Within the neural systems, it is useful to distinguish three types of units. They are input units, which receives data from outside the neural network, output units which send data out of the neural network and hidden units, whose input and output signals remain within the neural network (Hodzic *et al.,* 2006; Bakirtzis *et al*., 1996).

The output of artificial neural networks is some linear or non-linear mathematical function of its inputs (Mandal *et al*., 2006). Back propagation neural networks (BPNN) use continuously valued functions and supervised learning i.e., in this work, the actual numerical weights assigned to element inputs are determined by matching historical data (time, day, month, year, and other factors) to desired outputs (demand/load) in a preoperational training session.

The processing elements in an ANN are also known as neurons. These neurons are interconnected by means of information channels called interconnection. Each neuron can have multiple inputs, while there can be only one output. Inputs to a neuron could be from external or output of the other neurons. Copies of the single output that comes from a neuron could be input to many other neurons in the network. There is a connection strength or weight associated with each connection. When the weighted sum of the inputs to the neuron exceeds a certain threshold, the neuron is fired and an output signal is produced. The network can recognize input patterns, once the weights are adjusted via some kind of learning process (Lee *et al*., 1992). The basic mathematical model of an artificial neuron is shown in Figure 4.1. A set of weights, each of which is signalized by a strength of its own.



Source: Konar (1999)

Figure. 4.1: Basic model of an artificial neuron

An activation function defines the output of a neuron in terms of its input. For a single layer network with linear activation function, the output is simply given by the following equation:

$$Y = f(A)$$

$$Y = f\left(\sum_{i=1}^{n} wiXi + \theta\right) \quad (4.1)$$

Where w_i is the weights, x_i is the inputs, θ be the threshold function and *f*(A) be the activation function. In applying a neural network to electric load forecasting one among a number of architectures must be selected (i.e., back propagation), the number and connectivity of layers and elements, use of bi-directional or unidirectional links and the number format (binary or continuous) to be used by inputs and outputs internally. The most commonly used ANN structure illustrated by Hodzic *et al.* (2006) is shown in Figure 4.2.

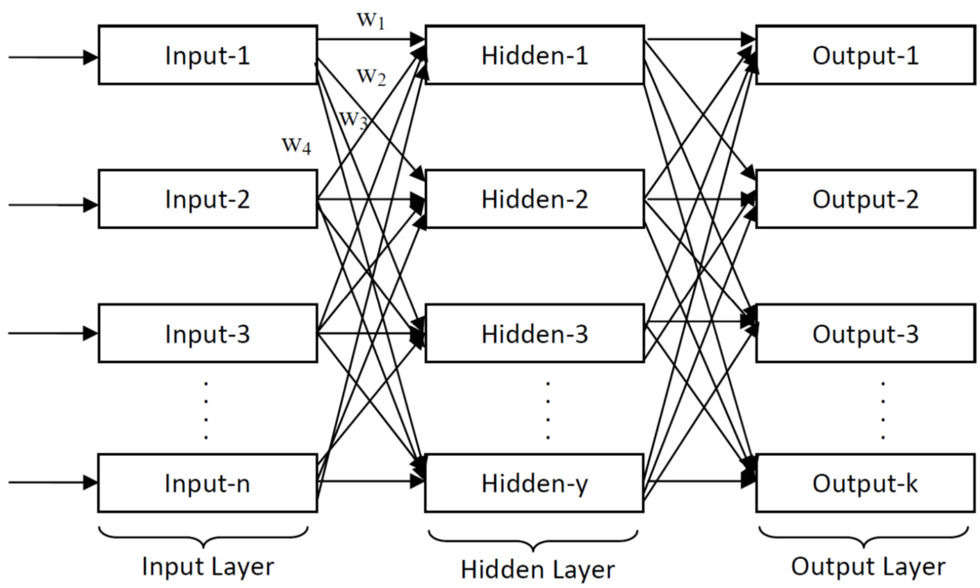


Figure 4.2: Basic model of ANN structure

The data passes from nodes in input layer through nodes in hidden layers to nodes in output layer. The nodes from one layer are interconnected to the nodes from the next layer. Figure 4.2 shows a feed forward multi-layer ANN. The input layer receives the signal from outer environment and distributes it to the neurons in the hidden layers. The hidden layers have computational neurons. The network computes the actual outputs of the neurons in the hidden and output layer by using the activation function. Each connection has an associated parameter indicating the strength of this connection called weight. By changing the weights, the network can learn in proportion to the error times the input signal, which reduces the error in the direction of the gradient (Lee *et al.*, 1992). The description of the procedure by means of which this weight adaption is performed is called learning or training algorithm.

The process of training a neural network can be broadly classified into three: supervised learning, unsupervised learning and reinforcement learning.

Supervised learning: The supervised learning process requires a trainer that submits both the input and the target patterns for the objects to get recognized.

Unsupervised learning: The process of unsupervised learning is required in many recognition problems, where the target pattern is unknown. The unsupervised learning process attempts to generate a unique set of weights for one particular class of patterns.

Reinforcement learning: This type of learning may be considered as an intermediate form of the above two types of learning (Konar, 1999).

Training is the process of determining the weights and bases of a given ANN architecture based on historical information. The most popular ANN architecture for electric load forecasting is back propagation. In this work a back propagation based supervised neural network is used. The central idea behind the back-propagation solution is that the errors for the units of the hidden layer are determined by back-propagating the errors of the units of the output layer. For this reason, the method is often called the back-propagation learning rule. Back-propagation neural network (BPNN) can also be considered as a generalization of the delta rule for non-linear activation functions and multi-layer networks.

4.2.2 Back Propagation Training Algorithm

Back propagation training requires a neural network of feed forward topology. Back propagation neural networks (BPNN) are based on the neuron structure of the brain and provide a powerful statistical approach for exploring solutions of non-linear systems. For instance, a study of Rumelhart *et al.* (1995) employed a back pre-operational neural network which was used to correlate input information with matched output values.

The back-propagation training requires a neural net of feed-forward topology. Since it is a supervised training algorithm, both the input and the target patterns are given. For a given input pattern, the output vector is estimated through a forward pass on the network. After the forward pass is over, the error vector at the output layer is estimated by taking the component-wise difference of the target pattern and the generated output vector. A function of errors of the output layered nodes is then propagated back through the network to each layer for adjustment of weights in that layer. The most significant issue of a BPNN is the propagation of error through non-linear inhibiting function in backward direction (Konar, 2000).

For training a network by this algorithm, one has to execute the following 4 steps in order for all patterns one by one.

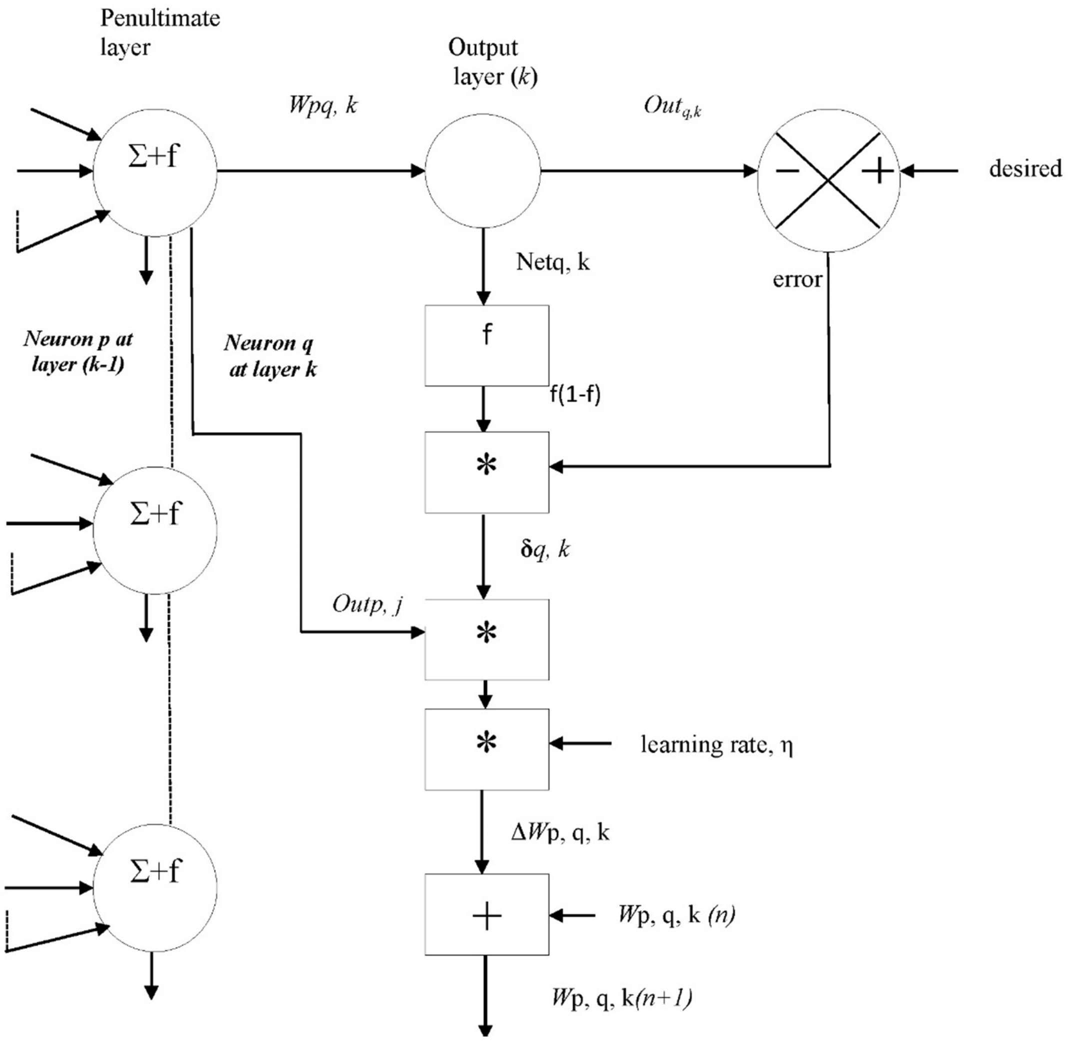
For each input-output pattern:

1. Compute the output at the last layer through forward calculation;
2. Compute δ at the last layer and propagate it to the previous layer by using Equation (4.5);
3. Adjust weights of each neuron by using Equation (4.3) and (4.4) in order;
4. Repeat from step 1 until the error at the last layer is within a desired margin;

End For;

The adaptation of the weights for all training instances, following the above steps, is called a learning epoch. A number of learning epochs are required for the training of the network. Generally, a performance criterion is used to terminate the algorithm. For instance, compute the square norm of the output error vector for each pattern and minimize the sum. Thus, the algorithm will be continued until the sum is reached below a given margin.

The flow chart for the back propagations learning algorithm for output layer and hidden layer pertaining to Equations 4.2 to 4.5 are shown in Figures 4.3 and 4.4.



Source: Konar (1999)

Figure 4.3: Features of neurons and weight adjustments by back propagation learning algorithm.

In Figure 4.3 shows two layers of neurons and weight adjustments by the back propagation learning algorithm. The left side layer is the penultimate $(k-1)^{th}$ layer, whereas the single neuron in the next k^{th} layer represents one of the output layered neurons. The top two neurons at the $(k-1)^{th}$ and k^{th} layer by neuron is denoted as p and q respectively. The connecting weight between them is denoted by $W_{p,q,k}$. For computing $W_{p,q,k}$ (n+1), from its value at iteration n and used the formula presented in Equation (4.4) to (4.5)

The error of a given output node, which is used for propagation to the previous layer, is designated by δ, which is given by the following equations:

$$\delta = f^1 \ * (target\text{-}Out) = Out\ (1\text{-}Out)\ (target\text{-}Out) \tag{4.2}$$

Weight adaptation in back – propagation

The weight adaptation policy is described by the following Equations (Konar,1999).

$$\Delta w_{p,q,k} = \eta \delta_{q,k}\ Out_{p,j} \tag{4.3}$$

$$w_{p,q,k}(n+1) = w_{p,q,k}(n) + \Delta w_{p,q,k} \tag{4.4}$$

where $w_{p,q,k}(n) =$ The weight from neuron p to neuron q, at nth step, where q lies in the layer k and neuron p in (k-1)th layer counted from the input layer.

$\delta_{q,k}$ = the error generated at neuron q, lying in layer k;

$Out_{p,j}$ = output of neuron p, positioned at layer j.

For generating error at neuron *p*, lying in layer *j*, it can be used the following Equation.

$$\delta_{p,j} = Out_{p,j}(1\text{-}Out_{p,j})\ (\sum_q \delta_{q,k} w_{p,q,k}) \tag{4.5}$$

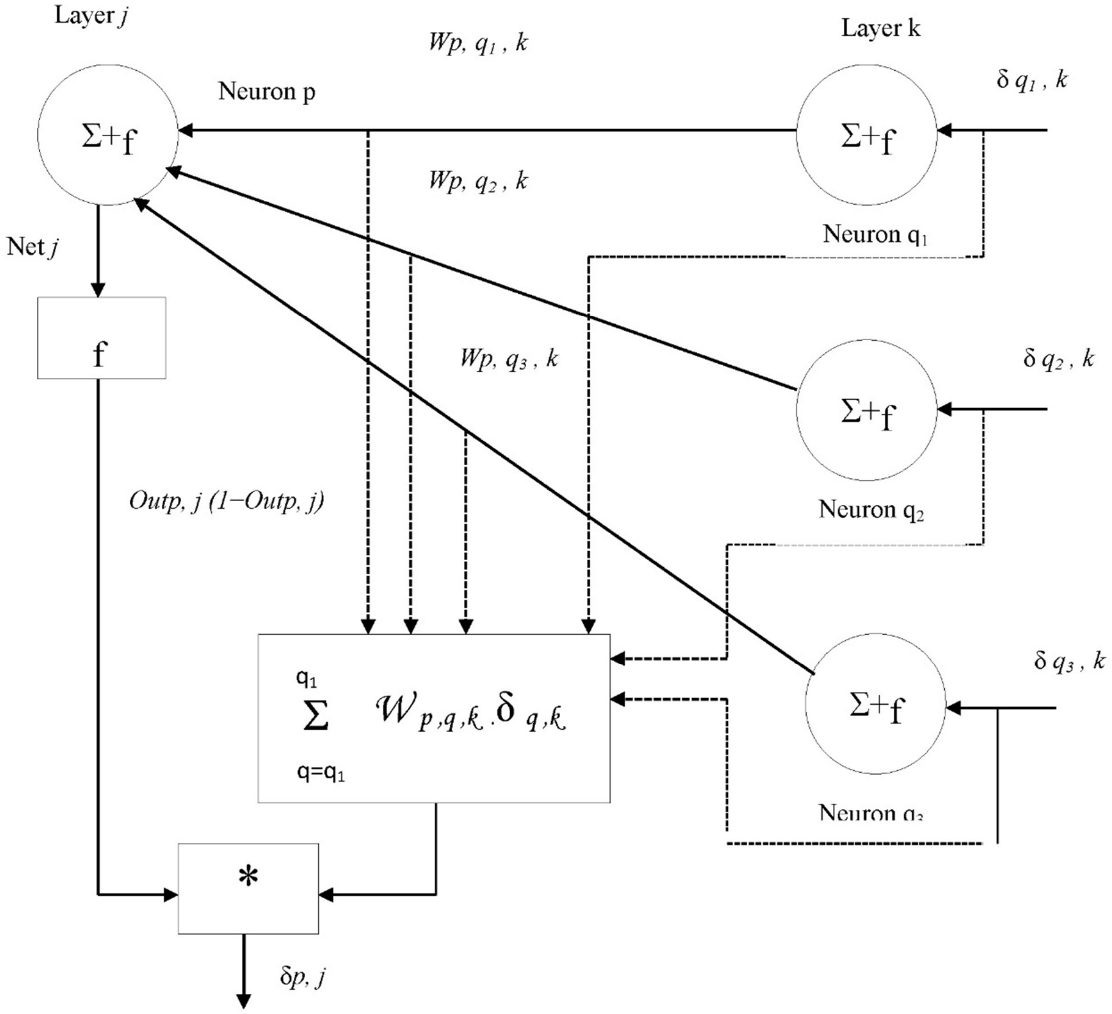
Where

$q \in \{q_1, q_2, q_3\}$ in Figure 4.4.

A momentum term was added to the rule of adjusting weights which can be expressed using the equation:

$$W_{p,q,k}(n+1) = W_{p,q,k}(n) + \eta\ \delta_{q,k}\ Out_{p,j} + \alpha\ \Delta\ w_{p,q,k}(n-1). \tag{4.6}$$

Where η is the learning rate of parameter and α is the momentum constant to determine the effect of past weight changes.



Source: Konar (1999)

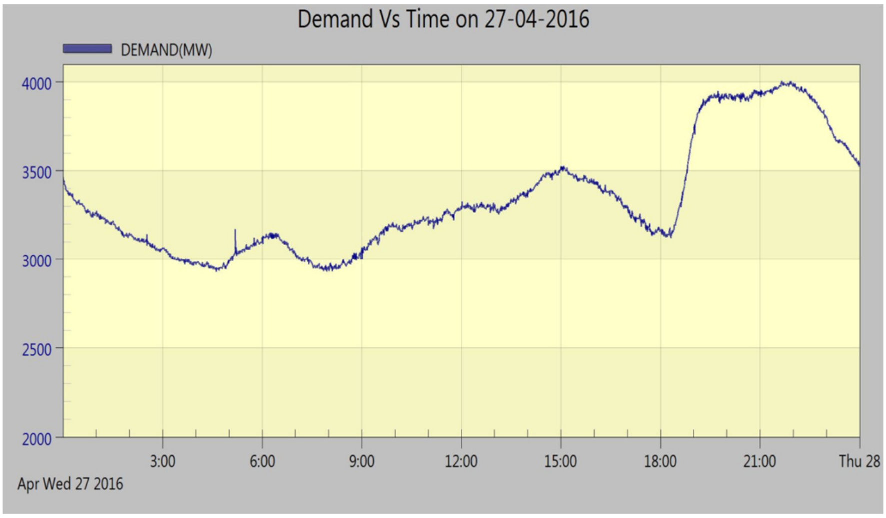
Figure 4.4: Flow chart shows the computation of δ_p at layer j (hidden layer)

The function of error is propagated from the nodes in the output layer to other layers for the adjustment of weight. This functional form of the BPNN error is presented in Equation (4.5) and illustrated in Figure 4.4. From the Equation (4.5) the contribution of the errors of each node at the output layer is taken into account in an exhaustively connected neural network.

There are some limitations on Back Propagation Algorithm. They are as follows: The network can be trapped in to local minima, slow convergence and once a network learns one set of weights, any new learning causes catastrophic forgetting.

4.3 DEMAND PROFILE ANALYSIS OF KERALA POWER SYSTEM

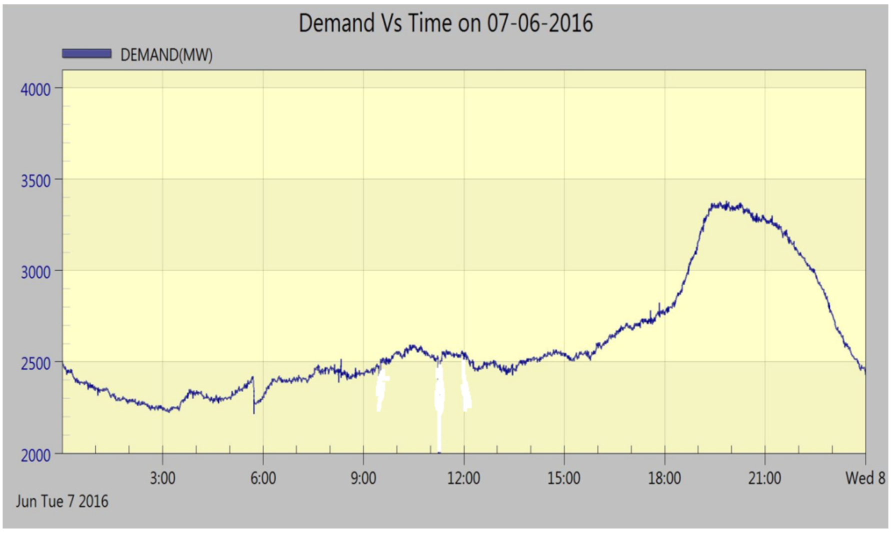
In this section, an analysis of maximum and minimum demand pattern is recorded at the State Load Dispatch Centre, Kalamassery on 27-04-2016. The maximum demand on the same day reached to 4000 MW as the Figure 4.5 shows. This is the maximum demand in the year 2016.



Source: State Load Dispatch Centre, KSEB Ltd., Kalamassery

Figure 4.5: Maximum demand curve

The Figure 4.6 shows the minimum demand in the year 2016 which is nearly 3400 MW on 7th June 2016. There is a difference of 600 MW between the maximum and minimum demand. The data is analyzed here to get the current demand profile on weekdays and weekend days.



Source: State Load Dispatch Centre, KSEB Ltd., Kalamassery

Figure 4.6: Minimum demand curve

Maximum and minimum demand pattern – Sundays and weekdays

The load on different weekdays also behaves differently as shown in Figure 4.7- 4.10. Figure 4.7 to 4.10 shows demand variations in Sundays and week days at peak and off-peak time slots. The collected data was analyzed in detail and classified. The following observations are arrived at:

Figure 4.7 indicate the load varied from 1305 MW to 2535 MW on Sundays of February 2013 to May 2013 at off peak time (1.00 pm to 4.30 pm). The load demand is less because the industries, offices, schools and colleges are not working on Sunday.

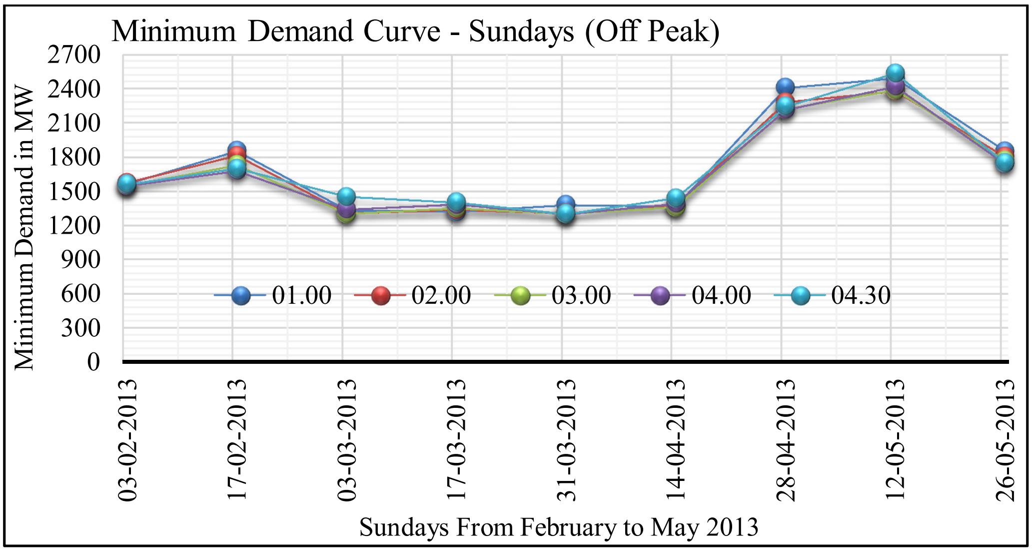


Figure 4.7: Minimum demand: Sundays

Figure 4.8 shows the maximum demand variation on Sundays of February 2013 to May 2013 from 18.00 hours to 22.00 hours. The load demand is varied from 1340 to 2803 MW.

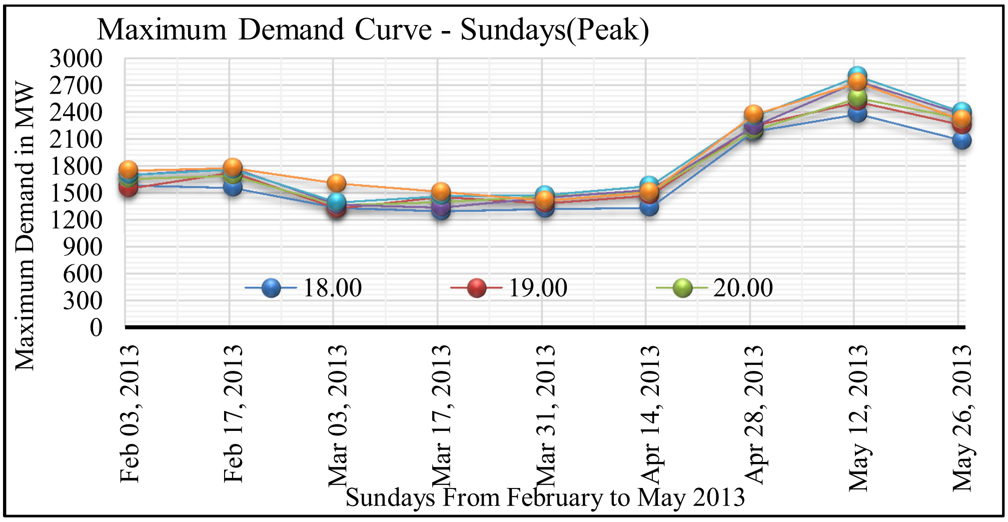


Figure 4.8: Maximum demand: Sundays

Minimum load demand variation of weekdays (Tuesdays, Wednesdays and Thursdays) of February 2013 to May 2013 is shown in Figure 4.9 which shows that there is no substantial variation between 01.00pm and 04.30 pm.

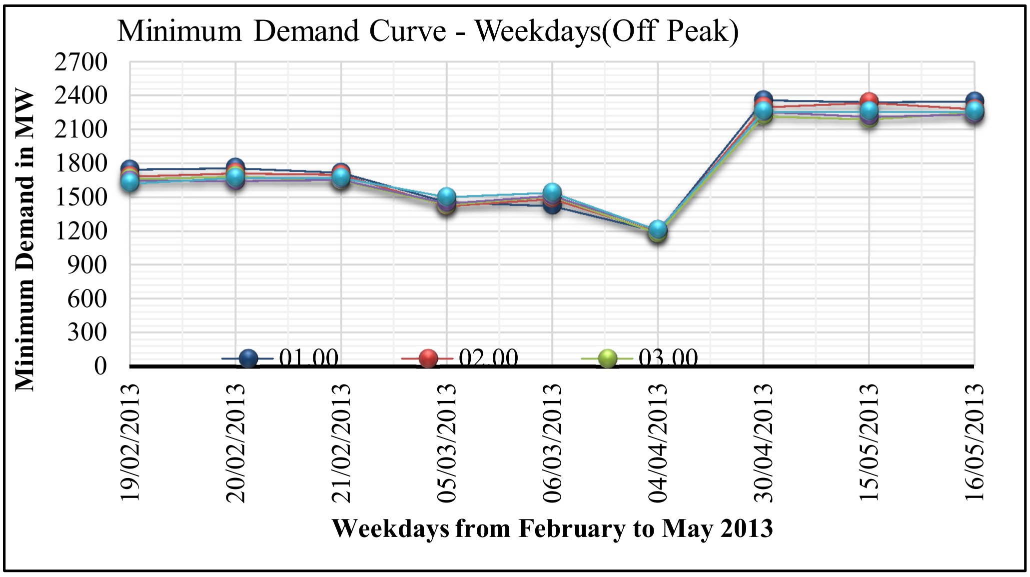


Figure 4.9: Minimum demand on weekdays

In week days from February to May 2013, there is more variation in maximum demand on peak time than during the same period in Sundays' demand. This is shown in Figure 4.10. That is, the variation is less in Sundays than in weekdays.

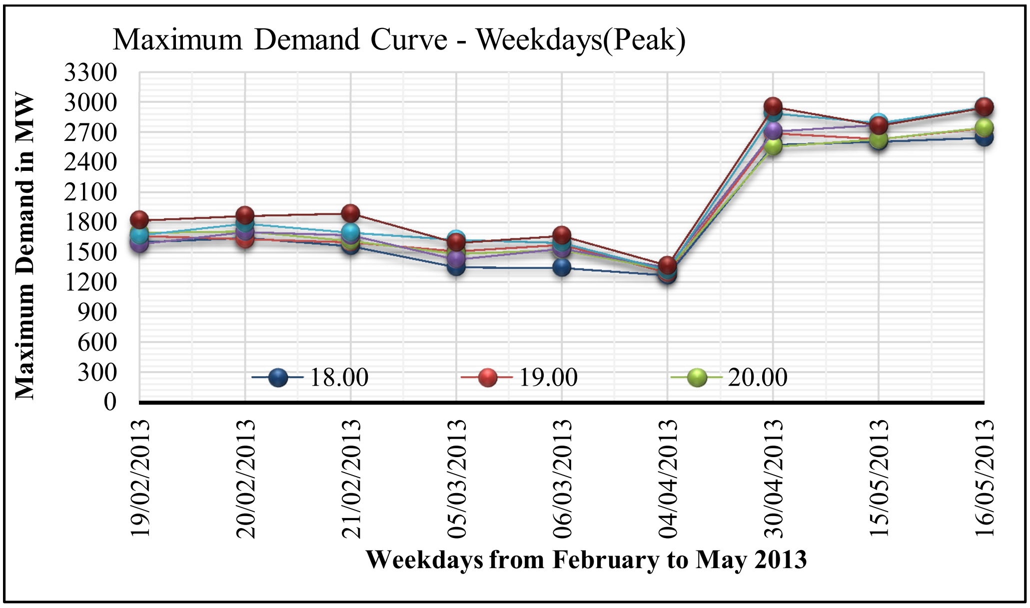


Figure 4.10: Maximum demand on weekdays

The shops, factories and other establishments are working on weekdays which are the reason for more variation in those days. The load consumption at evening peak of weekdays and Sundays is between 1273 MW and 2954.32 MW. The load consumption at peak time particularly on Sundays is between 1330 MW and 2803 MW. The minimum demand curves of weekdays and Sundays also shows variation. The minimum load consumption varies from 1308 MW to 2535 MW on Sundays and 1182 MW to 2358 MW on weekdays. To handle this complex and constrained system, a solution strategy through neural network is worked out.

4.4 MODELING OF NEURAL NETWORK FOR SHORT-TERM LOAD FORECASTING

There are many methods of electric load forecasting (Campbell and Adamson, 2006). In this section ANN is applied for short term load forecasting with the data of maximum demand profile presented in Section 4.4.2.

The STLF is aimed at predicting system load over a short time interval in a wide range of time leads an hour to several days. It has a pivotal role in the operation of power systems where basic operating functions such as energy transactions, unit commitment, security analysis, economic dispatch, fuel scheduling and unit maintenance are involved.

Short-term forecasts are also required by transmission companies when a self-dispatching market is in operation. The load on weekdays and weekend days are different. The diversity in demand pattern has been leading to develop complicated load forecasting methods. In this study, the factors to be considered for load forecasting are: the time factors, weather data, social factors, festivities, political factors, specialty of the day such as major cricket matches, world cup football and sports events etc. and peak load curtailment (Bakirtzis *et al.*, 1996). The time factors include the period of the year deciding the climatic conditions, the day of the week and the hour of the day. There are significant differences in load between week days and weekend days.

The data were analyzed and the load patterns were classified. The current load is affected by the past loads and the pattern in which the current load is included. During working days from Monday to Friday, the demand is increased slightly from Monday to Tuesday and it will reach at the maximum in Wednesday and it will decrease slightly from Thursday to Friday. The Monday loads are affected by loads of Sunday and Saturday and their load patterns are similar. Therefore, the non-linear load model is proposed for one-day ahead forecasting as follows (Lee *et al.*, 1992):

$$y(i) = F(W_{i,} Y(i-1)), \tag{4.7}$$

Where $y(i) = \{y(i,t) : t = 1, 2..........24\}$: the actual load vector at day i

y(I ,t): the actual load at day i, time t

$$Y(i-1) = [y(i-1), y(i-1)..., y(i-k)]^T$$

k: the weight vector

$F(W_{i,} Y(i-1))$; non-linear vector function represents artificial neural network. As against to the conventional approaches, the non-linear function is used with the weight vector to represent the load model. The load patterns are classified in to week day (Thursday) patterns and weekend day patterns.

Weekdays

For estimating the weekday load pattern for day i, three latest week days are used to adjust the weight as:

$$y(i-1)=F(\hat{W}_{i,}\, Y(i-2)) \tag{4.8}$$

Where the output data $y(i-1)$ is the latest weekday load, the load input data $Y(i-2)=[y(i-2), y(i-3)]^T$ is the next to latest weekday loads and W_i is the estimated weight vector using this input and output data.

Weekend days

To estimate the weekend day load patterns, the weekend day load patterns are grouped into 5 different loads, and the following model is proposed:

$$y(i_d)=F(\hat{W}_{i,}\, Y(i_d-1)), d=1,2,...,5 \tag{4.9}$$

Where i_d represents the previous type for day d. i_1 represents the previous Saturday when day i is a Saturday, i_2 for the previous 1st or 3rd Sunday, i_3 for the previous 2nd, 4th or 5th Sunday etc.

The weight vector is adjusted using Equations (4.7) or (4.8) according to the pattern in which the load to be forecasted is included. The error back propagation neural network is used to decrease the error, in the case of weekdays is minimized following the rule, Equation (4.8), until the error decreases to a predetermined tolerance. Once the weight vector for day i is estimated the load is forecasted using the following equations:

$$\in = (y(i-1)F(\hat{W}_{i,} Y(i-2))^T (y(i-1) - F(\hat{W}_{i,} Y(i-2)) \tag{4.10}$$

$$\hat{y}(i) = F(\hat{W}_i, Y(i_d - 1)) \tag{4.11}$$

Where $\hat{y}$(i) indicates the load forecast for day i. This scheme was simulated and errors in forecasting were analyzed using the following manner:

$$\hat{y}(i) = \left\{ \begin{matrix} F(\hat{W}_i^1\, Y(i-1)), t \in T_j = \{1,...,9\} \\ F(\hat{W}_i^2\, Y(i-1)), t \in T_j = \{10,...,19\} \\ F(\hat{W}_i^3\, Y(i-1)), t \in T_j = \{20,...,24\} \end{matrix} \right\}$$

where W_i corresponds to the estimated weight vector for time band T_1. Here the input data Y(i-1) is common and contains the previous 48 hours data, but the output *y(i)* depends on the time band and contains 1- hour and 6-hour data.

Once learnt, the network can provide with forecasted output load corresponding to any pattern of inputs instantaneously. This structure found to provide good results for STLF in Kerala power system.

4.4.1 Neural Network Model for Kerala Power System

A STLF model can be developed with the modeling approach discussed above. The neural network architecture used has only four hidden layers. The number of neurons in the hidden layer must be carefully chosen. Too many neurons make the network over spaced, leading to loss of generalizing capability. If there are not enough hidden layer neurons, the network may find it difficult to learn the behavior of the series. In this present work, varying number of hidden layer neurons was experimented with, the number ranging from four to ten. Four hidden layer neurons were finally utilized because it offered a better model characteristic.

In this work, a feed forward and back propagation algorithm is selected. The neural network model is trained by using the data. For solving STLF of Kerala power system, 8 inputs (coded with 12) were selected. Each input is coded as a 12-digit pattern. The details of logical coding of normalization of input data as a 12-digit pattern is shown in table 4.1. The inputs considered for identifying similar day and for estimation of the load are: day of the week, date, month, year and other factors. The effect of weather on the demand is indicated on a 1 to 5 scale based on consumption for the whole day. Normal and special days like holiday are given different weightage.

Table 4.1: Logic of coding for normalization of input data.

Digit Position	Description	Indication
1	Day of the week	Sunday-1, Monday-2, Tuesday-3, Wednesday-4, Thursday-5, Friday-6, Saturday-7.
2,3	Date: First day Second day Third day….	 01 02 03….
4,5	Month: January February March ….	 01 02 03 …
6,7	Year: 2013 2014 2015 2016 …	 13 14 15 16 …
8,9	Time: 00:30, 01:00, 01:30 … 24:00	1, 2, 3 … 48
10	Indication for weather on 1 to 5 scale based on consumption, i.e., on the consumption for the whole day	1- more than warm and humidity, 2- less than warm and humidity, 3- rainy, 4-hot, 5- cold
11	Type of the day	1-normal day,2- special day like holiday with low load
12	Peak load curtailment	1-load shedding, 2-system intervention, 3- normal load, 4-extra ordinary load

The neural network model is trained using BPNN. For the same historical data in terms of these 12 inputs along with the target (out of 24 hours) for a period of one to two years is used. While training the network, its weights are modified through back propagation and the error is converged after 3200 number of iterations.

The training of neural network continues unless and until the error becomes constant. After the error becomes constant, the learning procedure terminates. If the forecast time or day or week etc., is changed, neural network is retrained to obtain the relationship between load and temperature (climate) around the forecasted day. The ANN is trained on a different 80% of the training data and then validated on the remaining 20%. In this work, the implementation stage of the ANN, Matlab 7.0 software is used in the program. For training the neural network 12 numbers of inputs, 952 numbers of neurons and 4 numbers of hidden layers are used. The model of the designed neural network is shown in Figure 4.11.

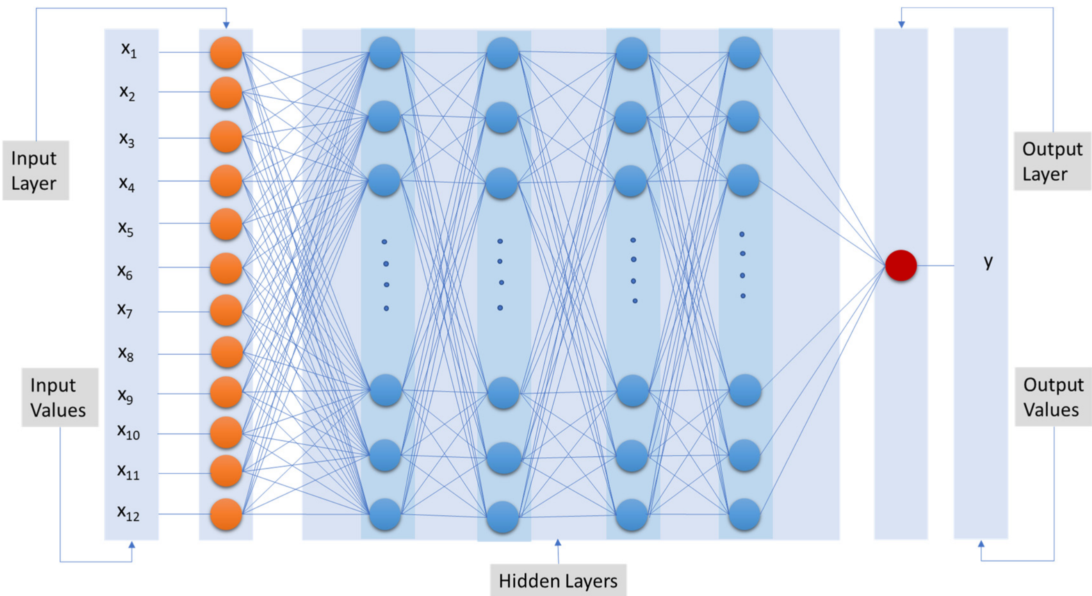


Figure 4.11: Designed neural network model

4.4.2 Simulation Study: Neural Network Based Load Forecasting

In this section STLF for different time period is attempted. Typical cases like one hour ahead, six hours ahead, one week ahead, weekdays and weekend holidays are selected for neural network based prediction. The same is compared with actual load for each of this case.

4.4.2.1 Short Term Load Forecasting

Case1: One hour ahead prediction of load demand

The neural network modeled in the previous section is used for one hour ahead prediction of load demand. Neural network is trained with data up to 9 am from October 6, 2013 to October 12, 2013 with one hour gap. For the simulation of this case, actual data corresponds to second week of October 2013 is selected for comparison. It can be seen that the maximum error between the actual and predicted load is 4.25%, which is considerably low. The Table 4.2 and Figure 4.12 show the actual and predicted load for 10 AM of second week of October 2013 (6^{th}-12^{th}) using data upto 9 a.m.

Table 4.2: Actual and Predicted load for 10 AM of second week(6^{th}-12^{th}) of October 2013

Date	Actual load in MW	Predicted load in MW
Oct 06, 2013	1963.38	2061.549
Oct 07, 2013	2303.1	2418.255
Oct 08, 2013	2291.55	2406.128
Oct 09, 2013	2135.92	2242.716
Oct 10, 2013	2193.17	2302.829
Oct 11, 2013	2226.99	1954.263
Oct 12, 2013	2325.11	2441.366

The actual load and predicted load for one hour ahead from October 2013 (6th-12th) is shown in Figure 4.12.

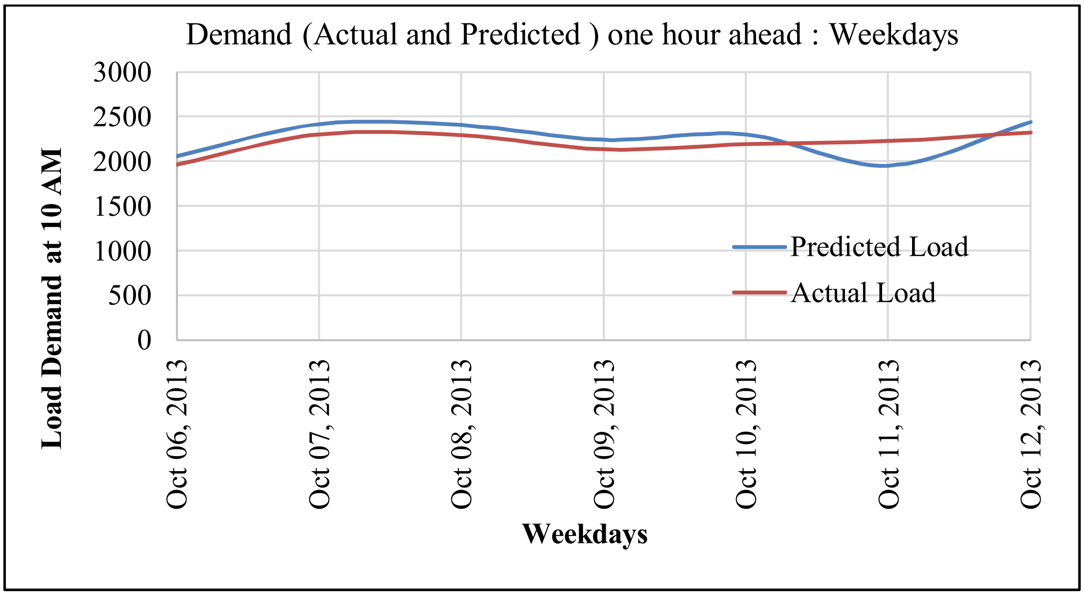


Figure 4.12: One hour ahead: Actual and predicted for 10 AM of second week of October 2013 (6^{th}-12^{th}) using data up to 9 AM

The difference between these load demands is around 100 MW up to October 1 and the predicted load is changed on the next two days. It can be seen that the actual load was closely matching with forecasted load.

Case 2: Six hours ahead prediction of load demand

Simulation is carried out to predict for 6 hours ahead load demand. Data corresponding to 10am of third week (10^{th}-16^{th}) of November 2013 is selected and the data used for simulation is up to 4 am and compared the forecasted results of the same with actual load as shown in Table 4.3 and Figure 4.13.

Table 4.3: Actual and Predicted load for 10 AM of third week (10^{th}-16^{th}) of November 2013

Date	Actual load in MW	Predicted load in MW
Nov 10, 2013	1893.91	1988.606
Nov 11, 2013	2220.72	2331.756
Nov 12, 2013	2208.72	2319.156
Nov 13, 2013	2220.61	2331.641
Nov 14, 2013	2406.15	2526.458
Nov 15, 2013	2298.35	2413.268
Nov 16, 2013	2347.74	2465.127

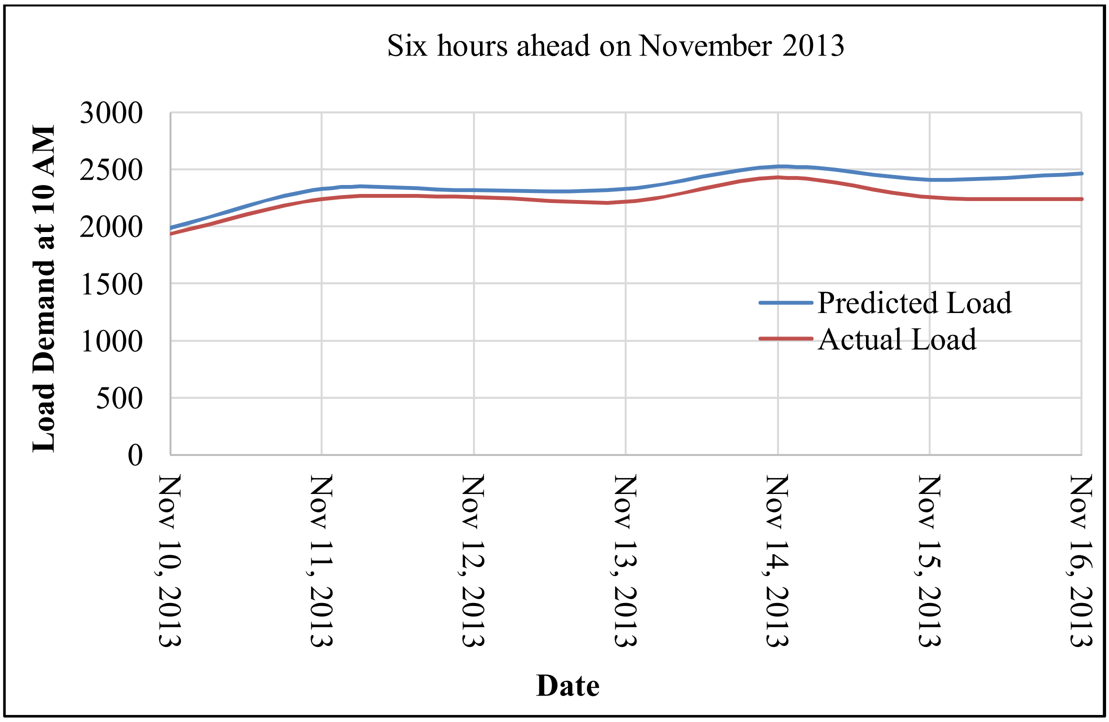


Figure 4.13: Six hours ahead: Actual and Predicted load for 10 AM of third week(10^{th}-16^{th}) of November 2013 using data up to 4 AM

From the above Figure, the difference between the actual load and predicted load is less than 100 MW up to November 14^{th} 2013 and less than 200 MW up to 16^{th} November 2013.

Case 3: One day ahead prediction of load demand

Simulation is carried out to predict for 24 hours ahead (one day ahead) load demand. Data corresponding to April 02, 2015 is selected for simulation and comparison. The results of the same are compared with actual load as shown in Table 4.4 and Figure 4.14.

Table 4.4: One day ahead actual demand, predicted demand and % error values of April 02, 2015

Time	Actual	Predicted	%Error	Time	Actual	Predicted	%Error	Time	Actual	Predicted	%Error
00:30	2209.5	2033.6961	-7.9567	08:30	2415.03	2388.371	-1.1038	16:30	2745.34	2753.822	0.30894
01:00	2243.7	2271.3813	1.23373	09:00	2527.34	2492.341	-1.3848	17:00	2711.36	2759.224	1.7653
01:30	2354.1	2367.2334	0.5578	09:30	2554.7	2446.488	-4.2358	17:30	2583.49	2471.245	-4.3446
02:00	2310.2	2323.702	0.5844	10:00	2639.4	2552.056	-3.3092	18:00	2497.5	2429.706	-2.7144
02:30	2287.9	2331.4777	1.9047	10:30	2710.69	2539.408	-6.3187	18:30	2636.6	2486.637	-5.6877
03:00	2261.7	2171.7175	-3.9785	11:00	2725.89	2740.424	0.5331	19:00	3124.09	3047.274	-2.4588
03:30	2285.2	2163.0653	-5.3446	11:30	2815.69	2781.773	-1.2045	19:30	3248.71	3034.118	-6.6054
04:00	2153.2	2117.8848	-1.6401	12:00	2773.28	2620.076	-5.5242	20:00	3281.56	3230.121	-1.5675
04:30	2201	2032.7784	-7.6429	12:30	2820.73	2814.678	-0.2145	20:30	3235.29	3112.72	-3.7885
05:00	2277.2	2306.2503	1.27570	13:00	2791.98	2690.743	-3.6259	21:00	3241.8	3248.818	0.21649
05:30	2356	2381.6521	1.08879	13:30	2808.3	2586.708	-7.8906	21:30	3281.3	3222.234	-1.8000
06:00	2543.4	2446.4385	-3.8122	14:00	2825.43	2640.185	-6.5563	22:00	3263.63	3166.554	-2.9744
06:30	2573.9	2372.929	-7.8080	14:30	2915.9	2805.21	-3.7960	22:30	3201.46	2995.508	-6.4330
07:00	2579.77	2559.8881	-0.7706	15:00	2854.18	2890.046	1.2566	23:00	2960.5	2820.93	-4.7144
07:30	2467.9	2495.0386	1.09966	15:30	2848.29	2684.141	-5.7630	23:30	2784.59	2753.391	-1.1204
08:00	2430.38	2381.6684	-2.0042	16:00	2788.34	2820.22	1.14334	24:00	2640.81	2637.785	-0.1145

Figure 4.14 shows one day ahead actual and predicted demand curve of April 02, 2015. This is the time for maximum demand required. The maximum demand was met by the power purchase from external sources. Thus, the error between the actual and forecasted values is negligible.

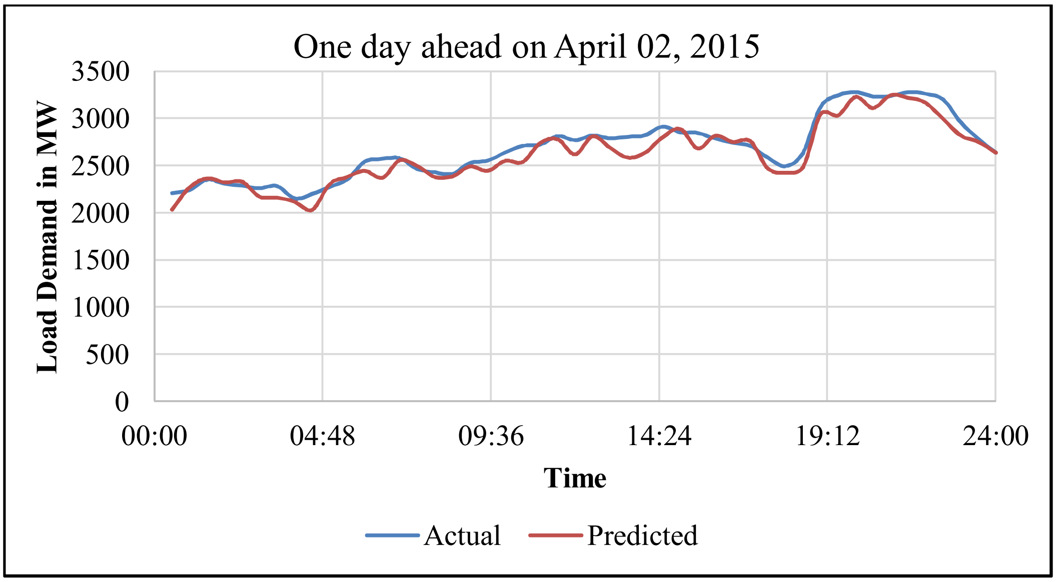


Figure 4.14: Actual versus predicted demand for one day ahead

The percentage error curve is shown in Figure 4.15. It can be seen that it was closely matching with the actual demand recoded.

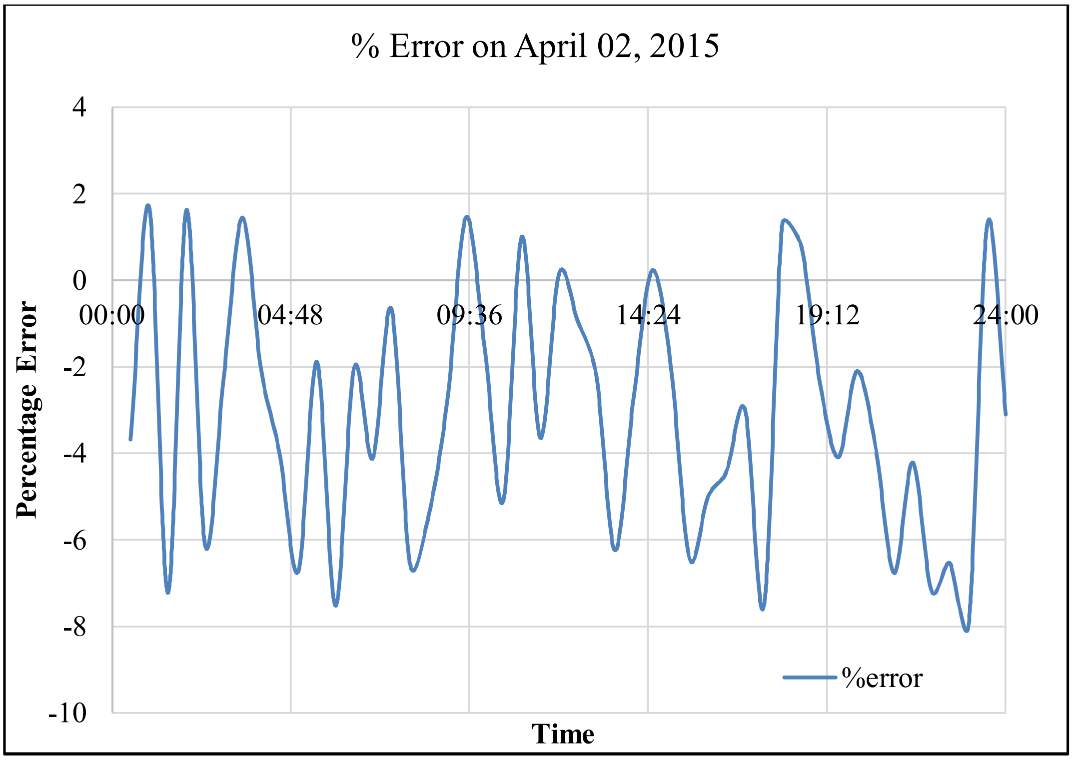


Figure 4.15: Percentage error plot for April 2, 2015

The maximum error between the actual and the predicted load on the mentioned day was below 1.6860 %.

Another set of data is selected for one day ahead prediction as 23rd November 2015. Simulation is done to predict for 24 hours ahead (one day ahead) load demand. Data corresponding to 23rd November 2015 is selected for simulation and comparison. The results of the same are compared with actual load and are shown in Table 4.5 and Figure 4.16.

Table 4.5 shows the data including the actual load demand and the forecasted demand of one day ahead on 23rd November 2015. The calculated value of percentage error is also included in this Table.

Table 4.5: One day ahead actual demand, predicted demand and % error values of November 23, 2015

Time	Actual	Predicted	%Error	Time	Actual	Predicted	% Error	Time	Actual	Predicted	%Error
00:30	2028.318	2069.59	2.0348	08:30	2363.91	2367.3	0.14349	16:30	2451.478	2545.26	3.82551
01:00	1969.267	2057.1	4.4602	09:00	2172.64	2164.6	-0.37028	17:00	2407.382	2499.8	3.83893
01:30	1988.572	2008.62	1.0081	09:30	2309.25	2320.6	0.49153	17:30	2419.217	2526.3	4.42636
02:00	2027.742	1989.9	-1.866	10:00	2352.33	2339.2	-0.5582	18:00	2896.919	2849.69	-1.6303
02:30	1888.892	1987.4	5.2151	10:30	2300.67	2357.8	2.4831	18:30	3160.028	3128.9	-0.9851
03:00	1882.152	1966.1	4.4602	11:00	2395.44	2398	0.10696	19:00	3043.483	3124.8	2.67184
03:30	1920.55	1962.1	2.1635	11:30	2434.15	2408.8	-1.04158	19:30	2870.235	3119.6	8.68797
04:00	1849.68	1971.9	6.6076	12:00	2527.37	2527.1	-0.01057	20:00	2924.506	3078.1	5.25198
04:30	1854.486	2005.5	8.1432	12:30	2486.36	2450.2	-1.4544	20:30	2936.917	3058.6	4.14322
05:00	2045.706	2089.69	2.1501	13:00	2398.77	2469.3	2.94025	21:00	2992.926	3045	1.73991
05:30	2165.828	2212.8	2.1688	13:30	2293.97	2431.34	5.98827	21:30	3026.839	3000.5	-0.8702
06:00	2277.64	2393.8	5.1	14:00	2513.48	2466.46	-1.87074	22:00	2890.859	2931.1	1.39199
06:30	2532.129	2549.5	0.686	14:30	2421.48	2550.92	5.34542	22:30	2655.718	2677.5	0.82021
07:00	2406.912	2544.3	5.7081	15:00	2353.7	2551.5	8.40376	23:00	2410.131	2484.9	3.10229
07:30	2432.427	2417.7	-0.605	15:30	2365.47	2509.9	6.10573	23:30	2223.612	2332.48	4.89599
08:00	2246.609	2404.1	7.0102	16:00	2500.79	2559.95	2.36545	24:00	2201.717	2210.1	0.38074

Figure 4.16 shows the graphical representation of actual and predicted demand for one day ahead forecasting on November 23rd 2015.

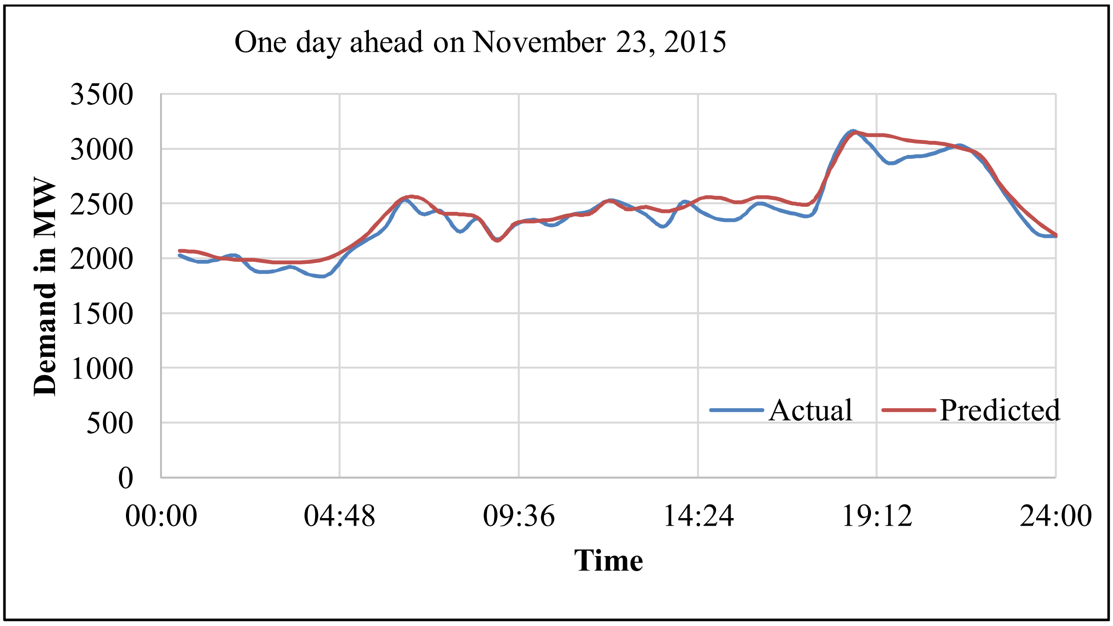


Figure 4.16: Actual and predicated curve for one day ahead

It can be observed that the predicted demand was closely matching with the actual demand recorded. The percentage error curve for the same day is shown in Figure 4.17.

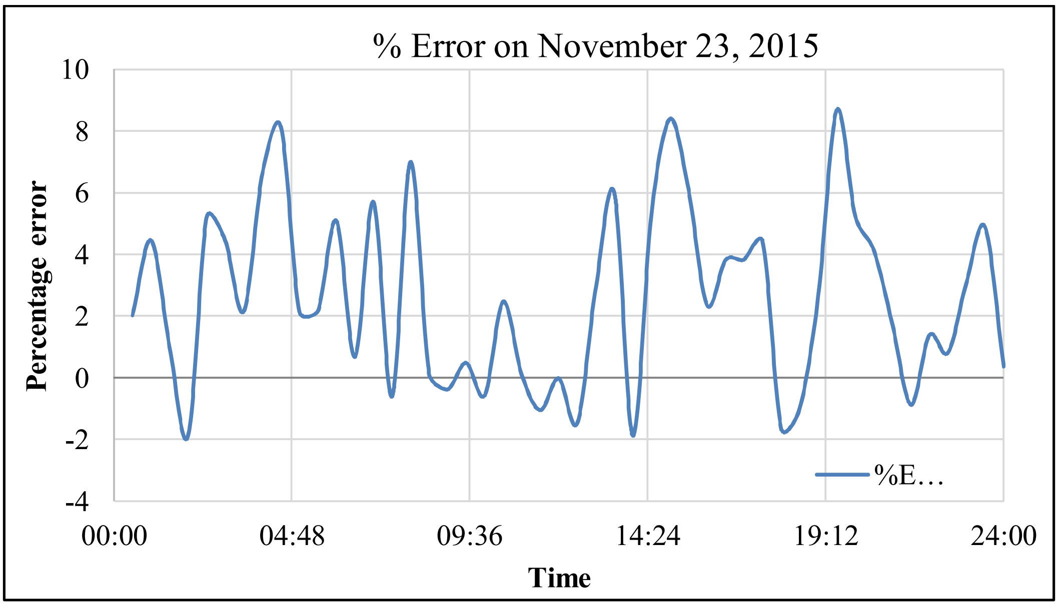


Figure 4.17: Percentage error, 1 Day ahead on November 23, 2015

The maximum error between the actual and forecasted values is less than 8.5 %. This error is affordable. The prediction error parameters are calculated and the numerical values are given in section 4.7.

Case 4: Holiday

In the case of holidays and weekdays the average curve of the predicted load is nearly matching with the actual load curve. (Appendix-III.E). The maximum demand is less than 2500 MW.

Figure 4.18 shows the actual and predicted demand curve of second Saturday, January 14, 2012. The actual load and forecasted load are different around 100 MW on off peak time and 200 MW on peak hours.

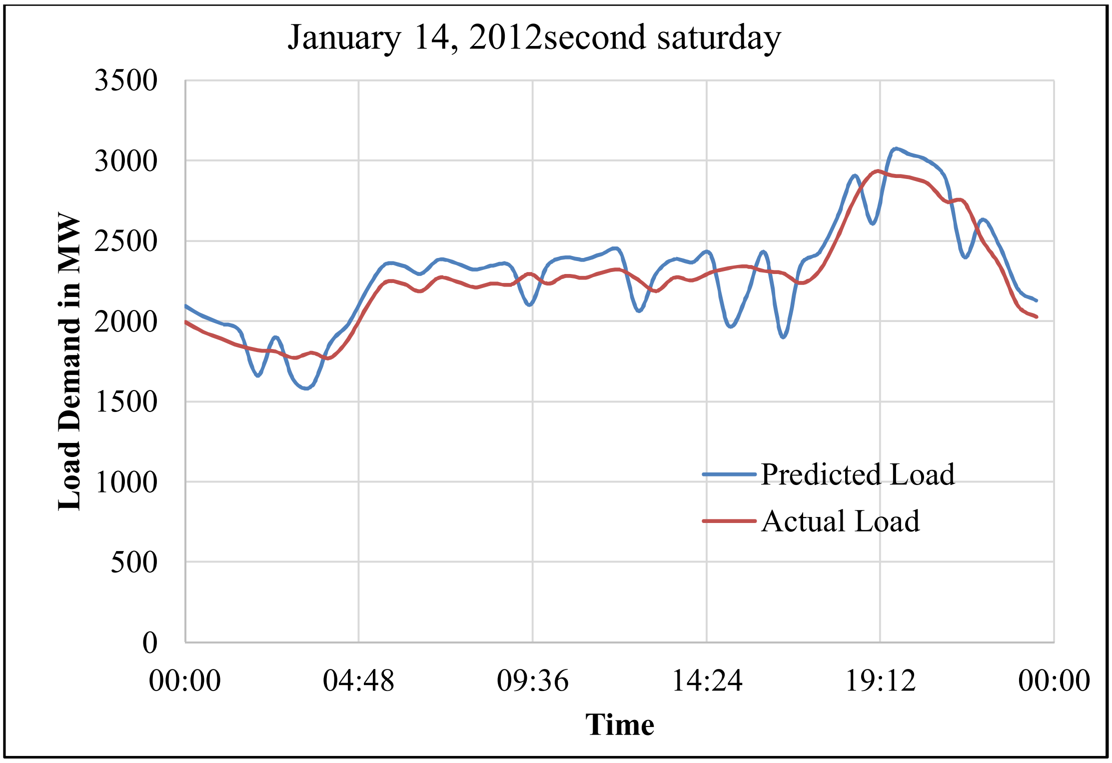


Figure 4.18: Load Demand for January 14, 2012 Second Saturday

Figure 4.19 shows the demand forecasting curve of a holiday included as January 15th, 2012 Sunday and a monsoon day for June 2, 2013, is also shown in Figure 4.20.

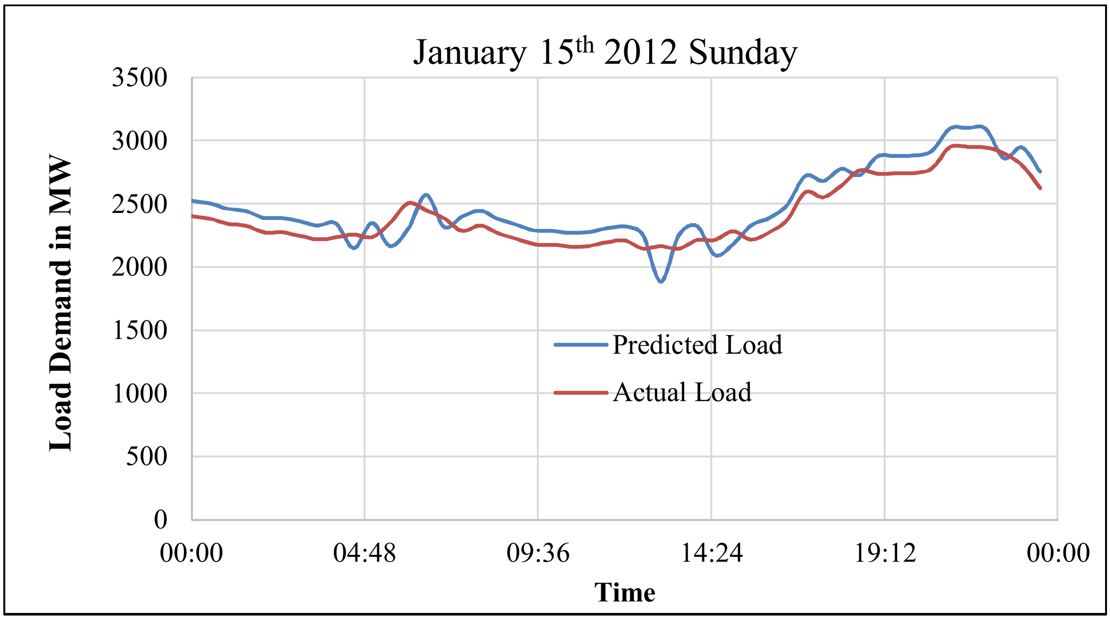


Figure 4.19: Load Demand for January 15th 2012 Sunday

The actual demand is varied from 2400 MW to 3000 MW on Sunday. The difference of actual load and predicted load is almost constant throughout the day.

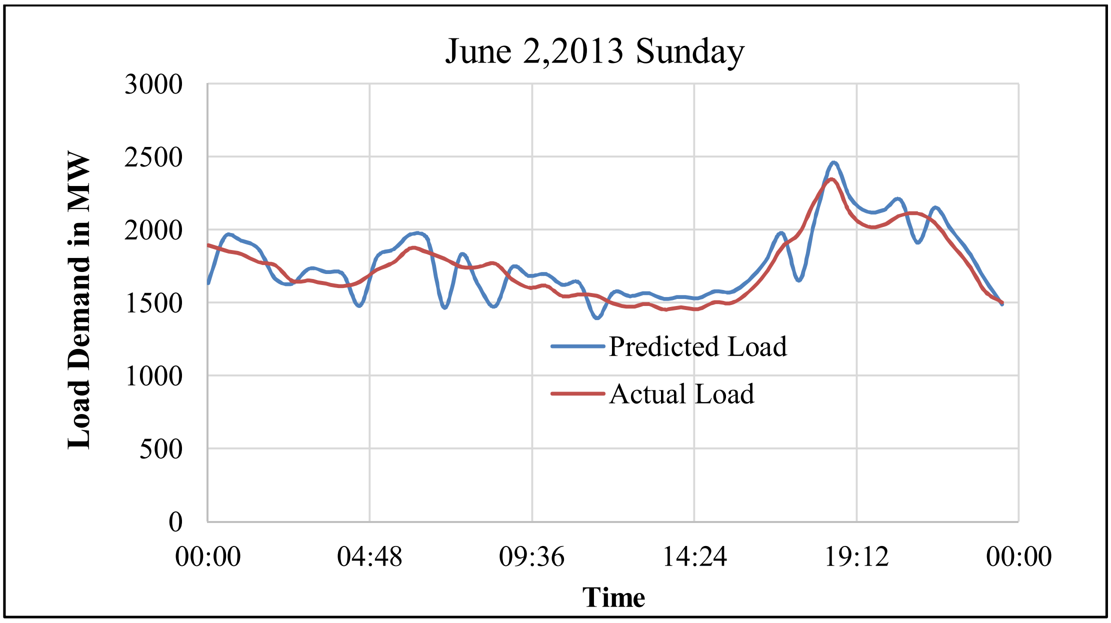


Figure 4.20: Load Demand for June 2, 2013 Sunday

From the analysis of these plots, the maximum demand on the two days (14th and 15th January 2012) is almost same.

Case 5: Weekdays

Two weekdays (Thursday) are selected for predicting the forecasted load and the curves are shown in Figures 4.21 and 4.22. From these Figures, it is clear that there is no substantial difference between the minimum demand on Thursdays of April and May 2013.

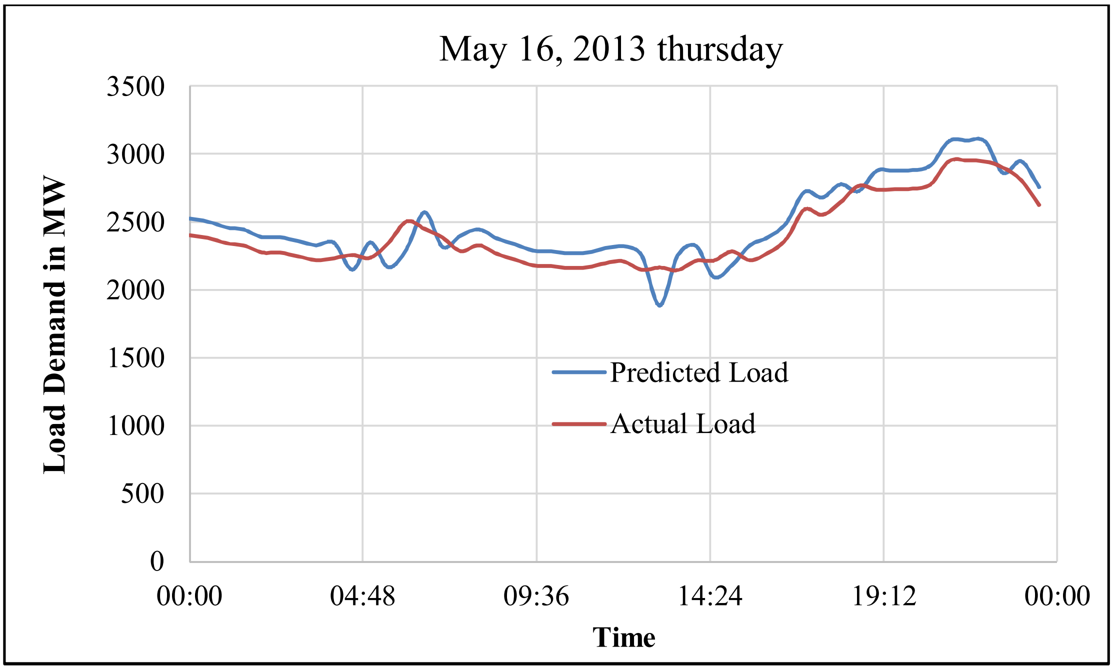


Figure 4.21: Load Demand for May 16, 2013 Thursday

From the comparative analysis of the peak demand on weekdays of the month of April as May 2013, it can be seen that there is no considerable variation in predicted load and actual load. Figures 4.21 and 4.22 show this curve.

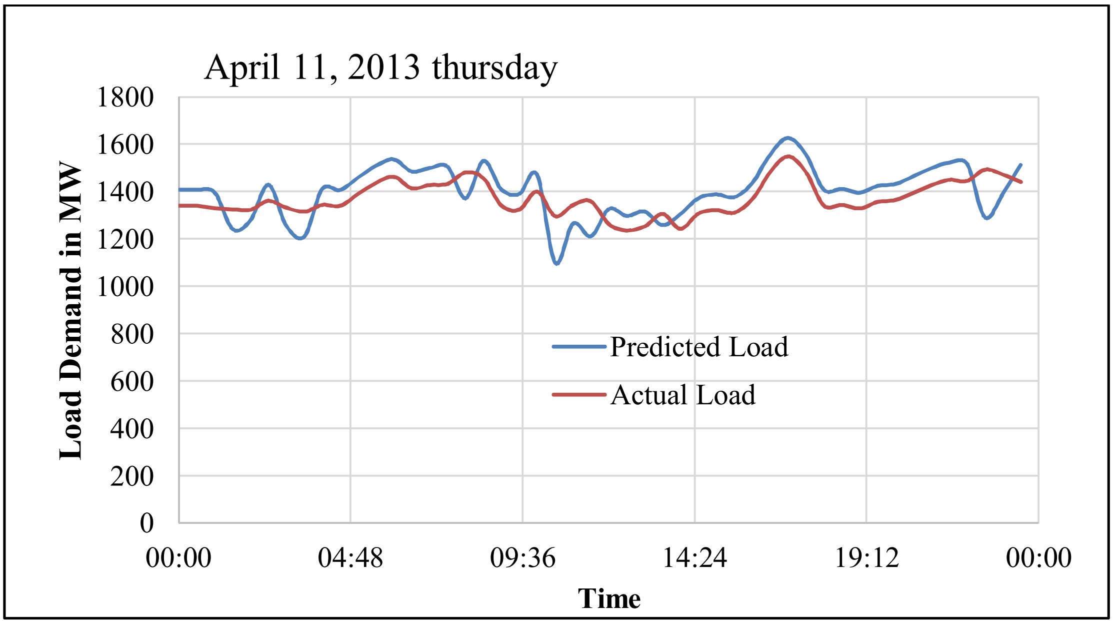


Figure 4.22: Load Demand for April 11, 2013 Thursday

Case 6: One week ahead

Figure 4.23 shows actual and predicted load curves for one week ahead during the period from October 04 to 10, 2015. The actual and predicted demand value are almost the same.

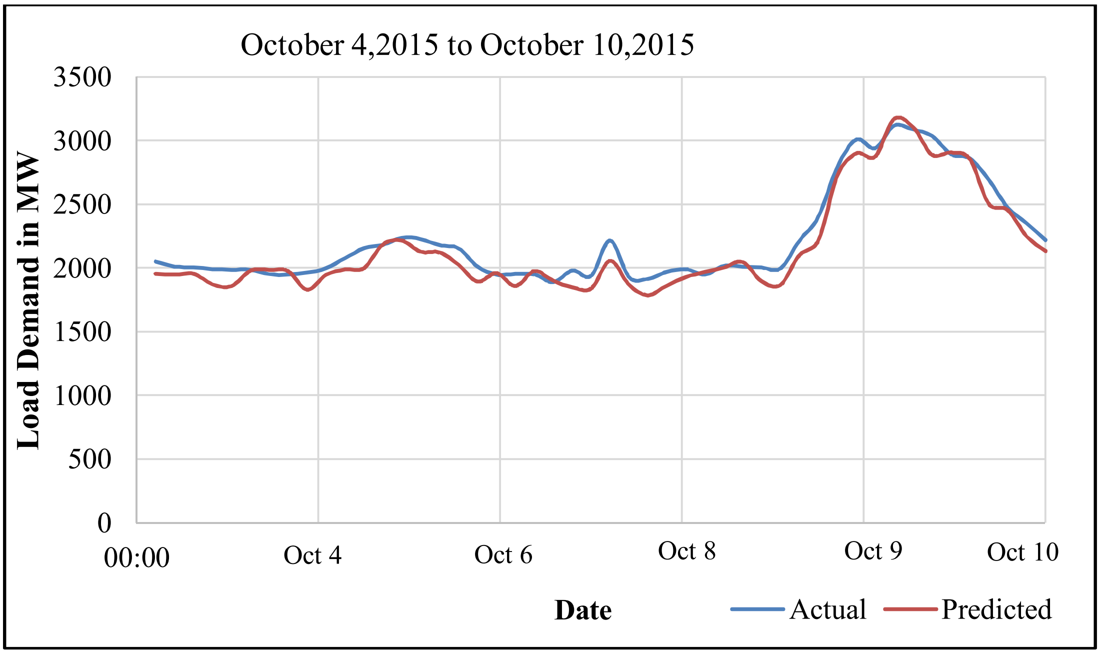


Figure 4.23: Actual versus predicted demand for one week ahead

The percentage error plot of one week ahead for the same period is shown in Figure 4.24. The maximum error between the actual and predicted value is only below 1.798%

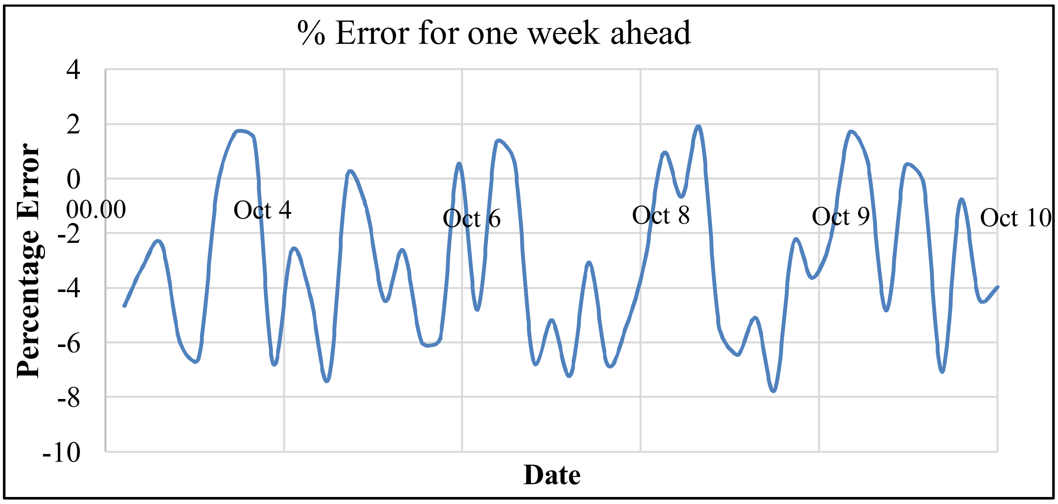


Figure 4.24 Percentage error curve for one week ahead

4.4.2.2 Mid-Term Forecasting

Case 1: One Month ahead

The mid-term forecasting is a period of one month to one year. Actual and predicted load curve for one month ahead is shown in Figure 4.25. The difference between the actual and the predicted values is considerably low.

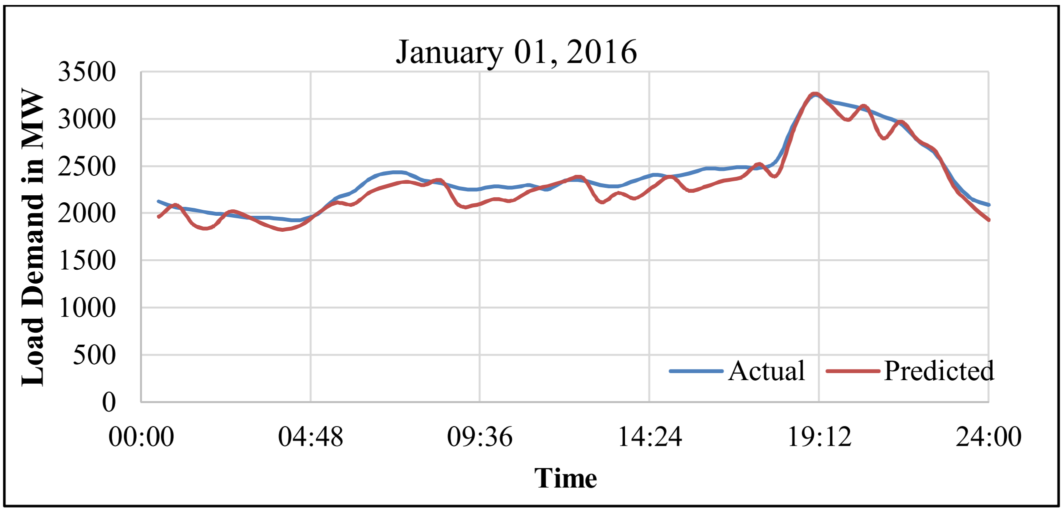


Figure 4.25: Actual and predicted curve for one month ahead

The percentage error curve shown in Figure 4.26 is as per the above predicted load curves. It is clear that the maximum error between the actual and predicated values is 1.6955 %.

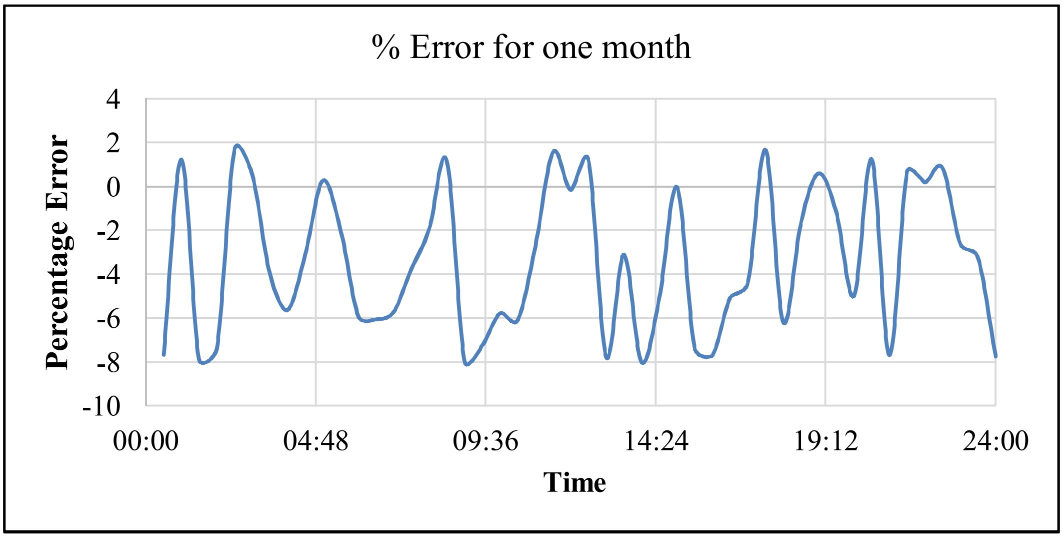


Figure 4.26: The percentage error curve for one month ahead

Case 2: One year ahead

In the case of one year ahead the actual versus predicted load curve of two different dates as 19th August 2013 and 1st April 2015 are shown in Figure 4.27 and 4.28 respectively.

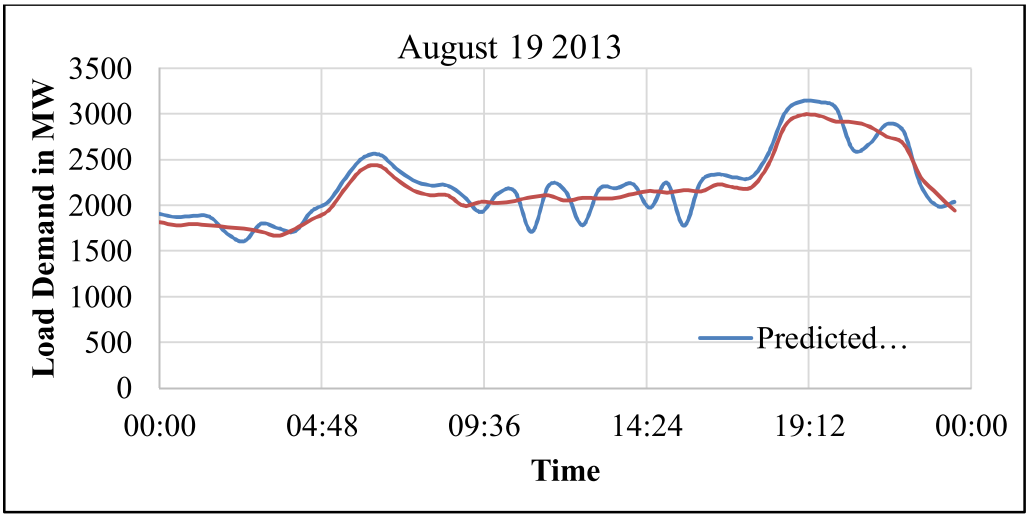


Figure 4.27: One Year ahead: Actual and Predicted demand for Aug 19 2013 using Aug 19 2012 data training

Figure 4.28 shows the variation of actual and predicted load using data up to April 01, 2014. The difference between the two shows that there is considerable variation of 100 t0 200 MW..

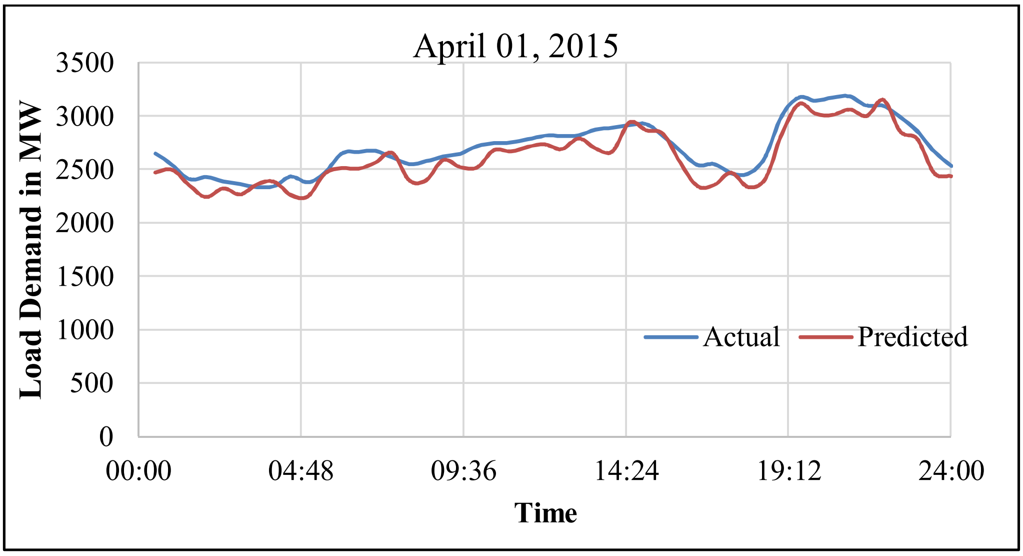


Figure 4.28: One Year ahead: Actual and Predicted demand for April 01, 2015 using April 01, 2014 data training

The percentage error curve for one year ahead is shown in Figure 4.29. It can be evaluated that the error between the actual and predicted values is less than 1.8488 %.

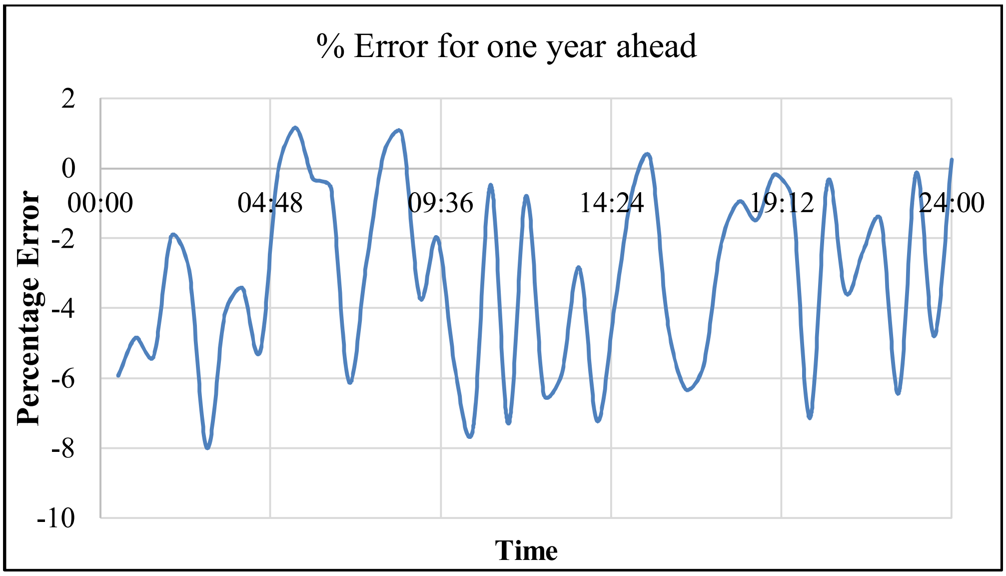


Figure 4.29: One year ahead % error curve

4.5 LONG TERM LOAD FORECASTING

For an efficient economic operation of a power system, the long-term prediction is of crucial importance. The long-term load forecasting methods can be classified in to parametric load forecasting methods and artificial intelligence methods. Parametric load forecasting methods can be generally categorized under three approaches- Regression methods, Time series prediction methods and grey dynamic methods (Al- Hamadi and Soliman, 2005). Regression models utilize the strong correlation of load with load affecting factors such as weather, national economic growth and social habits. Time series models include ARMA i.e., auto regression moving average is a well-known method used for forecasting time series, consisting out of an autoregressive component AR and a moving average component MA. Widely large amount of historical data is required to produce the optimal models of ARMA.

The end-use modeling, trend analysis and econometric modeling are most commonly used parametric methods for long term load forecasting. Energy consumption can directly estimate by using extensive information on end-use and end users, such as appliances, the customer use, the age of equipment, the size of the houses etc. (Islam, 2011) The econometric methods estimate a statistical model on historical data of load and its affecting factors.

From a theoretical and a practical standpoint LTLF is radically different than the equivalent STLF and therefore it is treated in different ways. The historical database used in the development of the LTLF considers the time period of one year to 5 or 10 or 25 years or more. Normally a fraction of the overall available database is reserved for validating the accuracy of the developed forecast model (Parlos *et al*., 1996). This reserved data set (forecasting set) is used for testing the true extrapolative properties of the developed forecast model.

One of the important factors for forecasting the long-term load in Kerala is to take in to account the past and present economic situations and power demand. The prediction of load demand in Kerala up to 2023 were performed with neural network and the results attained are compared with real data obtained from the KSEB Ltd., which represent the yearly peak load and off-peak load consumption in the State. The accuracy of LTLF has significant effect on developing future generation and distribution planning especially in Kerala. The LTLF is useful to determine the capacity of generation, transmission or distribution system additions and the type of facilities required in transmission expansion planning, annual hydro thermal maintenance scheduling etc. (Duan *et al*., 2008).

Generally, the next year load is predicted using only the historical data of the actual load of one year ahead and average monthly load for the last 4 years. It may normalize other factors as the digital value as the input and the actual hourly data as the target, will be used to train the network and update the neuron's weights in the neural network. Then the general trend of the predicted year can be simulated by using the trained neural network. The result shows a significant improvement on-long term predictions of load forecasting.

4.5.1 Simulation study: Long term load forecasting

The long-term load forecasting ranges from five to ten years or more is relevant in expansion and planning of a power system. In this work, the load prediction with neural network is done with a period of five years starting from 2013 onwards.

Figure 4.30 shows the actual and predicted load curve on January 10, 2013 versus January 10, 2018. It shows that the demand of January 10, 2018 has been substantially increased from January 10, 2013. That is in 2013, the maximum demand is 3000 MW and on the same day of 2018 the maximum demand is found to be nearly 4600 MW.

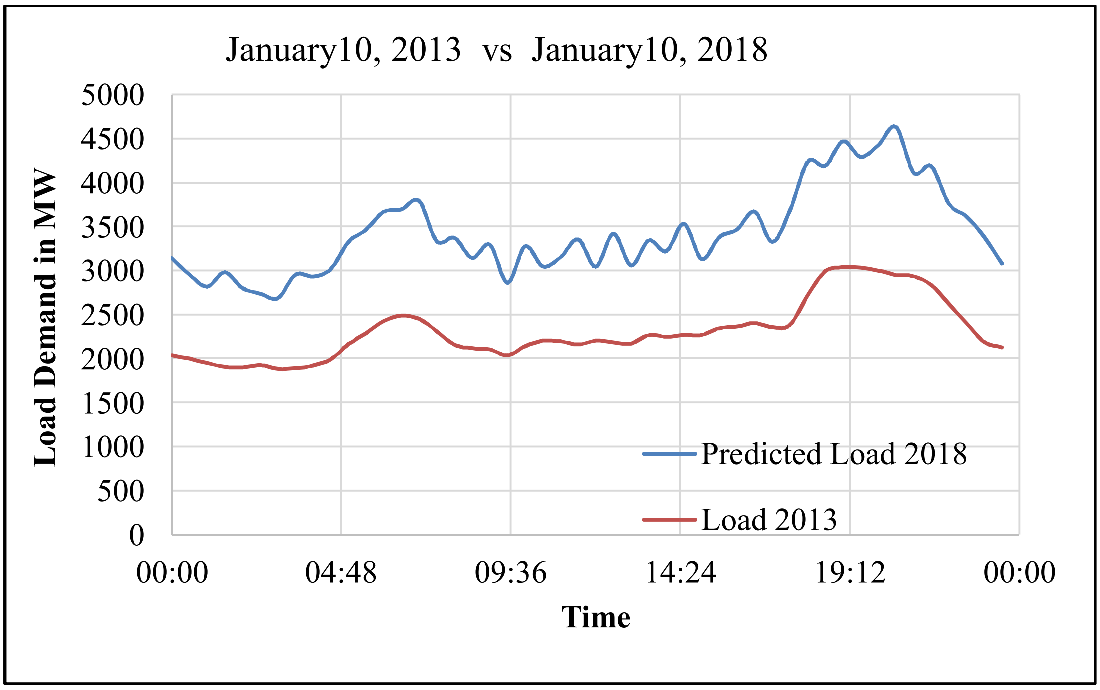


Figure 4.30: Load demand (January10, 2013 Vs January10, 2018)

Figure 4.31 shows the demand curve predicted from the load data of January 10, 2013 to January 10, 2023 (the prediction period is ten years).

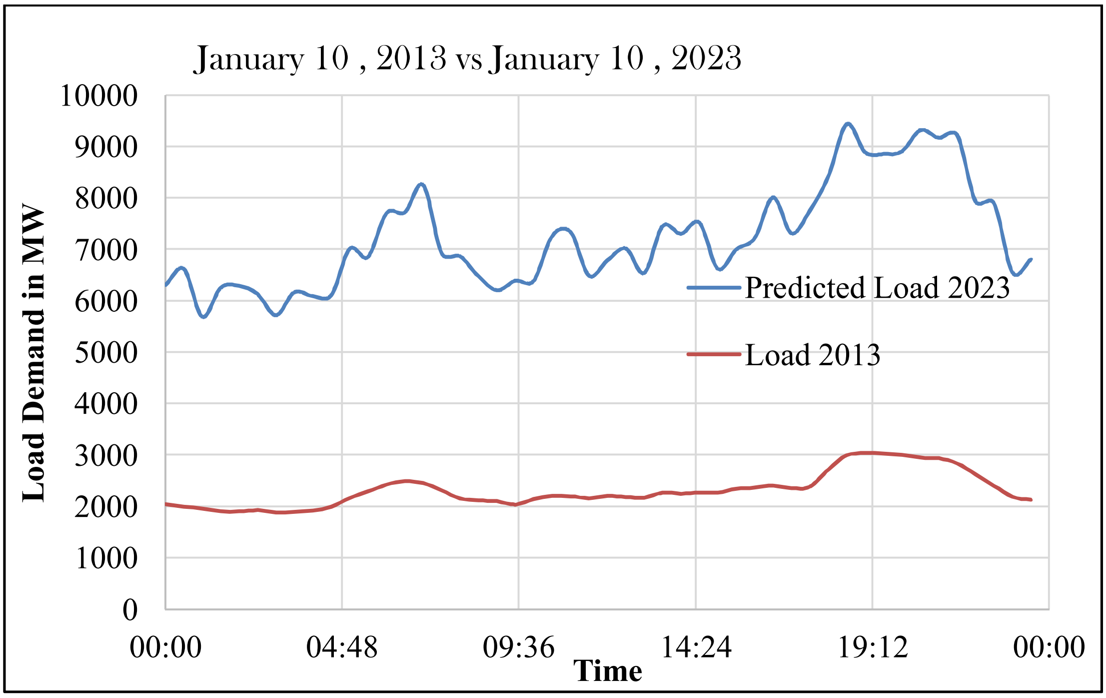


Figure 4.31: Load demand (January 10, 2013 vs January 10, 2023)

Figure 4.31 shows a long-term prediction curve for ten years ahead for the period of January10, 2013 and January 10, 2023. The difference between the actual and predicted values points out that the requirement of the power is very high on January 10, 2023 as compared to the actual value of the period of January 10, 2013. The maximum predicted demand on January 10, 2023 is 9200 MW.

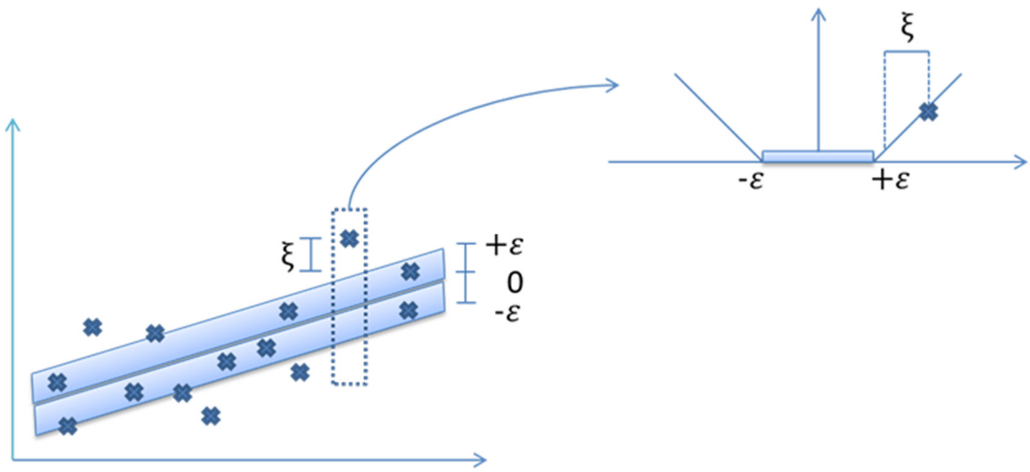
4.6 SUPPORT VECTOR MACHINE

Support Vector Machines (SVM) is the most powerful and very recent technique for the solution of classification and regression problems. This technique was known from the work of Vapnik's, statistical learning theory. While the neural network and other intelligent systems try to define the complex functions of the inputs, support vector machines use the nonlinear mapping of the data into high dimensional features by using the kernel functions mostly. In SVM, simple linear functions are used to create linear decision boundaries in the new space (Christiani *et al.,* 2000). In the case of neural network, the problem is in the choosing of architecture and in the case of SVM, problem is in choosing a suitable kernel. Chen *et al.,* (2004) developed a new machine learning method. It was the first work which successfully applied SVM on load forecasting.

4.6.1 Support Vector Regression

Support vector machine is a form of supervised learning algorithm and a statistical learning algorithm. It is a best algorithm to develop decision support system. In data mining, SVM becomes famous due to the performance in various applications. The applications of SVM are categorized into two areas - classification and regression. Support vector classification is a learning technique which attempts to separate different groups in a data set. SVR is based on the support vector, used for prediction by developing a real function. In support vector classification, the output can be either one or zero but in SVR, the output is a real number.

SVM was largely developed at AT&T Bell Laboratories by Vapnik and co-workers (Boser *et al.,* 1992; Guyon *et al.,*1993; Cortes *et.al.,* 1995; Scholkopf *et al.,* 1996, 1997, Vapnik *et al.,* 1997). It is a machine learning algorithm for classification or regression applications. The main objective of this algorithm is to find a hyperplane in an N dimensional space, where N is the number of features that classifies the data point. There can be many hyperplanes and need to find a plane that has the maximum margin, i.e the maximum distance between data points of classes. In other words, hyperplanes are decision boundaries that help classify data points. SVR model inherits some properties of SVM. It is basically a classification of regression errors that are greater or less than a threshold value as shown in figure Figure 4.32.



Source: Smola et al. (2004)

Figure 4.32: The Boundary margin and loss setting for a linear SVR

Moreover, SVR is applied to solve non-linear regression problems by mapping non-linear regression problems to linear regression (Paudel *et al.,* 2015). For example, vector x_i represents i^{th} sample of input features (temperature, humidity, rainfall and load on weekdays, weekend days and public holidays) and y_i represents corresponding target value (load), then total dataset can be represented by $\{(x_i, y_i)|i = 1{:}\,n\}$, where $x_i \in \mathbb{R}^m$ with m features $y_i \in \mathbb{R}$ and n represents total number of samples in datasets. Then, SVM approximates linear relationship between input and output as shown in Equation (4.12).

$$f(x) = w^T x + \theta \tag{4.12}$$

In Equation (4.12), w and θ represents weight and bias and these are estimated by minimizing regularized risk function as shown in Equation (4.13) (Vapnik *et al.,* 2013)

$$\frac{1}{2}w^T w + \mathrm{C}\sum_{i=1}^{n} |y_i - f(x_i)|_\varepsilon \tag{4.13}$$

Where, $|y_i - f(x_i)|_\varepsilon = f(x) = \begin{cases} 0, \; if \; |y_i - f(x_i)| < \varepsilon \\ |y_i - f(x_i)|_\varepsilon, \; otherwise \end{cases}$

In Equation (4.13) C is the regularization term and $|y_i - f(x_i)|_\varepsilon$ is empirical error measured by ε insertion loss function. Parameter C controls trade-off between approximation error and weight vector. Insertion loss function, ε, is minimized in order to estimate the parameters. Equation (4.13) thus, illustrates that when values predicted by SVR model $f(x)$ lies within the defined tolerance level ε, then values of loss function is zero and magnitude of the difference between values predicted by SVR model and tolerance level is ε when it is outside ε. Equation (4.13) will be transformed to a new objective function with the introduction of slack variables (Paudel *et al.,* 2015), and with suitable kernel function such as linear, polynomial or radial basis function (Friedman *et al.,*2001), these objective functions are optimized to estimate the parameters *w* and θ.

4.6.2 Simulation Study Based on Support Vector Regression

4.6.2.1 Short Term Load Forecasting

Case 1: One day ahead prediction of load demand

The data using from January 2014 to March 2014 for predicting one day ahead load of April 01, 2014 are as follows. The features are holidays, weekend days, temperature and rainfall. The actual and predicted load for one day ahead on April 01, 2014 in shown in Figure 4.33.

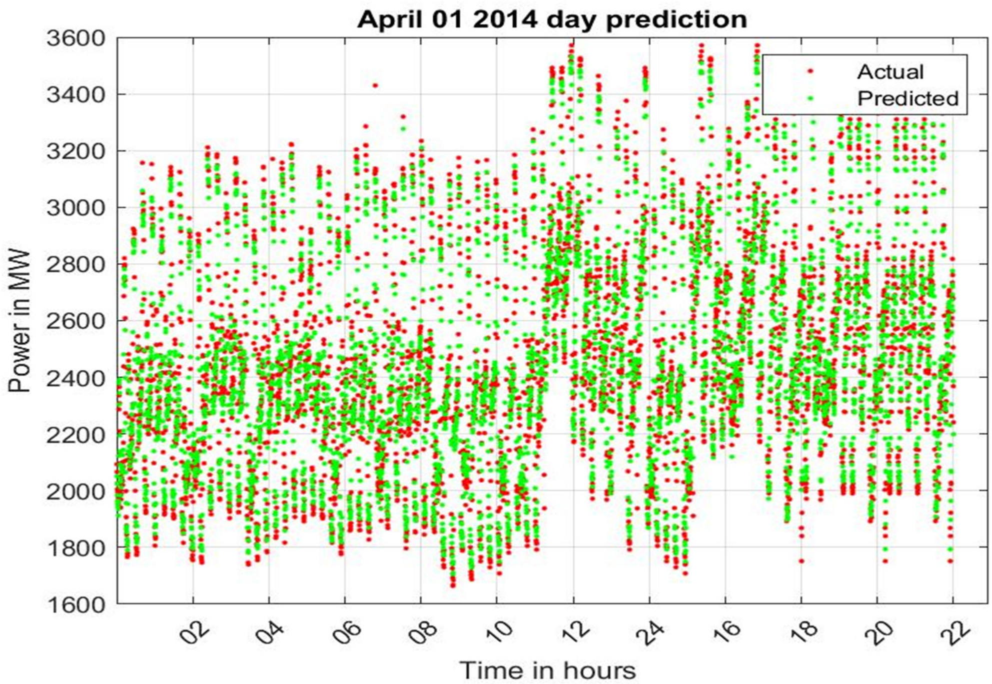


Figure 4.33: One day ahead actual and predicted load for April 01, 2014

The predicted value is 2256.2562 and the prediction error parameters are obtained as MAPE: 1.7365, MAD: 41.8466, MSE: 2905.3215, and RMSE: 53.901. The values of actual and predicted load of one day ahead prediction is given in Appendix V.

The actual and predicted load for one day ahead is shown in Figure 4.34.

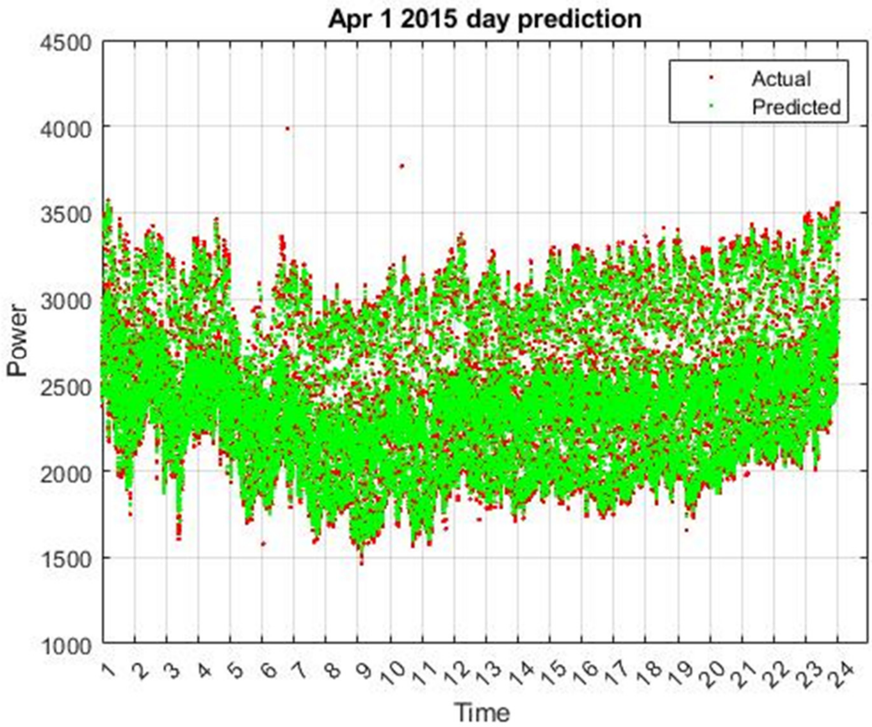


Figure 4.34: One day ahead actual and predicted load for April 01, 2015

The zoomed version of one day ahead prediction of Figure 4.34 is shown in Figure 4.35. A part of the Figure 4.34 is zoomed as shown in Figure 4.35.

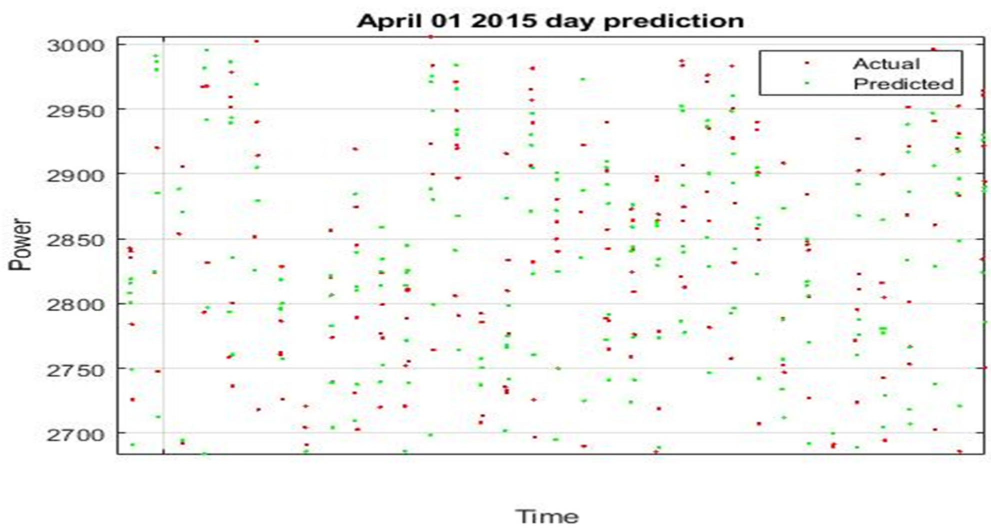


Figure 4.35: Zoomed version of one day ahead actual and predicted load for April 01, 2015

Case 2: Holiday

In the case of holidays and weekdays the average curve of the predicted load is nearly matching with the actual load curve. Figures 4.36 shows the actual and predicted demand curve of second Saturday, January 14, 2012.

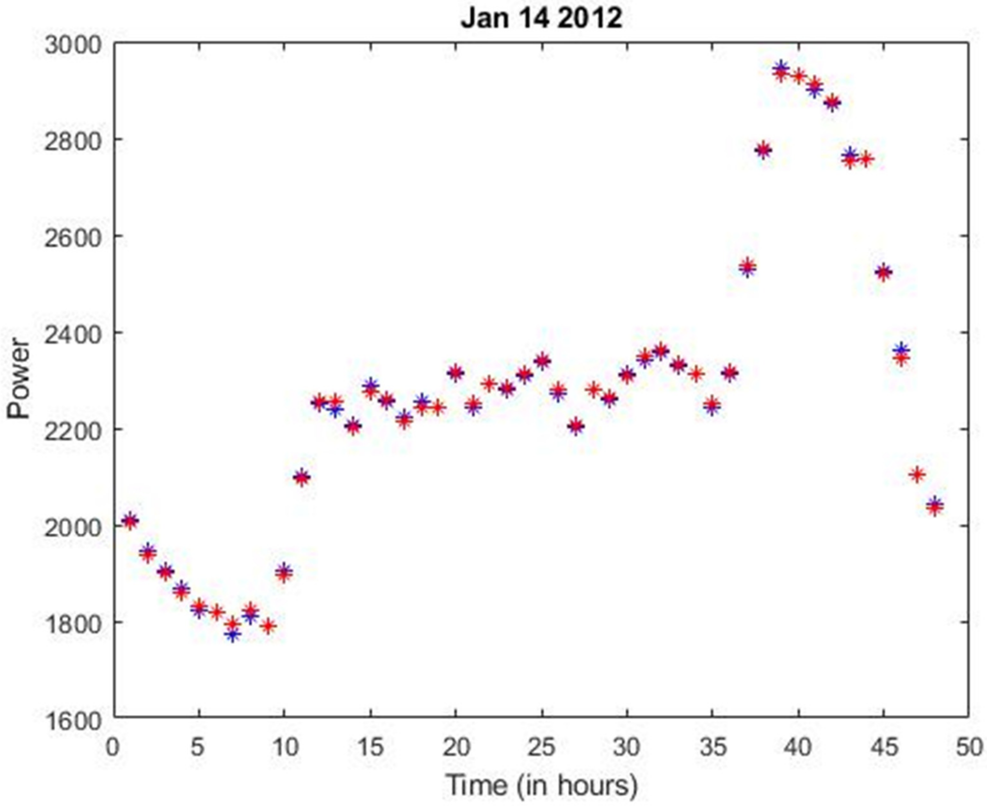


Figure 4.36: Load Demand for January 14, 2012 Second Saturday

The maximum demand on the peak time reaches up to around 3000 MW. On this day all the shops and industries are open at peak time, whereas on Sundays most of the industries and shops remain closed. Variation of actual demand and forecasted demand on January 15, 2012 Sunday is shown in Figure 4.37.

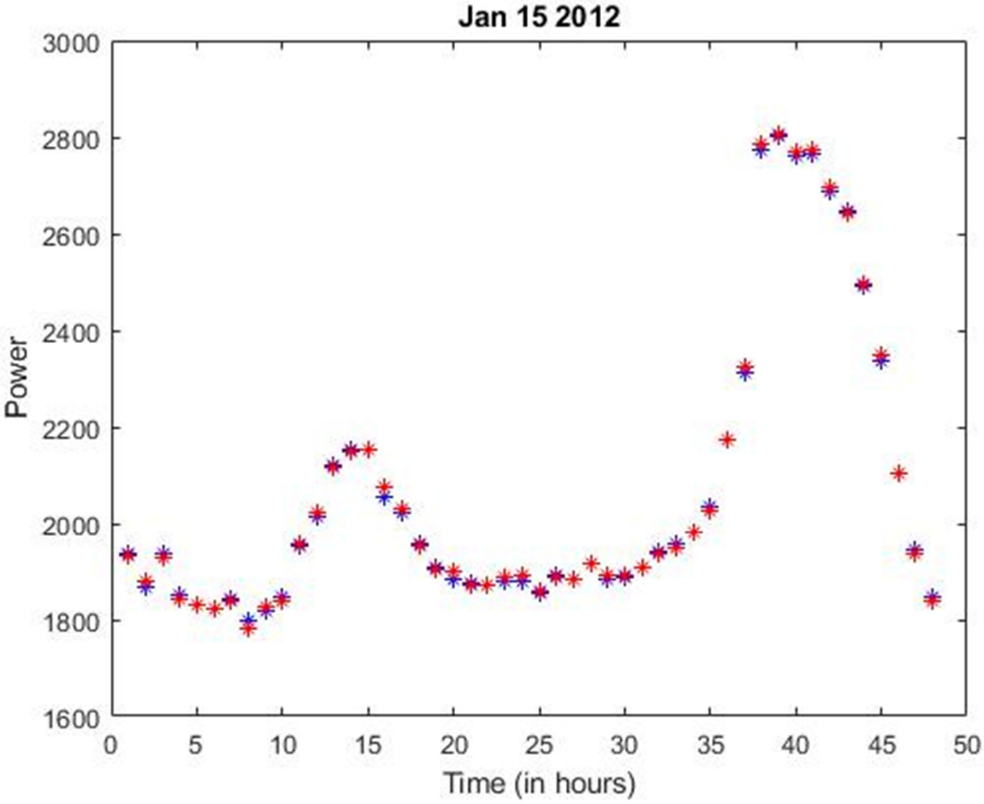


Figure 4.37: Load Demand for January 15th 2012 Sunday

From the analysis of these plots, the maximum demand on the above two days (second Saturday and Sunday) have come around 100 MW.

With regard to load demand on June 3, 2013, a monsoon day, the predicted and actual load is given in Figure 4.38. The maximum demand on that Sunday is less than 2000 MW.

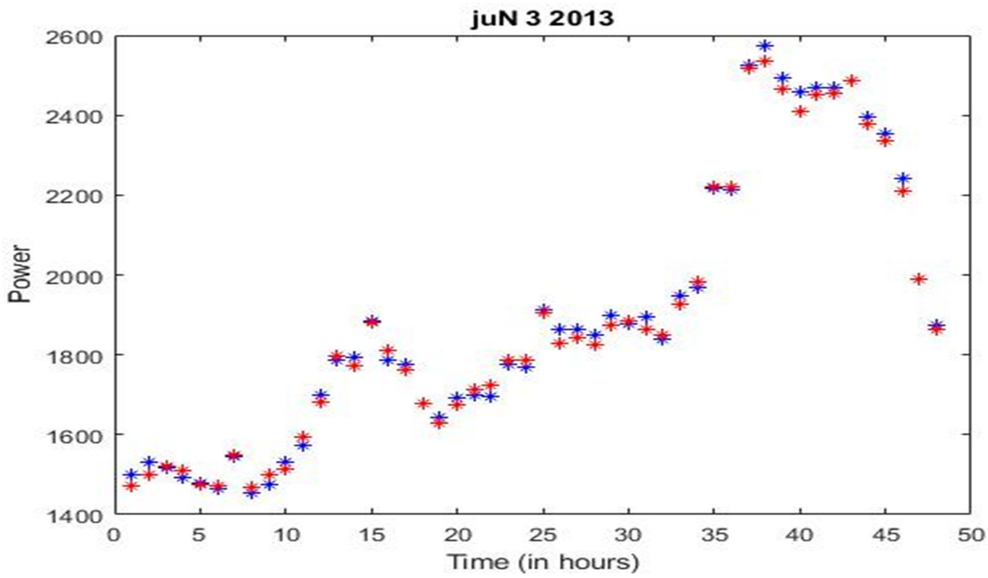


Figure 4.38: Load Demand for June 3, 2013 Sunday

Generally, the demand on the monsoon days is very less as compared to the summer days. The difference of maximum demand at off peak time on the monsoon day and a summer day (16th May 2013) is around 800 MW. Figure 4.39 shows a summer week day prediction.

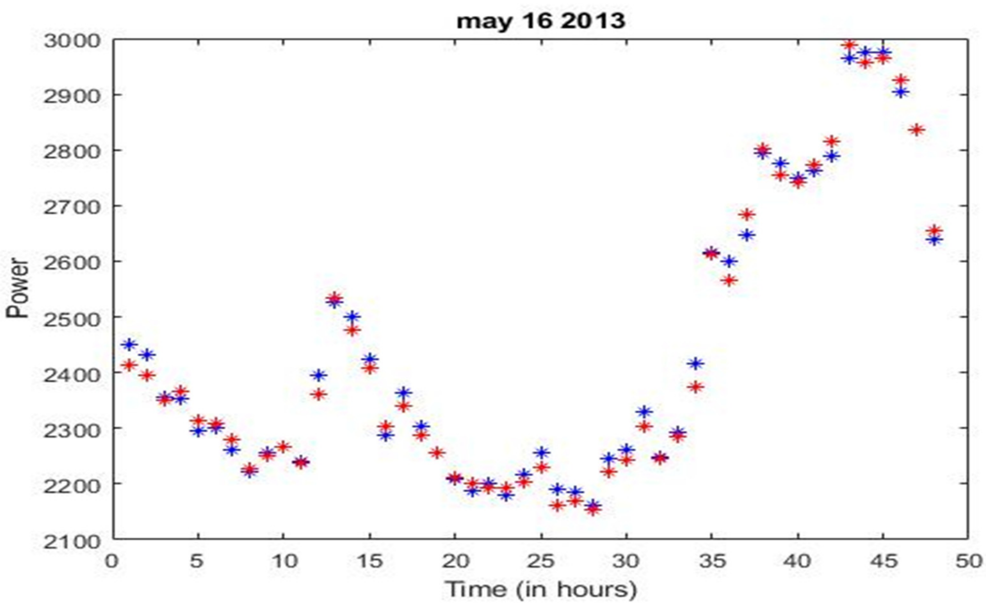


Figure 4.39: Load Demand for May 16, 2013 Thursday

Two weekdays (Thursday) are selected for predicting the forecasted load and the curves are shown in Figures 4.39 and 4.40. From these Figures, it is clear that there is no substantial difference between the minimum demands on Thursdays of April and May 2013. From the comparative analysis of the peak demand on weekend days and weekdays there is a slight variation.

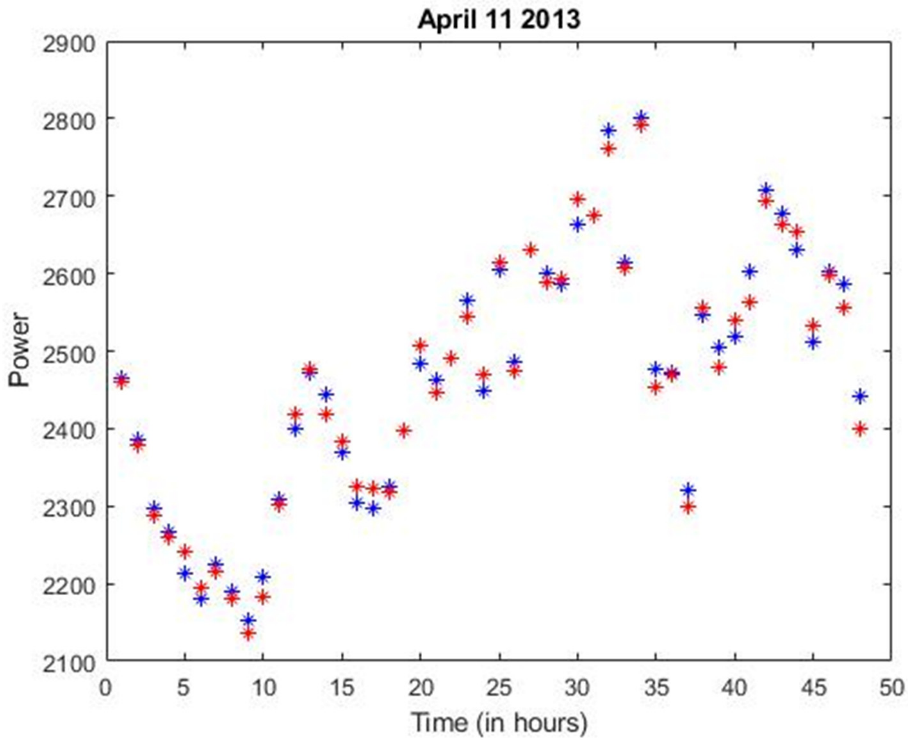


Figure 4.40: Load Demand for April 11, 2013 Thursday

Case 2: One-week ahead prediction of load demand

For predicting load demand by using SVR for April 01, 2015 to April 07, 2015, the load data from 1st April 2014 to 31st March 2015 have been used. The Figure 4.41 depicts the actual and predicted load for one week with load in y axis and day (time) in x axis. The value of errors obtained are MAPE: 1.42, MAD: 33.645, MSE: 2114.5691 and RMSE:45.9844.

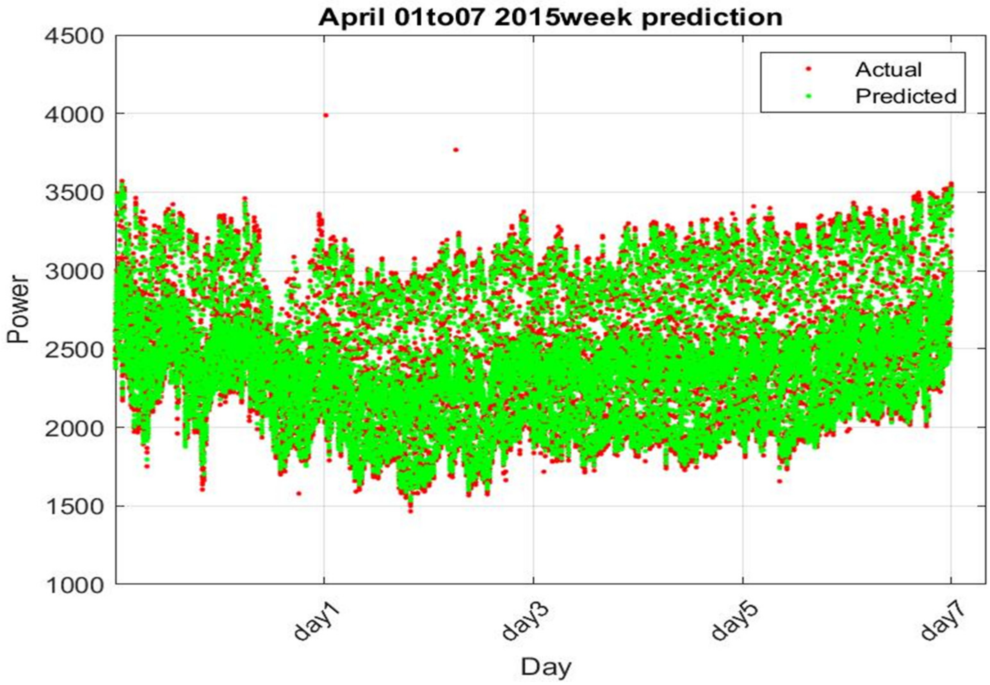


Figure 4.41: One week ahead actual and predicted load for April 01, 2015 to April 07, 2015

The zoomed version of one week ahead actual and forecasted load on April 01, 2015 to April 07, 2016 is shown in Figure 4.42. A 24-hour load is considered for zooming.

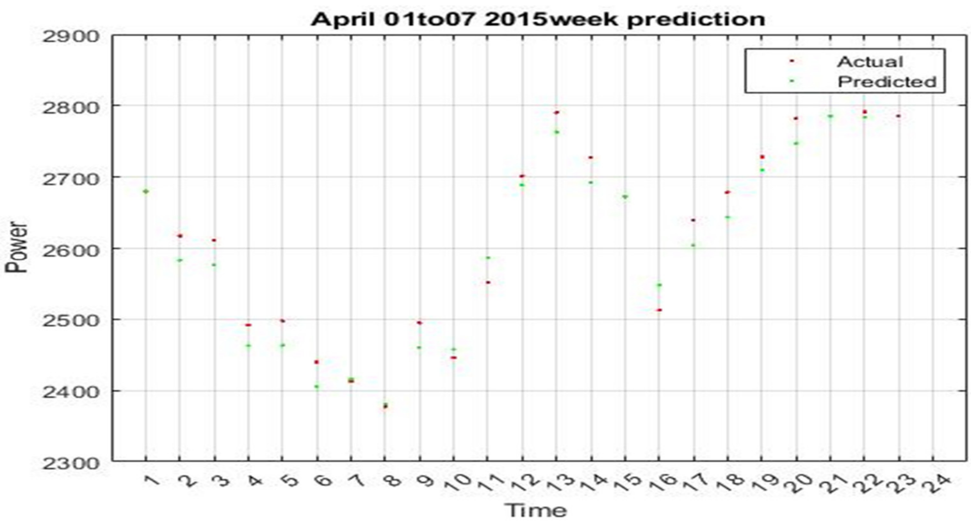


Figure 4.42 Zoomed version of one week ahead actual and predicted load for April 01, 2015 to April 07, 2015

Case 3: One month ahead prediction of load demand

For predicting one month ahead load of April 2015 load data from 1st April 2014 to 31st March 2015 has been used. The Figure 4.43 depicts the actual and predicted load for one month.

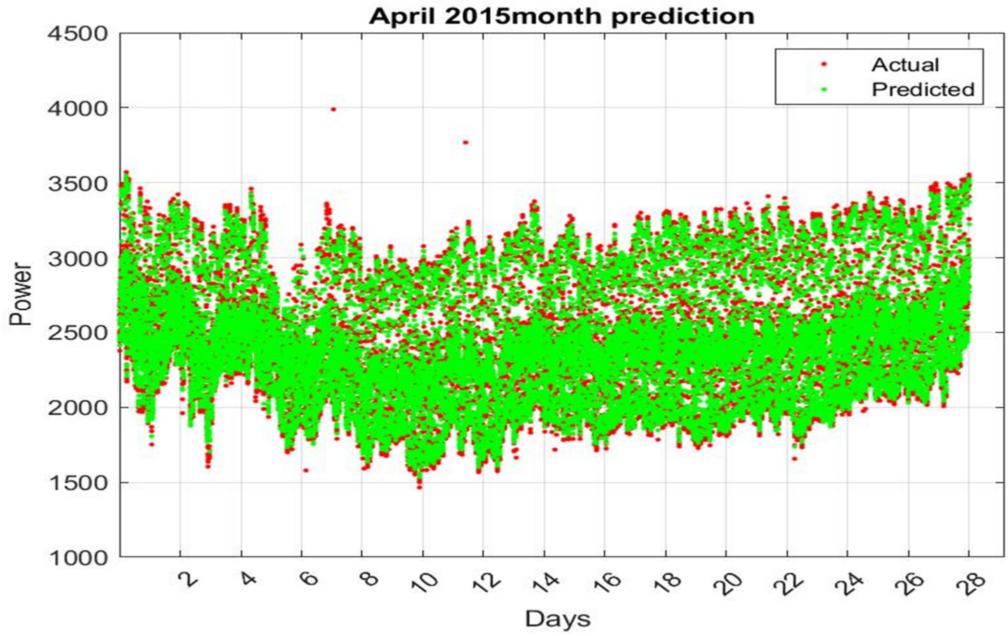


Figure 4.43: One month ahead actual and predicted load for April 2015

The values of prediction error parameters are obtained as: MAPE: 1.4128, MAD: 34.1123, MSE:2173.858, and RMSE:46.6246. The zoomed version of the same is shown in Figure 4.44. A 48-hour load is considered for zooming.

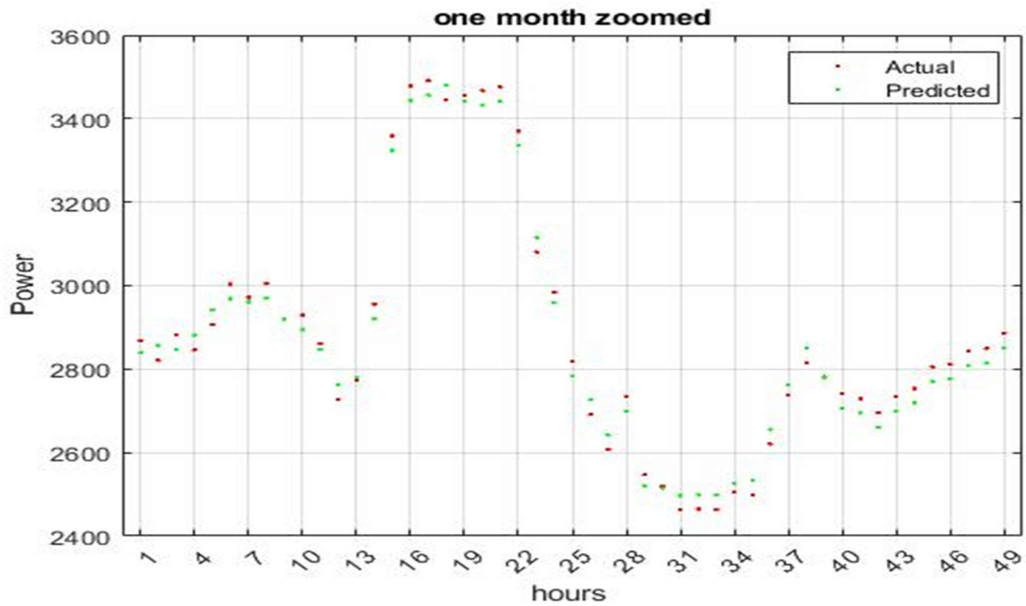


Figure 4.44: Zoomed version of one month ahead actual and predicted load for April 2015

4.6.2.2 Mid-term Load forecasting

Case 4: Six month ahead prediction of load demand

For predicting six months ahead load from 1st April 2016 to 30th September 2016, the load data was used from 1st April 2015 to 31st March 2016. The Figure 4.45 depicts the actual and predicted load for six months. The values of error obtained are: MAPE: 1.4128, MAD: 34.112, MSE: 2173.858 and RMSE: 46.6246.

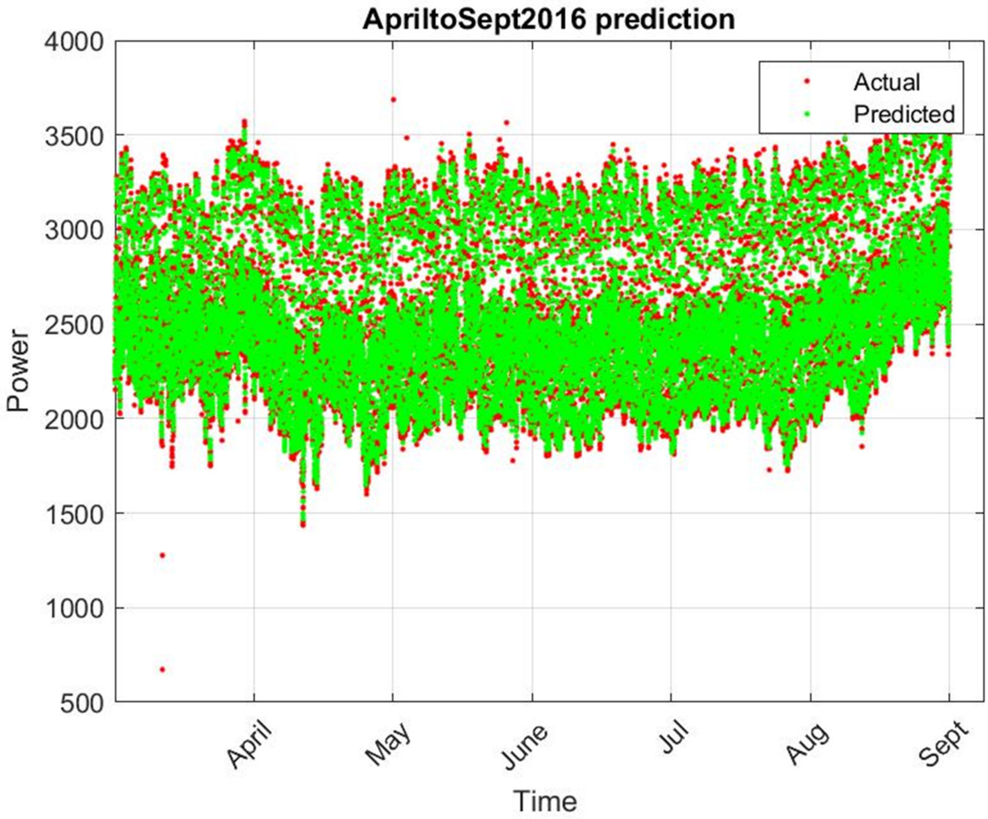


Figure 4.45: Six months ahead actual and predicted load for April 2016 to September 2016

Case 5: One year ahead prediction of load demand

For predicting one year ahead load from 1st April 2015 to 31st March 2016, the load data of the previous year, i.e., from 1st April 2014 to 31st March 2015 is used. The Figure 4.46 depicts the actual and predicted load for one month.

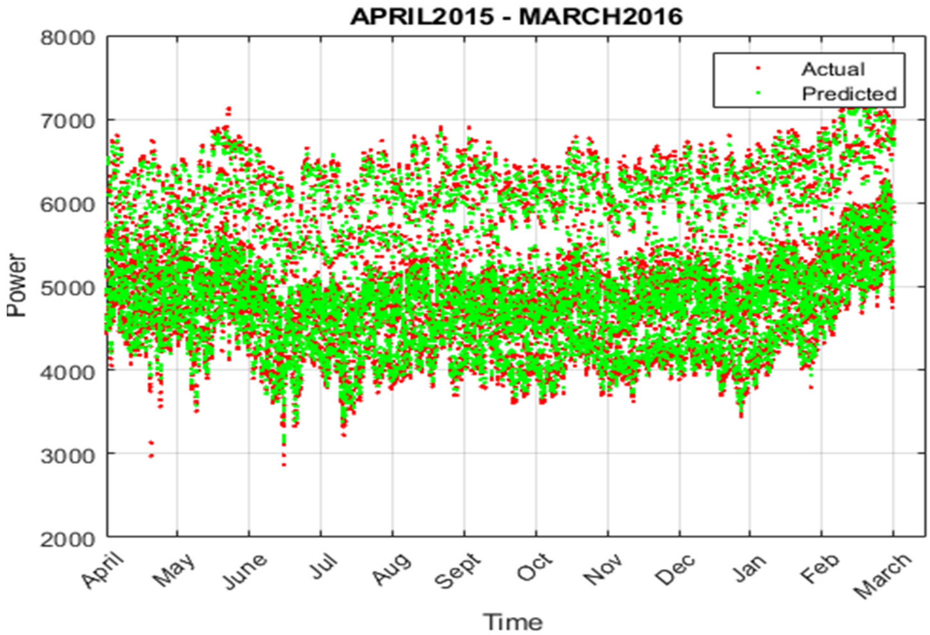


Figure 4.46: One year ahead actual and predicted load for April 2015 to March 2016

The values of error obtained are MAPE: 1.4216, MAD: 33.6775, MSE: 2106.5705 and RMSE: 45.8974. The zoomed version of one year ahead actual and predicted load for April 2015 to March 2016 is shown in Figure 4.47. A three days' load is considered for zoomed version.

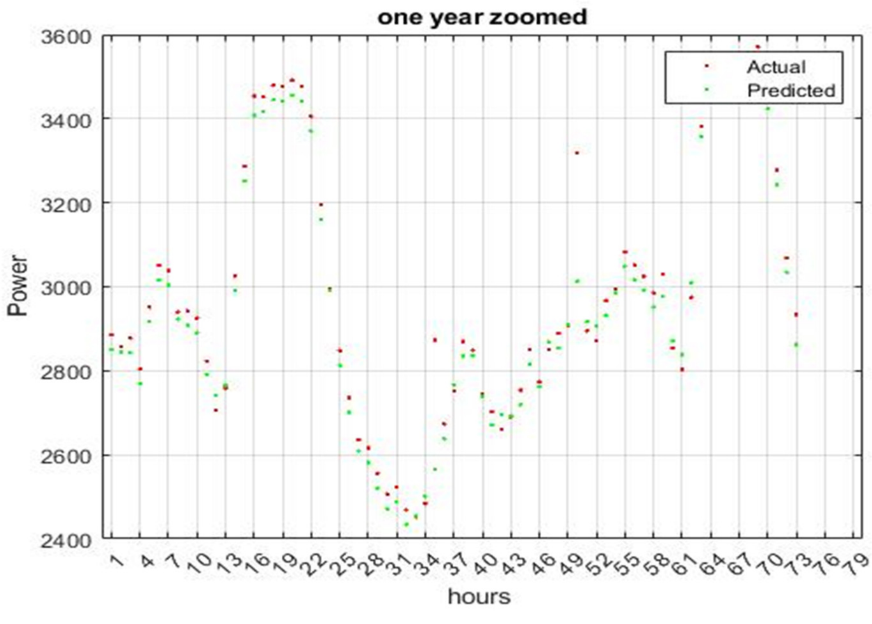


Figure 4.47: Zoomed version of one year ahead actual and predicted load for April 2015 to March 2016

4.7 EVALUATION OF FORECASTED ERRORS OF NEURAL NETWORK AND SVR: A COMPARISON

The case study by the proposed two methods are carried out forecasting hourly, daily, weekly and monthly electric load using the data collected from Kerala State Electricity Board Ltd. The results are obtained for three years from 2014 to 2016. The comparison of forecasted load and actual load are shown from Figures 4.12 - 4.47. The experimental models give better forecasting results with the overall average percentage error of 6.58%. Generally, 10% forecasting error is said to be acceptable for long term load forecasting. The RMSE statistics also indicates that ANN model provides the most accurate forecasts. The computational time of SVR for one hour ahead for the year 2014, 2015 and 2016 are 34.87 seconds, 17.44 seconds and 28.22 seconds respectively. Table 4.6 to 4. 9 shows the actual forecast error statistics for each model across the five error measures.

Table 4.6: Prediction Error Parameters- One day ahead

ANN	MAE/MAD	MPE	MAPE	MSE	RMSE
APRIL 01, 2014	35.0175	0.216	1.2826	3576.6525	50.7607
APRIL 01, 2015	28.0175	0.2311	1.3837	1891.1952	43.4878
APRIL 01, 2016	31.5506	0.3650	1.3875	1980.6084	44.5040
SVR	MAE/MAD	MPE	MAPE	MSE	RMSE
APRIL 01, 2014	41.8466	0.5632	1.7365	2905.3215	53.901
APRIL 01, 2015	33.2331	0.6731	1.4044	1984.2151	44.5445
APRIL 01, 2016	33.0756	0.8712	1.3659	2047.1748	45.2457

Table 4.6 shows the prediction error parameters by using the ANN and SVR methods of one day ahead forecasting for the period of 2014 to 2016. The MAE statistics

indicate that ANN model provides the most accurate forecasts and the SVR model ranks a close second.

Table 4.7 shows the prediction error parameters by using the ANN and SVR method of one week ahead forecasting for the period of 2014 to 2016.

Table 4.7: Prediction Errors- One Week ahead

ANN	MAE/MAD	MPE	MAPE	MSE	RMSE
APRIL01 - 07, 2014	37.3845	0.2143	1.3734	2864.026	53.5165
APRIL 01 -07, 2015	30.042	0.6511	2.1869	2318.3367	48.1499
APRIL 01 -07, 2016	32.4584	0.8305	1.3822	2292.3605	47.876
SVR	MAE/MAD	MPE	MAPE	MSE	RMSE
APRIL01 - 07, 2014	41.8466	0.4376	1.7365	2905.3215	53.901
APRIL01 - 07, 2015	33.645	0.7942	2.42	2114.5691	45.9844
APRIL01 - 07, 2016	34.5066	0.8623	1.4302	2243.4271	47.36between48

The MAPE statistics give a relative indication of overall forecasting performance. There is no considerable difference between the values of MAPE and MPE of the two methods.

Table 4.8: Prediction Errors- One month ahead

ANN	MAE/MAD	MPE	MAPE	MSE	RMSE
APRIL 2014	38.3468	0.4328	1.7322	1969.5583	44.3797
APRIL 2015	35.4029	0.389	0.1155	1971.2105	44.3983
APRIL 2016	33.8342	0.2197	1.2419	2457.707	49.5752
SVR	MAE/MAD	MPE	MAPE	MSE	RMSE
APRIL 2014	40.1083	0.6580	1.697	2102.9247	45.8577
APRIL 2015	34.1123	0.5477	1.4128	2173.858	46.6246
APRIL 2016	33.6775	0.542	1.4216	2106.5705	45.8974

Table 4.8 also shows the prediction error parameters by using the ANN and SVR method of one month ahead forecasting for the period of 2014 to 2016. The value of RMSE shows very small variation between the two methods.

Table 4.9: Prediction Errors- One Year ahead

ANN	MAE/MAD	MPE	MAPE	MSE	RMSE
APRIL2014 - MAR 2015	43.3657	0.35409	11.8951	3978.7713	63.0775
APRIL 2015-MAR 2016	37.7022	0.72681	1.4071	2010.0977	44.83
APRIL 2016 -MAR 2017	31.0417	0.72681	1.3554	5255.1884	72.4927
SVR	MAE/MAD	MPE	MAPE	MSE	RMSE
APRIL2014 - MAR 2015	84.056	0.6973	Infinity	9876.5602	99.3809
APRIL 2015-MAR 2016	33.6775	0.8641	1.4216	2106.5705	45.8974
APRIL 2016 -MAR 2017	34.1123	0.9358	1.4128	8277.6382	90.9815

Table 4.9 shows the prediction error parameters of ANN and SVR method of one year ahead forecasting for the period of 2014 to 2016. Numerical values of each parameters show a minimal variation on both methods.

4.8 CONCLUSION

Artificial neural network method is applied in the short-term, mid-term and long term load forecasting. There are different patterns of one hour ahead, six hours ahead, one-day ahead, and one week ahead for STLF. One month ahead and one year ahead are predicted. For long term forecasting there are two patterns of prediction. A non-linear load model is proposed and the weights are estimated using a back-propagation learning algorithm which is robust in estimating the weight in non-linear equation.

The ANN have been successfully used to forecast the integrated load. It is found that the implemented forecasting system performed with reliable and a satisfactory accuracy. A further increase in forecast accuracy can be achieved by distributing the forecasting task between a set of parsimoniously designed neural networks.

The network is used for a particular day depending on climatic conditions and a certain period of the day with a unique pattern of load dynamics. Data available from KSEB Ltd. were used in this work for testing and demonstrating the performance of the ANN and SVR models for the STLF. From the result, it is observed that the forecasted load by ANN model is similar to the actual load. The performance evaluation parameters MAPE, MPE, MAD, MSE and RMSE have used for testing this forecasting models. The percentage error values of these parameters are found to be low for ANN model as compared to the SVR model. It is clear from the testing results that the ANN technique works more effectively than the SVR model as shown in table 4.6-4.10. It is observed that the percentage error exceeds up to 11% in SVR prediction. An improved result can be obtained in STLF with neural network.

The LTLF has been done from 2013 onwards for a period of five years and ten years. A comparison with the available data of KSEB Ltd. up to 2018 and 2023 also used to predict the load demand for the month of January 2018 to June 2018. When the different load forecasting technique is compared it is seen that, the ANN approach has produced better results than the other models. The ANN approach forecasted load is used for optimization. That is explained in the following chapter 5 of the present thesis.

CHAPTER 5

PSO AND GA BASED ECONOMIC DISPATCH OF KERALA POWER SYSTEM

5.1 INTRODUCTION

The objective of economic dispatch problem is to achieve minimum operating cost in a multiple source generation environment, which includes thermal, hydro, renewable energy sources etc., subject to operating constraints of generating units as well as a power system. The economic dispatch problem includes a proper commitment of an array of units out of a total array of units to serve the expected load demands in an optimal manner. The economic dispatch and unit commitment consist of the selection of generators that must be operated and number of units that is to be allocated to each unit so as to meet the forecasted load demand on the system over a period of time so that operating cost can be minimized while satisfying a set of operational constraints (Wood and Wollenberg, 2007; Ahmed and Hassan, 2004). The generating costs are the capacity related costs for generation which vary with the quantity of plant and equipment and the associated investment.

One of the major objectives of this research work is to develop a strategy for cost optimization that can be used for Kerala power system. In this work, cost optimization is carried out on the basis of Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) in a multiple source environment, which includes a combined cost optimization of hydro and thermal units.

The major qualitative factors reckoned in power industry are frequency, voltage and stability. The Kerala power system imports hundreds of MW of power from Central Generating Stations and other States through tie lines. Since the hourly consumption of power is several thousands of MW even a single paisa per MW can save several crores of Rupees to Kerala power economy. Hence optimization is required in scheduling power from various sources, including external import.

This chapter highlights the cost optimization through PSO for economic dispatch problem of Kerala power system. The result obtained is compared with GA based optimization. The problem formulation is done separately for thermal and hydro units, which are combined to get a coordinated cost optimization function. The computational tools used for this work–PSO, GA–are also discussed.

5.2 MODELING OF ECONOMIC LOAD DISPATCH PROBLEM FOR GENERATING SYSTEM

In hydro-thermal power systems, the power sources have their own hydro units and thermal units and have different operating characteristics, different optimization goals and constraints.

The external import of power is a major problem in dealing with economic load dispatch (ELD) of hydro-thermal generation systems in Kerala Power System. This problem is addressed in this work. In Kerala, extensive amount of power is drawn daily from external sources, despite the load being much lesser than the installed capacity. Hence, this ELD formulation is an attempt to reduce the import of power and thus to attain self-sustainability in the power system.

The ELD problem tries to minimize the cost of production or attain the least cost dispatch for the system. The cost is divided into two kinds, internal generation cost and import cost. The system structure followed in this work is depicted in Figure 5.1.

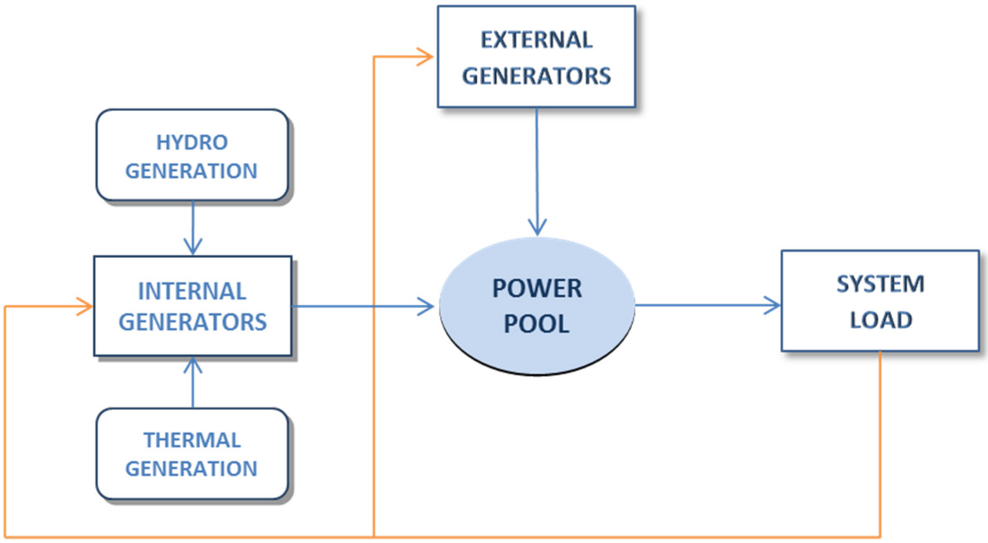


***Figure 5.1: Power system structure followed in this study*.**

Based on the data obtained from KSEB Ltd., the required parameters are made into an economic dispatch formulation. The objective function of the ELD problem (Park *et al.*, 2005, Ahmed and Hassan, 2004) can be commonly expressed in the following equation:

$$Min(F) = \sum_{i=1}^{N_G} C_i\left(P_{i,t}\right) \tag{5.1}$$

$$= \sum_{i=1}^{N_{G_{int}}} C_i\left(P_{i,t}\right) + \sum_{i=1}^{N_{G_{ext}}} C_i\left(P_{i,t}\right) \tag{5.2}$$

Where,

$N_G -$	Total number of Generators
$P_{i,t} -$	Output power of ith generator at time 't'
$C_i -$	Cost of production of ith generator
$N_{G_{int}} -$	Number of internal generators
$N_{G_{ext}} -$	Number of external (imported) generators

The generators are coupled with the on and off stages, Equation (5.2) shall be retrofitted with a status parameter similar to unit commitment parameter. This parameter $u_{i,t}$ is a discrete/binary parameter outing the status of the generator. If the generator is on, $u_{i,t} = 1$, and if off, $u_{i,t} = 0$. The final objective function becomes as in equation:

$$Min(F) = \sum_{i=1}^{N_{G_{int}}} u_{i,t} C_i\left(P_{i,t}\right) + \sum_{i=1}^{N_{G_{ext}}} u_{i,t} C_i\left(P_{i,t}\right) \tag{5.3}$$

The objective function in Equation (5.3) is minimized subjected to a set of constraints. The various constraints to be considered in the ELD problem are: system power balance constraints, generator constraints, special constraints for thermal units etc.

5.2.1 Mathematical Modeling of Hydro Generating System

In day ahead generation scheduling, the purpose of optimization is to make full use of hydro power and minimize the cost of coal fired units and reduce the cost of imported power. In Equation (5.2) second part is not considered due to the lack of data regarding the generator wise imported power from the tie lines. The first part of Equation (5.2) is considered for hydro and thermal generation separately. The objective function (Gaing, 2003, 2009) of ELD problem based on hydro generating system is:

$$Min(F) = \sum_{i=1}^{N_{G_H}} C_i\left(P_{i,t}\right) \tag{5.4}$$

This objective function is to simultaneously minimize the generation cost and to meet the load demand of a power system over an appropriate period while satisfying the constraints. C_i is the hydro generation cost function of the ith generator. In the case of hydro generation water is free and assumed that the fuel cost is negligible. But the operation and maintenance cost of different stations varies with respect to production. In this work minimization of total cost of hydro generation is done by modeling the operation and maintenance cost as a quadratic polynomial.

The generation cost function $C_i\left(P_{i,t}\right)$ is usually expressed as a quadratic polynomial as in the following equation:

$$Min(C_T) = \sum_{i=1}^{N_{G_H}}(\alpha_i + \beta_i P_i + \gamma_i P_i^2) \tag{5.5}$$

Where,

C_T	-	Total generation cost
N_{G_H}	-	Number of hydro generating units
P_i	-	Power output of ith generator at time t
$\alpha_i, \beta_i, \gamma_i$	-	Cost coefficients of ith generator

Each generating unit has a unique production cost defined by its cost coefficients. Here curve fitting method is used in order to find the cost coefficients $\alpha_i, \beta_i, \gamma_i$ by giving input as matrices of load in MW and cost in Rupees per hour. Curve fitting tool in MATLAB is used to obtain the value of cost coefficient.

Constraints

i. System power balance constraint is mathematically expressed in the following equation:

$$\sum_{i=1}^{N_{G_H}}(P_{i,t}) = P_d(t) + P_{loss}(t) \tag{5.6}$$

Where, $P_{i,t}$ – is the scheduled optimal generation of i^{th} unit.

$P_d(t)$ – is the active power load at forecasted time period, *t*.

$P_{loss}(t)$ – is the estimated loss at forecasted time period, *t*.

ii. Generator constraint is expressed as in the following equation:

$$P_{i,min} \leq P_{i,t} \leq P_{i,max} \tag{5.7}$$

Where, $P_{i,min}$ – is the minimum schedulable generation for i^{th} unit.

$P_{i,max}$ – is the maximum schedulable generation for i^{th} unit.

5.2.2 Mathematical Modeling of Economic Load Dispatch Problem Formulation by Thermal Generation

The economic load dispatch problem is a nonlinear optimization problem, which is a sub problem of the unit commitment problem. The main objective of ELD problem is to find the optimal combination of power generation that minimize the cost associated with power production in thermal system, such as fuel costs, startup costs and shut down costs. This is expressed in the following equation:

$$Min(F) = \sum_{i=1}^{N_{G_{Th}}} C_i\left(P_{i,t}\right) \tag{5.8}$$

The fuel cost function of each thermal generating unit (Pothiya *et al.,* 2008; Dasgupta and Banerjee,2014b) is expressed as a quadratic function as shown below:

$$Min(F) = \sum_{i=1}^{N_{G_{Th}}} (a_i + b_i P_i + c_i P_i^2) \tag{5.9}$$

Where,

$N_{G_{Th}}$ - Number of thermal generating units

P_i - Power output of i^{th} generator at time t

a_i, b_i, c_i - Cost coefficients of i^{th} generator.

Constraints

The objective function of ELD problem is subjected to the constraints which are described as:

i. System power balance constraints:

The output power of the generators should be equal to the load demand and transmission loss at a particular time interval t, expressed in the following Equation (5.10):

$$\sum_{i=1}^{N_{G_{Th}}} (P_{i,t}) = P_d(t) + P_L(t) \tag{5.10}$$

Where,

$P_d(t)$ – is the active power load at forecasted time period, *t*.

$P_L(t)$ – is the system transmission loss.

ii. Operating balance constraints are:

$$P_{i,min} \leq P_{i,t} \leq P_{i,max} \tag{5.11}$$

Where,

$P_{i,min}$ – is the minimum operating limits of generator *i*.

$P_{i,max}$ – is the maximum operating limits of generator *i*.

iii. Ramp rate limits are:

$$P_i(t) + P_i(t-1) \leq UR_i \quad \text{- if power increases} \tag{5.12}$$

$$P_i(t-1) + P_i(t) \leq DR_i \quad \text{- if power decreases} \tag{5.13}$$

The objective function components are formulated as a model to minimize the cost of thermal units and making full use of hydro power by satisfying the above constraints. Finally, the problem formulation equation (5.5) and (5.9) are optimized separately and then combined.

i.e. Min (F_T) = Min (C_T) + Min(F). The combined form of hydro and thermal generation is shown as:

$$Min(F_T) = \sum_{i=1}^{N_{G_H}}(\alpha_i + \beta_i P_i + \gamma_i P_i^2) + \sum_{i=1}^{N_{G_{Th}}}(a_i + b_i P_i + c_i P_i^2) \tag{5.14}$$

5.3 COMPUTATIONAL TOOLS USED FOR OPTIMIZATION AND ANALYSIS

Optimization problems consist of the quantitative study of optimum and methods for finding them. The objective is to maximize or minimize a mathematical function, is called objective function. The constraint functions and simple variable limits are grouped under the term constraints. The region defined by the constraints is said to be the feasible region for the independent. If the constraints do not have such region, there are no values for the independent variables that satisfy all the constraints, where the problem is said to have an infeasible solution (Wood and Wollenberg, 2005).

The complex nature of generation of electricity signifies ample opportunity of improvement towards the optimal power generation solution. The demand of power system varies throughout the day and reaches a different peak value from one day to another. To satisfy this demand, start-up and shut-down of a number of generating units at various power stations each day is needed. The difficult task is to decide when and which generating units to turn on and turn off together with minimizing the total cost. Similarly, the total generation must be equal to the forecasted demand of power. For reducing the generation cost, optimized scheduling for ELD is necessary (Ahmed, 2004).

Thus, the economic dispatch is one of the most important problems to be solved in the operation and planning of a power system. The primary objective of the electric power generation is to schedule the committed thermal unit outputs so as to meet the required load demand at minimum operating cost while satisfying all unit and system equality and inequality constraints. In the traditional economic dispatch problem, the cost function for each generator has been approximately represented by a single quadratic function and is solved using mathematical programming based on the optimization techniques (Dasgupta *et al.*, 2015).

The optimization methods can be classified into two main groups: Deterministic and Heuristic. The conventional methods are dynamic programming, Linear programming, Integer and mixed integer linear programming, Lagrange relaxation method, Bundle method, Quadratic programming and Network flow method.

The modern heuristic optimization techniques (Lee, *et al*., 2008) based on operational research and artificial intelligence concepts as evolutionary programming, genetic algorithm, simulated annealing (SA), ant colony optimization (ACO), Tabu search (TS), neural network (NN) and particle swarm optimization (PSO). PSO is one of the modern heuristic techniques used as a tool for solving the ELD problem.

In this work, the cost optimization of Kerala power system is attempted based on the economic load dispatch. The STLF is concerned with ELD and load management. The STLF based forecasted demand is utilized in this work to schedule generators. PSO is used as a major tool in scheduling generators in a cost optimized way.

5.3.1 Particle Swam Optimization based Economic Load Dispatch

The Particle Swarm Optimization (PSO) algorithm is a sociologically inspired stochastic optimization algorithm introduced by Kennedy and Eberhart in 1995. Swarm behavior can be modeled with a few simple rules. Schools of fishes and swarms of birds can be modeled with such simple methods. The behavioral rules of each individual (agent) are simple; but the behavior of the swarm can be complicated. The simple rules are: step away from the nearest agent, go towards the destination and go to the center of the swarm.

In PSO (Eberhart, 1995, 2001, 2004), the potential solutions, called particles, "fly" through the problem space by following some rules. All of the particles have fitness values based on their position and have velocities which direct the flight of the particles. PSO is initialized with a group of random particles (solutions), and then searches for optima by updating generations. In every iteration, each particle is updated by following two "best" values. The first one is the best solution (fitness) the particle has achieved so far. This value is called “pbest” or the individual particle best. Another "best" value that is tracked by the particle swarm optimizer is the best value obtained so far by any particle in the population. This best value is a global best and called “gbest” or the global best among all the considered particles, considering the current as well as all the previous iterations. After finding the two best values explained above, the particle updates its parameters, velocity and position with Equations (5.15) and (5.16) (Lee *et al.*, 2008).

$$V_n(k+1) = w * V_n(k) + c_1.rand_1.\left(Pbest_n(k) - P_n(k)\right) + c_2.rand_2.\left(G_{best} - P_n(k)\right) \quad (5.15)$$

$$P_n(k+1) = P_n(k) + V_n(k+1) \quad (5.16)$$

Where, w is the inertia coefficient which slows velocity over time; $V_n(k)$ is the nth particle velocity after the kth iteration; $P_n(k)$ is the current nth particle position in the search space;$Pbest_n(k)$ and $Gbest$ are the"personal" or individual best (describe the individuality) and global best (describing the social nature of the particle); $rand_1$ and $rand_2$ random numbers between (0,1); c_1 and c_2 are learning factors (Lee *et al.*, 2008). The stop condition is usually the maximum number of allowed iterations for PSO to execute or the minimum error requirement. As with the other parameters, the stop condition depends on the problem to be optimized.

In summary, the advantages of the PSO over other algorithms are that (a) it is computationally simple and efficient; (b) each agent only needs to know its own local information and the global best to compute the new position, so there is a minimal amount of data transfer among the agents; and (c) the results from all agents in the population are not required to form the next generation, eliminating the need of a centralized processor. It requires only four multiplies and four add/subtracts to update the velocity and then one adds to update the position. There is no complicated iterative equation solving required and no exponential or trigonometric functions to implement.

The PSO is also a distributed algorithm. Each agent, (particle or bot) can update its own velocity and position. The only external information is the global best i.e., the best value by any particle within the population. The calculation of the global best can be done with a simple comparative statement. The updated position is relative to the current position so there are no jump changes in position or random movements. If there are constraints on the movement of the bot during each iteration, then limitations can be placed on the maximum and minimum velocity that is allowed for each particle/Bot.

5.3.2 Time Varying Inertia Weight

Shi and Eberhart (1998) introduced the concept of inertia weight to the original version of PSO, in order to balance the local and global search during the optimization process. Shi and Eberhart have found a significant improvement in the performance of the PSO method with a linearly varying inertia weight over the generations. Hence, instead of keeping w at a suitably constant point, the value is updated in every iteration along with the position and velocity of each individual in the next stage. The inertia weight w is decreased linearly, as in Figure 5.2, from maximum value w_{max} to minimum value w_{min} in every iteration till T, the maximum number of permissible iterations as expressed in the following:

$$w = w_{max} - k.\frac{w_{max}-w_{min}}{k_{max}} \tag{5.17}$$

Through empirical studies, Shi and Eberhart (1998) have observed that the optimal solution is improved by varying the value of inertia weight from 0.9 at the beginning to 0.4 at the end of the search for most applications. This version of PSO, referred to as time-varying inertia weight factor method (PSO-TVIW) as shown in Figure 5.2, is used in this work.

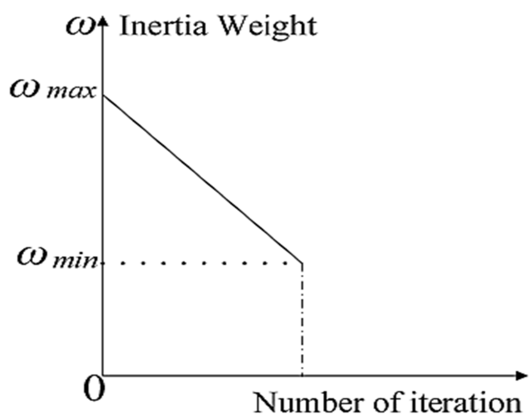


Figure 5.2: Linear variation of inertia weight in PSO-TVIW

The total power flow to the power pool is considered from external generators (power import) and internal generators as shown in Figure 5.1. The algorithm used for this optimization is detailed in section 5.4.

5.3.3 Economic Dispatch Problem based on Genetic Algorithm

A genetic algorithm (GA) is a problem-solving method that uses genetics as its model of problem solving. It is a search technique to find approximate solutions to optimization and search problems. In order to apply a GA to a given problem, decision must be taken on how the parameters of the problem will be mapped in to a finite string of symbols known as genes (with constant or dynamic length), which encoding a possible solution in a given problem space (Goldberg *et al.*, 1988). ELD problem can be solved by the genetic algorithm using either the unit input-output curve solution or incremental cost curves. The input-output solution uses the standard objective function and the system power balance constrains. The iteration process of GA consists of the following steps (Sivanandam and Deepa, 2008):

- Selection: The first step consists in selecting individuals for reproduction. This selection is done randomly with a probability depending on the relative fitness of the individuals so that best ones are often chosen for reproduction than poor ones.
- Reproduction: In the second step, offspring are bred by the selected individuals. For generating new chromosomes, the algorithm can use both recombination and mutation;
- Evaluation: Then the fitness of the new chromosomes is evaluated; and
- Replacement: During the last step, individuals from the old population are killed and replaced by the new ones.

For optimizing hydro-thermal system, 57 hydro generators and 12 thermal generators are considered as individuals. The optimization is done for 100 generations with single point crossover and with a mutation rate of 0.8. The selection process, recombination and mutation are done with default MATLAB function GA. The flow chart used for optimization of individual hydro generation is shown in Figure 5.3 following the section 5.4

5.4 ALGORITHM AND FLOW CHART FOR ELD USING GA AND PSO

A simple genetic algorithm involves the following steps: code the problem, randomly generate initial population strings, evaluate each strings fitness, select highly fitness strings as parents and produce offspring according to their fitness, create new strings by matching current off springs, apply cross over and mutation and finally the new strings replace the existing ones. For large optimization problems, the initial population of individuals of various fitness, the operators of GA begin to generate a new and improved population from the new previous one. The execution of GA iteration is basically a two-stage process. Iteration starts with the current population.

5.4.1 Flow Chart of Genetic Algorithm

The economic dispatch problem is a classical optimization problem, the elements of that must to be optimized according some criteria (here expressed by the fitness function). The chromosome for this study is composed by all generated power of each unit, represented by Pi. Here the fitness function selected is the objective function which is modelled in Section 5.2 of this chapter. Hydro generating systems and thermal generating systems are optimized separately to get the optimum value of generation. The Equation (5.5) and (5.9) are selected as fitness function for hydro generation and thermal generation respectively (Sivanandam and Deepa, 2008). The detailed flow chart is given in Figure 5.3.

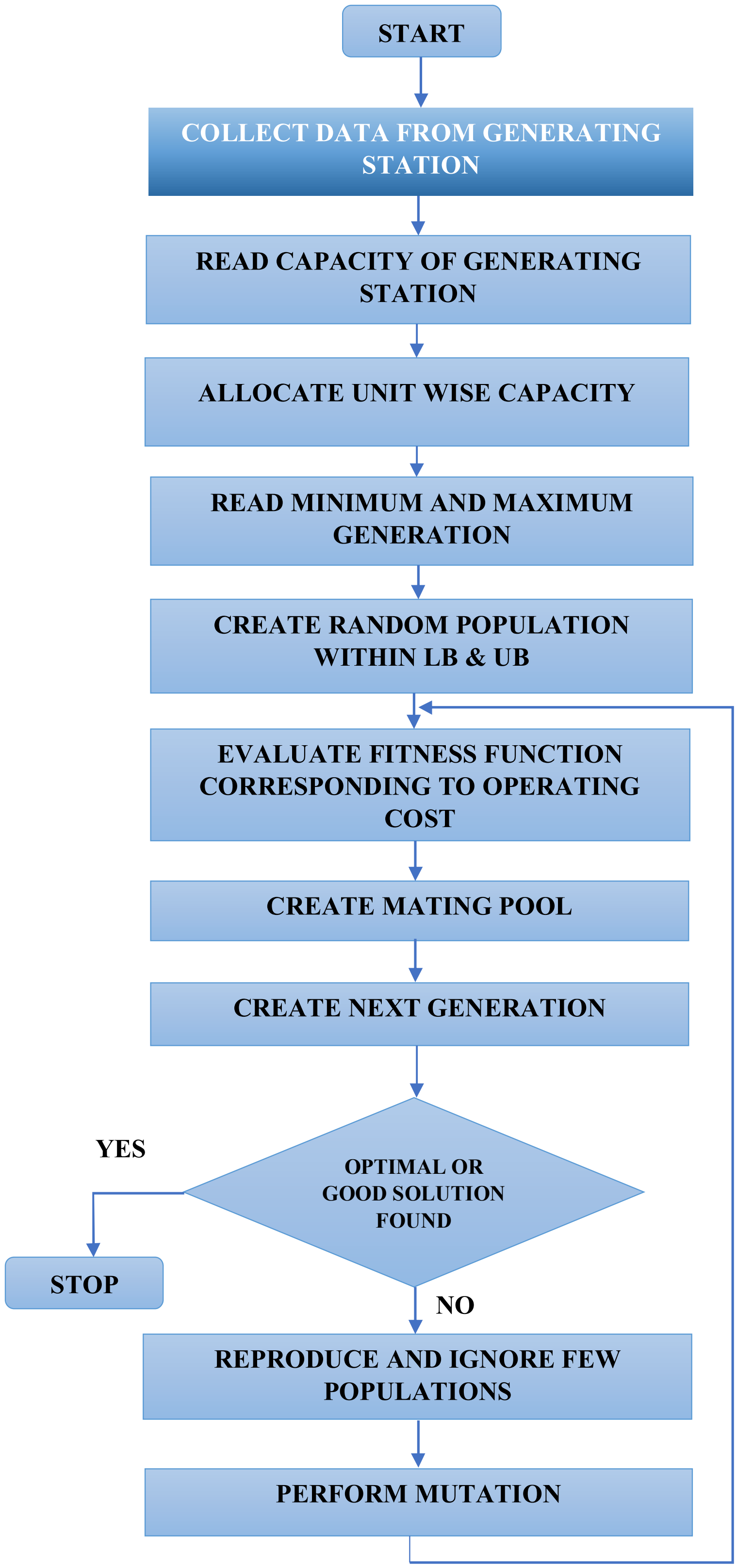


Figure 5.3: Flow chart of GA based economic load dispatch

5.4.2 Algorithm and Flow Chart of PSO

A total of major 57 generators are considered as internal generating stations.

While applying PSO a particle of size 30 is selected and a matrix of size 57×30 is initialized. For each of these generators, *pbest* and *gbest* are found in each iteration. Cost per unit is selected as *pbest* for each of the particles. The constraints explained in the system such as equation (5.6), (5.7) and (5.10) to (5.13) are considered while optimizing the cost of production in each iteration. A similar approach is used for optimizing the cost of thermal generators available in the system. A total of 12 thermal units viz., Brahmapuram Diesel Power Plant (BDPP), Kozhikkode Diesel Power Plant (KDPP) and Rajiv Gandhi Combined Cycle Power Project (RGCCPP) are considered here. The optimized generation from hydro generating stations and thermal generating stations are considered for calculating the net import required under optimized condition. The algorithm is detailed below:

Step 1: Read internal generation available for time 't'. (Here 57 major generators are taken as internal generators as explained);

Step 2: Read external generation availability for time 't';

Step 3: Read load profile from forecasted data for time T. (Short term load forecasting of April 01,2015 data is used in this case for getting optimum schedule);

Step 4: Initialize particle size, number of iteration and maximum error, learning factors (c_1, c_2) and inertia weight (w). Define initial velocity and position of particles for each generating unit;

Step 5: Calculate dispatch and cost per unit and select cost per unit as *pbest*;

Step 6: Check maximum minimum conditions of dispatch from each unit;

Step 7: Select *gbest* (minimum of cost per unit);

Step 8: Update particle parameters;

Step 9: Calculate new dispatch and cost per unit and update *pbest*;

Step 10: Check maximum and minimum conditions of dispatch and update *gbest*;

Step 11: Check and enforce pattern of internal and external generations;

Step 12: Increment time slot; and

Go to step 10.

In this process, the PSO with time varying inertia values are used (PSO-TVIW). The optimal solution is improved by varying the value of inertia weight from 0.4 to 0.9. The entire methodology is summarized in Figure 5.4 (Lee and El-Sharkawi, 2008).

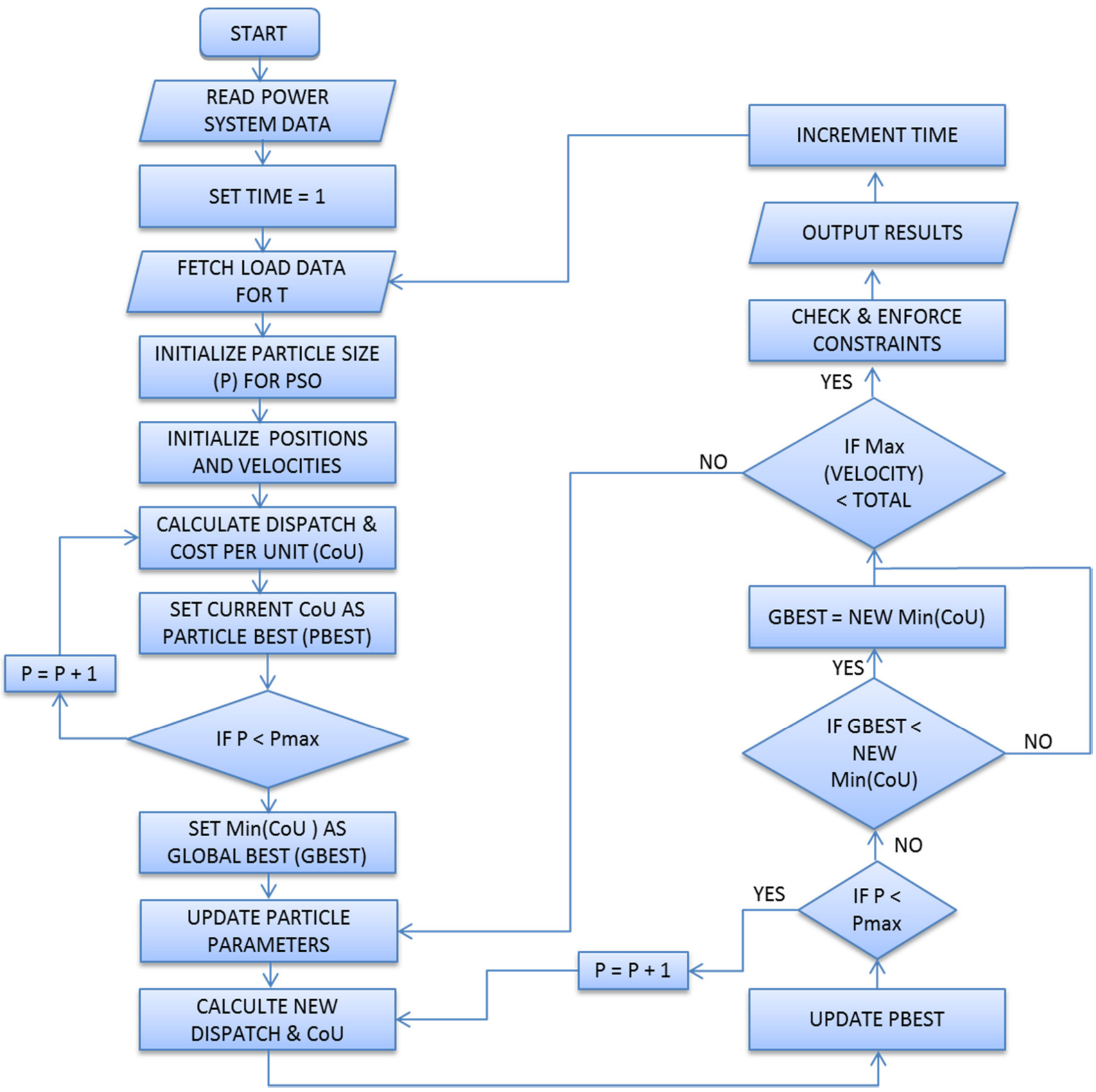


Figure 5.4: Flow chart of PSO based economic load dispatch

5.5. RESULTS AND DISCUSSION: COST OPTIMIZATION WITH GA BASED SCHEDULING

Case – 1: One day optimum scheduling

The evaluation of generation cost of the entire day can be done by changing the time slot from 00.30 to 24.00 hours in steps of one-hour time slots. In this work, variation in daily operating cost is not considered and is taken as constant. In this section data collected from KSEB Ltd. (Appendix V-A) are analyzed for getting optimum schedule with genetic algorithm. The operating cost details used in this work are given in Appendix V- B. Cost coefficients of hydro generators are found by using the data given in Appendix V-B and the values mentioned in Appendix V-C for hydro and the optimized power and cost shown in V-D respectively. Cost coefficient of thermal generators are shown in Appendix V-E. One day optimized power output of hydro and thermal by using GA and PSO is also shown in Appendix V-F to V-J.

5.5.1 Generation, import and Cost details from KSEB Ltd.

The same data from KSEB Ltd are used for both GA and PSO methods. The cost of imported power is to be included so as to maximize the overall profit. For April 01 2015, the cost per unit for hydro and thermal units can be calculated from the data given in Appendix-V. B as follows: Cost per kWhr of hydro generation = Rs. 0.93, cost per kWhr of thermal generation = Rs. 8.41 and cost per unit of imported power = Rs. 4.12. The thermal generation were worked 4.5 hours only on the same day.

Hydro power generation = 958 MW

Thermal power generation = 54.462 MW

Total power generation = 1012.462 MW

Cost of generation	=	cost of hydro generation + cost of thermal generation
	=	Rs. (958×1000×0.93×24) + Rs. (54.462×8.41×1000×4.5)
	=	Rs. 21382560 + Rs.2061114.39 = Rs.23443674.39
	=	Rs. 2.3443674 Crore

Power consumption = **3231 MW**

Power imported by KSEB Ltd = 3231-1012.462 = **2218.538 MW**

Cost of imported power = Rs. 2218.538×1000×24×4.12 = Rs. 21.9369037 Crore.

5.5.2 Generation, import and Cost details from Optimized Scheduling

The short-term load forecasting of April 01, 2015 is made out of the data from KSEB Ltd. for getting the optimum schedule with genetic algorithm. Forecasted demand for the time slot of 00.30hrs to 24.00hrs is considered. This optimized schedule to be followed for minimizing cost of imported power. The value obtained through genetic algorithm-based optimization of thermal and hydro is shown in Appendix V-E and V-G respectively. The optimal values are the following:

Optimized power of hydro generation	=	1728.806 MW
Optimized power of thermal generation	=	86.58587 MW
Total optimized generation	=	(1728.806+86.58587)
	=	1815.3918 MW
Consumption for one day	=	**3231 MW**
After optimization, the required imported power had been	=	3231-1815.3918
	=	**1415.6082 MW**
Optimized cost of imported power	=	Rs.1415.6082×1000×4.12×24
	=	13.9975319 crore

A total reduction of imported power	=	(2218.538-1415.6082)
	=	802.9298 MW
Cost of the reduction of imported power	=	802.9298×1000×4.12×24
	=	Rs.79393698.62
Therefore, a total savings per day	=	Rs. 21.9369037 - 13.9975319
	=	Rs. **7.9393698** crore

Case – 2: One week scheduling

A similar approach is used for obtaining the total reduction of imported power and total savings per week. Data used in this case for the period from April 01, 2015 to April 07, 2015 are obtained from KSEB Ltd. They are as follows:

Hydro power generation	=	6447.9 MW
Thermal generation	=	714.0 MW
Total generation	=	6447.9 + 714.0 = 7161.9 MW
Consumption for one week	=	**23205 MW**
Power imported by KSEB Ltd	=	23205-7161.9 = **16043.1 MW**
Cost of imported power	=	Rs.16043.1×1000×4.12×24
	=	Rs.158.6341728 Crore

The evaluation of the entire week can be done by changing the time slot to one hour. The weekly savings that could have been obtained by using genetic algorithm are made. The thermal generation were worked 110.5 hours only on the same week.

The optimal value for hydro generation	=	11987.58 MW
The optimal value for thermal generation	=	929.6748 MW
Total optimal generation (hydro + thermal)	=	11987.58 + 929.6748=12917.2548 MW
Cost of optimized generation	=	(11987.58×1000×0.93×24) +
		(929.6748×1000×8.41×24)

= Rs.26.75627 + 18.6455616

= Rs. 45.4018401 Crore

After optimization, the required imported power had been = 23205 - 12917.2548

= **10287.7452 MW**

Therefore, reduction in required imported power =16043.1-10287.745 = 5755.35 MW

Therefore, cost savings per week = 5755.35×1000×4.12×24 = Rs. 56.9089482 Crore

Case- 3: One month scheduling

This is based on the monthly data including demand and station wise data which were collected from KSEB Ltd for April 2015 (Appendix VI-A). For getting the optimum schedule, genetic algorithm is used. The following analysis is made out of the data for a period of one month:

Hydro power generation	=	26084.5029 MW
Thermal generation	=	1921.791 MW
Total generation	=	28006.2939 MW
Power consumption	=	**77973.750 MW**
power imported by KSEB Ltd	=	77973.750 -28006.2939 = **49967.457 MW**

The evaluation of the month of April 2015 can be done by the monthly saving that could have been obtained by using genetic algorithm. For the cost calculation, data used in this work are given in Appendix VI-B. Thus:

The optimal value for hydro generation	=	43937.607 MW
Optimal value of thermal generation	=	2714.789 MW

Total optimal generation (hydro + thermal)	=	(43937.607 + 2714.789)
	=	46652.396 MW
Required power to be imported	=	77973.750 - 46652.396
	=	31321.354 MW

After optimization, the reduction in imported power had been

	=	49967.457 - 31321.354 MW
	=	18646.103 MW
Therefore, cost savings per month	=	18646.103×1000×4.12×24
	=	Rs.184.372666 Crore

This process is repeated for different months of the complete year to evaluate annual savings. The monthly saving that could have been obtained by using the optimal scheduling obtained by using GA for the months April 2015 to March 2016 is summarized as follows:

Case- 4: One Year Scheduling

KSEB Ltd details (One Year)

Hydro power generation for one year	=	280036.828 MW
Thermal power generation for one year	=	6433.8039 MW
Total power generation	=	286470.6319 MW

Cost of generation = cost of hydro generation + cost of thermal generation

= Rs. (280036.828 ×1000×0.93×24) +
Rs. (6433.8039 ×7.4241×1000×24)

= Rs. 6250422001 + Rs.1146364885 = Rs.7396786886

= Rs. 739.678688 Crore

Power consumption for one year = **951514.1667 MW**

Power imported by KSEB Ltd = 951514.1667-286470.6319 = **665043.5348 MW**

Cost of imported power = Rs. 665043.5348×1000×24×4.12 = Rs. 6575.95047 Crore

The evaluation of the year of April 2015 to March 2016 can be done by each monthly saving that could have been obtained by using genetic algorithm. Per unit cost of thermal generation is varied in each month and therefore average value is taken. Details are given in Appendix VI-B and VI-C (both GA&PSO). Optimized values and for one year calculations are as follows:

The optimal value of hydro generation for one year	=	536028.512 MW
The optimal value of thermal generation for one year	=	36384.083 MW
Total optimal generation (hydro + thermal)	=	536028.512 +36384.083
	=	572412.595 MW
Cost of optimized generation	=	(536028.512×1000×0.93×24) +
		(36384.083×1000×7.4241×24)
	=	Rs.1196.415639 + Rs.648.2857694
	=	Rs.1844.7014 Crore
After optimization, the required imported power had been	=	951514.1667-572412.595
	=	**379101.5717 MW**
Therefore, reduction in required imported power	=	665043.5348-379101.5717
	=	285941.9631 MW
Therefore, cost savings for one year	=	285941.9631×1000×4.12×24
	=	Rs. 2827.3941 Crore

5.6 RESULT AND DISCUSSION: COST OPTIMIZATION WITH PSO BASED SCHEDULING

5.6.1 PSO-TVIW based Optimum Scheduling with Generator-wise Data

The short-term load forecasting of April 01,2015 data is used in this case for getting optimum schedule with particle swarm optimization - time varying inertia weight factor (PSO-TVIW). The forecasted demand for the time slot of 00.30hrs to 24.00hrs is considered. The station wise internal generation and imported load for April 2015 is given in Appendix V-A and are used for MATLAB programming to optimize the generation scheduling. For each time slot with an interval of one hour, an optimum generating schedule is obtained. This optimized schedule is to be followed for minimizing the cost of generation.

Case-1: One day scheduling

The value obtained through PSO-TVIW factor is shown in Appendix V-H. The optimal values are as follows:

Hydro generation	=	1797.73 MW
Thermal generation	=	98.1861 MW.
Total generation (1797.73 + 98.1861)	=	1895.9161 MW.
Consumption for one day	=	**3231 MW**
Required power to be imported (**3231-1895.9161**)	=	1335.0839 MW
Power imported by KSEB Ltd for one day	=	**2218.538 MW**
Therefore, reduction in imported power had been	=	2218.538-1335.0839 MW
	=	883.455 MW
Cost of imported power for one day	=	883.455×1000×4.12×24
	=	Rs. 87356030.4
Therefore, cost savings per day	=	Rs. 8.7356030 crore

Case- 2: One week scheduling

A similar approach is used for obtaining the total reduction of imported power and total savings per week. Same data are also used in this case for the period from April 01, 2015 to April 07, 2015.

The evaluation of one week can be done by changing the time slot to one hour. The weekly saving that could have been obtained by using PSO-TVIW algorithm is made. The cost calculation details used in this work are shown in Appendix-VI-C.

Power imported by KSEB Ltd for one week	= **16043.1 MW**
Consumption for one week	= **23205 MW**
The optimal value for hydro generation	= 12404.7 MW
Optimal power of thermal generation	= 1002.396 MW
Total optimal generation (12404.7 + 1002.396)	= 13407.0967 MW
After optimization the power to be imported	= 23205-13407.0967
	= 9797.9033 MW
Therefore, the reduction in imported power	= 16043.1- 9797.9033
	= 6245.1967 MW
Cost of imported power	= 6245.1967×1000×4.12×24 = Rs.6175250497
Therefore, cost savings per week	= Rs.61.75250497 crore

Case- 3: One month scheduling

The generation cost evaluation of the entire day can be done by changing the time slot from 00.30 to 24.00 hours in steps of one-hour time slots. Hence optimum production cost per day and for each day of a month can be obtained by aggregation of the optimal cost per half hourly time slots. In this work, variation in daily operating cost is not considered and is taken as constant. The operating cost details used in this work are detailed in Appendix VI-C.

Consumption	= **77973.750 MW**
Power imported by KSEB Ltd	= **49967.457 MW**
The optimal value for hydro generation	= 51375.6365 MW
Optimal value of thermal generation	= 2899.764 MW
Total optimal generation (hydro + thermal)	= 51375.6365+2899.764 = 54275.4005 MW
After optimization the required power to be imported	= 77973.750-54275.4005 = 23698.3495 MW
Therefore, reduction in imported power	= 49967.457-23698.3495 = 26269.1075 MW
Therefore, cost savings per month	= 26269.1075×1000×4.12×24 = Rs.259.748935 crore

This process is repeated for different months of the complete year to evaluate annual savings. The monthly saving that could have been obtained by using the optimal scheduling obtained by using PSO-TVIW for the months April 2015 to March 2016 is summarized as follows:

Case- 4: One year Scheduling

The optimal value of hydro generation for one year	= 625069.5053 MW
The optimal value of thermal generation for one year	= 37397.3333 MW
Total optimal generation (hydro + thermal)	= 625069.5053+37397.3333 = 662466.8386 MW
Cost of optimized generation	= $(625069.5053\times1000\times0.93\times24)$ + $(37397.333\times1000\times7.4241\times24)$
	= Rs.1395.155136 + 666.339658
	= Rs. 2061.494794 Crore
After optimization, the required imported power had been	= 951514.1667-662466.8386
	= **289047.3281 MW**
Therefore, reduction in required imported power	= 665043.5348-289047.3281 = 375996.2067 MW
Therefore, cost savings for one year	= $375996.2067\times1000\times4.12\times24$ = Rs. 3717.85049 crore.

Table 5.1 shows the details of hydro and thermal generation of one day, one week, one month and one year in KSEB Ltd. The numerical values of imported power and cost of imported power are also shown in Table 5.1.

Table 5.1: Details of generation, consumption and imported power for one day, one week, one month and one year of KSEB Ltd.

	ONE DAY	ONE WEEK	ONE MONTH	ONE YEAR
Hydro Generation	958 MW,	6447.9 MW	26084.5029 MW	280036.828 MW
Thermal Generation	54.462 MW	714.0 MW	1921.791 MW	6433.8039 MW
Total Generation	1012.462 MW	7161.9 MW	28006.2939 MW	286470.6319 MW
Consumption	3231 MW	23205 MW	77973.750 MW	951514.1667 MW
Imported power	2218.538 MW	16043.1 MW	49967.457 MW	665043.5348 MW
Cost of imported Power	Rs.21.9369 crore	Rs.158.634 crore	Rs.494.0782crore	Rs. 6575.950472 crore

Table 5.2 shows the details of summarized numerical results of optimized values of hydro and thermal generation by GA method for one day, one week, one month and one year. Consumption details for the same period, the reduction in imported power and savings on cost of imported power are also shown in the table.

Table 5.2: Details of optimized power generation and cost based on GA

	ONE DAY	ONE WEEK	ONE MONTH	ONE YEAR
Hydro Generation	1728.806 MW	11987.58 MW	43937.607 MW	536028.512 MW
Thermal Generation	86.58587 MW	929.6748 MW	2714.789 MW	36384.083 MW
Total Generation	1815.3918 MW	12917.2548 MW	46652.396 MW	572412.595 MW
Consumption	3231 MW	10287.7452 MW	77973.750 MW	951514.1667 MW
Reduction in Imported power	802.9298 MW	5755.35 MW	18646.103 MW	285941.9631 MW
Savings on cost of imported power	Rs. 7.9393698 crore	Rs.56.9089482 crore	Rs.184.372666crore	Rs.2827.394131crore

Table 5.3 shows the details of optimized values of hydro and thermal generation, consumption of power on the mentioned period, reduction in imported power and savings of cost reduced by using PSO method.

Table 5.3: Details of optimized power generation and cost based on PSO

	ONE DAY	ONE WEEK	ONE MONTH	ONE YEAR
Hydro Generation	1797.73 MW	12404.7 MW	51375.6365 MW	625069.5053 MW
Thermal Generation	98.1861 MW	1002.396 MW	2899.764 MW	37397.3333 MW
Total Generation	1895.9161 MW	13407.096 MW	54275.4005 MW	662466.8386 MW
Consumption	3231 MW	13407.0967 MW	77973.750 MW	951514.1667 MW
Reduction in Imported power	883.455 MW	6245.1967 MW	26296.1075 MW	375996.2067 MW
Saving of cost of Imported power	Rs.8.7356030 crore	Rs.61.752509 crore	Rs.259.748935 crore	3717.8504 crore

Table 5.4 shows the computational time for PSO and GA method for hydro and thermal generation on one day, one week, one month and one year.

Table 5.4: Computational Time for GA and PSO

OPTIMIZATION ALGORITHM	ONE DAY	ONE WEEK	ONE MONTH	ONE YEAR
PSO - HYDRO	40 seconds	4 minutes and 30 seconds	16 minutes and 20 seconds	3 hours and 10 minutes
GA- HYDRO	1 minutes and 50 seconds	6 minutes and 40 seconds	30 minutes and 20 seconds	7 hours and 10 minutes
PSO-THERMAL	20 seconds	2 minutes and 10 seconds	7 minutes and 25 seconds	1 hour and 20 minutes
GA-THERMAL	1 minutes and 06 seconds	5 minutes and 20seconds	20 minutes and 20 seconds	3 hours and 6 minutes

Table 5.5 shows the optimized cost of hydro and thermal generation with respect to the methods of PSO and GA. The total optimized cost of hydro generation and thermal generation are also shown.

Table 5.5: Details of optimized cost of power generation based on PSO & GA

Month	**Optimized hydro generation cost in RS. PSO**	**Optimized cost of thermal generation Rs. PSO**	**Total optimized cost in Rs. PSO**	**Optimized hydro cost in RS. GA**	**Optimized cost of Thermal generation Rs. GA**	**Total optimized cost Rs. GA**
Apr-15	1146704207	299812480.1	1446516687	980687388.7	291688760	1272376149
May-15	1184931007	299812480.1	1484743487	1013365278	291688760	1305054038
Jun-15	1146700281	299812480.1	1446512761	980656688.9	291688760	1272345449
Jul-15	1184949446	224989600.1	1409939046	1013322674	218900880	1232223554
Aug-15	1184924041	224989600.1	1409913641	1013375185	218900880	1232276065
Sep-15	1146693984	224989600.1	1371683584	980690090.5	218900880	1199590971
Oct-15	1184919003	224989600.1	1409908603	1013348127	218900880	1232249007
Nov-15	1146700372	224989600.1	1371689972	1013347109	218900880	1232247989
Dec-15	1184914310	224989600.1	1409903910	947965446.4	218900880	1166866326
Jan-16	1184921325	1639721600	2824642925	1013365200	1595212080	2608577280
Feb-16	1070264440	1639721600	2709986040	980654926.7	1595212080	2575867007
Mar-16	1184928943	1777124800	2962053743	1013378279	1729098800	2742477079
Total	13951551357	7305943041	21257494398	11964156394	7107994520	1.9072E+10

Figure 5.5 shows the comparison of monthly optimized cost of hydro and thermal generation by using PSO and GA.

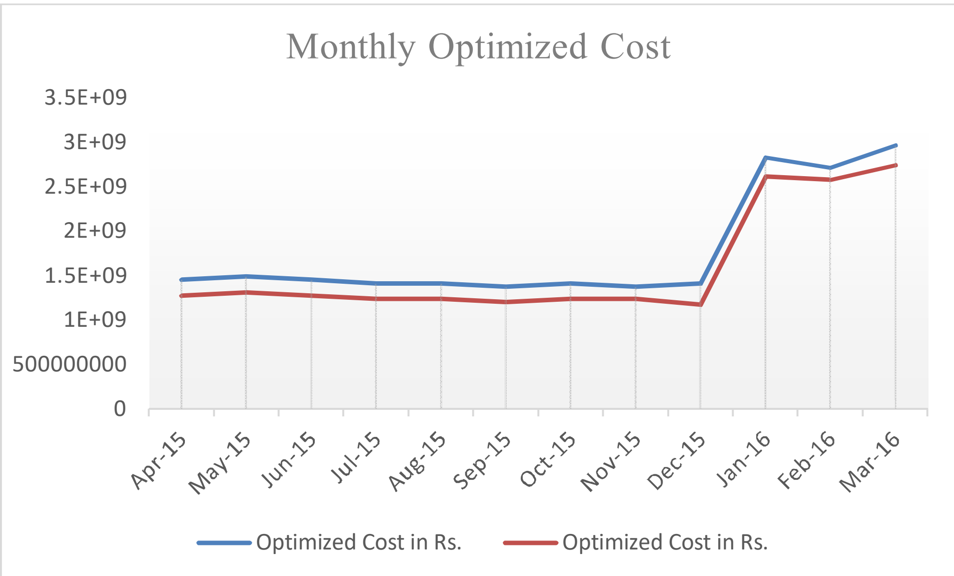


Figure 5.5: Monthly optimized cost of power by using PSO and GA

From the comparison of the total optimized cost of the above two methods the power generation is more in the case of PSO method than in the GA method.

Table 5.6 shows the monthly savings of cost from April 2015 to March 2015 by using the optimization method for reducing the imported cost of power in KSEB Ltd.

Table 5.6: Optimized cost savings of power generation based on PSO & GA

Total optimized cost in Rs.	Total expenditure by KSEB in Rs.	Savings in Rs.(PSO)	Total optimized cost in Rs.	Total expenditure by KSEB in Rs.	Savings in Rs. (GA)
1446516687	779795049.7	666721637.1	1272376149	779795049.7	492581099
1484743487	871173880.7	613569606.4	1305054038	871173880.7	433880157.7
1446512761	633371079.6	813141681	1272345449	633371079.6	638974369.3
1409939046	750066475.6	659872570.1	1232223554	750066475.6	482157078.8
1409913641	715895093.3	694018547.8	1232276065	715895093.3	516380972.1
1371683584	798253479.1	573430105.1	1199590971	798253479.1	401337491.4
1409908603	585372741.9	824535861.6	1232249007	585372741.9	646876265.2
1371689972	424869880	946820092.2	1232247989	424869880	807378109.1
1409903910	399764278	1010139632	1166866326	399764278	767102048.5
2824642925	394162310.6	2430480614	2608577280	394162310.6	2214414970
2709986040	425605860.8	2284380179	2575867007	425605860.8	2150261146
2962053743	674112635.5	2287941107	2742477079	674112635.5	2068364443

The Figure 5.6 shows the savings of cost of power generation by the use of PSO and GA optimization method. The detailed values of optimized cost of thermal and hydro generation and the power in MW are given in Appendix VI-B and VI-C. The power generation, cost of power generation and expenditure of KSEB Ltd. are shown in Appendix VI-D.

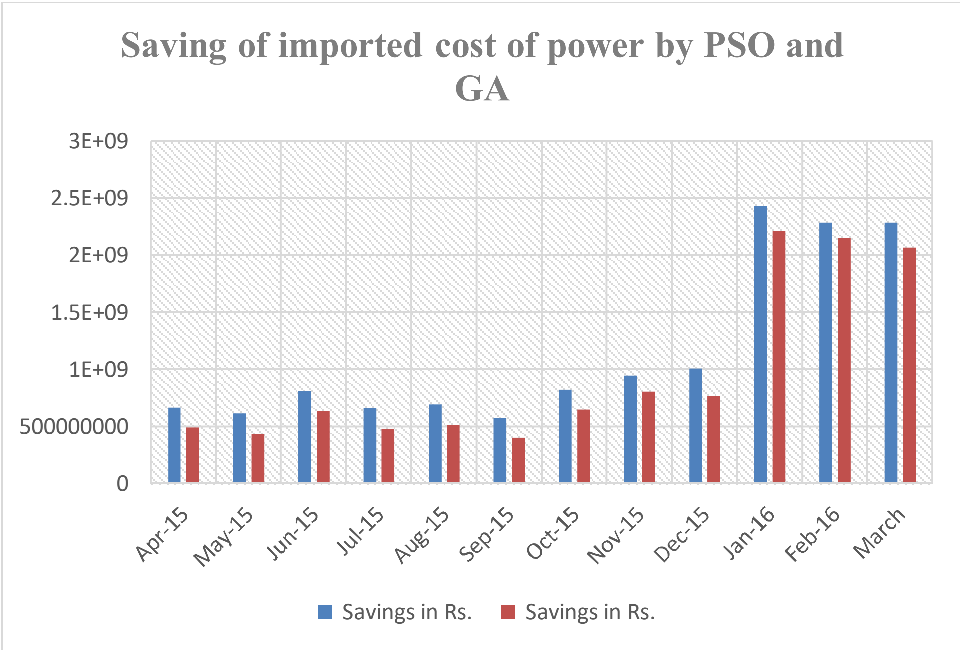


Figure 5.6: Monthly optimized cost savings of power by using PSO and GA

From this figure it is found that the savings of cost is more in PSO method than the GA method. This savings are based on the optimized cost of generation and total expenditure of KSEB Ltd. The average monthly cost savings used by PSO method are Rs. 115.04209 Crore and the average monthly cost savings by using GA method are Rs. 96.830901 Crore.

5.7 CONCLUSION

In this chapter, the cost optimization of Kerala power system based on economic load dispatch has been done. The particle swarm optimization and genetic algorithm are used as tools for solving the economic load dispatch problem. PSO-TVIW based optimum scheduling with STLF data has been carried out. The algorithm used in this program and the results in each are described in detail. Half-hourly economic scheduling and cumulative daily and monthly optimal cost evaluation and steps involved in yearly cost calculation are also described. It is clear from the result that the actual expenditure occurred in KSEB Ltd is higher than that obtained by using PSO and GA. That means, the total production cost of KSEB Ltd can be minimized by applying the above two algorithms. The computational time for GA and PSO algorithms is shown in Table 5.4.

From the above results, it can be seen that the two algorithms are good. However, the generation cost and optimized generation cost are calculated with GA and PSO algorithms. After the optimization process, a total reduction of imported power and corresponding cost savings are estimated for the period of one day, one week, one month and one year. The savings of imported cost is Rs. 7.93936 Crore per day by GA method and that of Rs.8.7356 crore per day by using PSO algorithm. Similarly, Rs.56.90894 Crore per week and Rs.184.372666 Crore per month by using GA and that of Rs.61.752504 Crore per week and Rs.259.89435Crore per month by using PSO. This shows that, in this work, the performance of PSO is better than GA.

CHAPTER 6

CONCLUSIONS AND FUTURE WORK

6.1 INTRODUCTION

The use of scientific tools for forecasting the load demand is of prime importance. The existing strategy followed by KSEB Ltd is the conventional method and not based on any scientific tools. This research work was an attempt to address the challenges of improvements to be made in load forecasting of Kerala power system and to utilize the forecasted demand of electrical power for optimization of load dispatch in view of the existing shortcomings. The data from KSEB Ltd, IMD etc., are utilized for executing this work.

A thorough review of literature on state-of-the-art of Kerala power system, load forecasting and optimization of load dispatch are carried out. Different types of soft tools used in load forecasting and optimization are analyzed. The major research challenge is to predict the timely demand so as to find an adequate resource in advance. This research study successfully carried out the demand forecasting of Kerala power system with the application of neural network, which is found to be the best tool for load forecasting.

The strategy adopted by KSEB Ltd is to fill the deficiency of power through power purchase agreement, which resulted in huge financial loss due to lack of proper scheduling. This research work evaluated a PSO based coordinative economic dispatch with forecasted demand pattern and showed an improved revenue compared to the existing scheduling strategy. The summary of the research findings is followed in the next section.

6.2 SUMMARY OF THE FINDINGS

The motivation behind this work on load forecasting and cost optimization is that the KSEB Ltd has been running at huge loss due to the power purchase for meeting the demand of the State. On analyzing the state-of-the-art of Kerala power system, it is evident that there is a need for using scientific tools in demand forecasting. Thus, the thesis addresses the problem of lack of scientific tools in load forecasting techniques adopted by KSEB Ltd., and identified the ANN as an appropriate tool for this purpose. The forecasted demand, with the selected scientific tools, is used in this study for cost optimization which resulted in reducing the cost of generation to a great extent. This can, in turn, reduce the import of power.

Different patterns of short-term load forecasting have been done. They are: one hour ahead, six hours ahead, one-day ahead, one week ahead, one month ahead and one year ahead. For load forecasting, a non-linear load model is proposed and the weights are estimated using a back-propagation learning algorithm. The performance of the ANN is evaluated and compared with time series, multiple linear regression and SVR models for the short-term and mid-term load forecasting. The performance of the ANN is also evaluated in long- term load forecasting. The major performance evaluation parameters taken are: MAPE, MAE, MSE, RMSE and MPE. The cost optimization of Kerala power system based on economic load dispatch has been carried out by using PSO and GA.

The strategy adopted by KSEB Ltd is to fill the deficiency of power through power purchase agreement and existing strategies like reserving the storage of water in reservoirs for the use in summer season. For prediction of the load demand of a day is calculated by KSEB Ltd on the basis of the demand of that day in the previous week and previous year. This calculation is subjected to the occurrence of rain during previous day, week or year. The present strategy adopted by the KSEB Ltd is not accurate due to the lack of using scientific tools for predicting the load. Therefore, an efficient load forecasting methodology based on scientific tools and the use of the forecasted data in the cost optimization are the felt necessities for the economic operation of Kerala power system.

6.2.1 Application of Times Series, Multiple Linear Regression, ANN and Support Vector Regression for demand forecasting of Kerala power systems.

The application of statistical methods of time series and multiple linear regression for load forecasting in Kerala power system is carried out. The autocorrelation and partial autocorrelation function for transformed data with first difference of the residuals are obtained. Multiple regression technique is used to model the relationship between dependent variable that is to be taken as consumption and independent variables as weather factors. The weather data (temperature, rainfall and humidity) were obtained from Indian Meteorological Department, Thiruvananthapuram. The performance evaluation of these tools is carried out and compared with error prediction parameters. The calculated values of MAE, MSE, MAPE, RMSE and MPE show that the error in time series model is less than that of multiple linear regression model.

The application of artificial intelligence techniques such as neural network and SVR for demand forecasting pertaining to Kerala power system is evaluated. An attempt is made for demand forecasting of both short term and mid-term with support vector regression technique. Demand forecasting of short term, mid-term and long-term is made with artificial neural network. In this work, back propagation-based ANN is selected for analysis.

In short term forecasting there are one hour ahead, six hours ahead, one day and one week ahead are predicted by ANN and the percentage error is found to be varying with in a band of +8% and -8%. Support vector regression is used for short term and mid-term load forecasting. The maximum percentage error in support vector machine varies from +4.5% to -3.15%. In mid-term load forecasting of one month ahead and one year ahead, the percentage error is 1.69 and 1.98 respectively. Therefore, ANN is more suitable method for load forecasting than support vector regression. For long term load forecasting the ANN is applied for five years and ten years ahead. There is a high difference in predicted load and actual load which shows that energy requirement is increasing year by year. Table 6.1 shows the results of all the above-mentioned load forecasting methods.

Table 6.1 Results of Load forecasting methods

Load forecasting methods	Period														
	2014					2015					2016				
Error parameters	MAE	MAPE	MSE	RMSE	MPE	MAE	MAPE	MSE	RMSE	MPE	MAE	MAPE	MSE	RMSE	MPE
Time Series	164.899	15.9072	177095	420.8275	-15.7888	174.65	17.57	203619	451.242	-16.5529	131.1829	5.0351	26248	162.0138	0.22954
MLR	120.2385	5.79458	31063.07	153.61	-3.18771	195.2435	9.142	69230.85	263.1176	-3.72727	184.9083	8.94653	73768.46	271.6027	-5.06388
ANN	35.0175	1.2826	3576.6525	50.7607	0.216	28.0175	1.3837	1891.1952	43.4878	0.2311	31.5506	1.3875	1980.6084	44.504	0.365
SVR	41.8466	1.7365	2905.3215	53.901	0.5632	33.2331	1.4044	1984.2151	44.5445	0.6731	33.0756	1.3659	2047.1748	45.2457	0.8712
Period	One day ahead (April 01, 2014)					One day ahead (April 01, 2015)					One day ahead (April 01, 2016)				
ANN	35.0175	1.2826	3576.6525	50.7607	0.216	28.0175	1.3837	1891.1952	43.4878	0.2311	31.5506	1.3875	1980.6084	44.504	0.365
SVR	41.8466	1.7365	2905.3215	53.901	0.5632	33.2331	1.4044	1984.2151	44.5445	0.6731	33.0756	1.3659	2047.1748	45.2457	0.8712
Period	One week ahead (April 01-07, 2014)					One week ahead (April 01-07, 2015)					One week ahead (April 01-07, 2016)				
ANN	37.3845	1.3734	2864.026	53.5165	0.2143	30.042	2.1869	2318.3367	48.1499	0.6511	32.4584	1.3822	2292.3605	47.876	0.8305
SVR	41.8466	1.7365	2905.3215	53.901	0.4376	33.645	2.42	2114.5691	45.9844	0.7942	34.5066	1.4302	2243.4271	47.3648	0.8623
Period	One month ahead (April 2014)					One month ahead (April 2015)					One month ahead (April 2016)				
ANN	38.3468	1.7322	1969.5583	44.3797	0.4328	35.4029	0.1155	1971.2105	44.3983	0.389	33.8342	1.2419	2457.707	49.5752	0.2197
SVR	40.1083	1.697	2102.9247	45.8577	0.658	34.1123	1.4128	2173.858	46.6246	0.5477	33.6775	1.4216	2106.5705	45.8974	0.542
Period	One year ahead (April 2014-March 2015)					One year ahead (April 2015-March 2016)					One year ahead (April 2016-March 2017)				
ANN	43.3657	11.8951	3978.7713	63.0775	0.35409	37.7022	1.4071	2010.0977	44.83	0.72681	31.0417	1.3554	5255.1884	72.4927	0.72681
SVR	84.056	Infinity	9876.5602	99.3809	0.6973	33.6775	1.4216	2106.5705	45.8974	0.8641	34.1123	1.4128	8277.6382	90.9815	0.9358

6.2.2 PSO based Co-ordinative Economic Dispatch of Kerala Power System

The optimized generation cost is calculated with GA and PSO algorithms. The results show that the actual expenditure incurred in KSEB Ltd is higher than that obtained by using PSO and GA.

For validation of the proposed technique the data for the year 2015 is selected. After the optimization process, a total reduction of imported power and corresponding cost savings are estimated for the period of one day, one week, one month and one year. The savings of imported cost are Rs. 7.93936 crore per day based on genetic algorithm optimization method and Rs.8.7356 crore per day by using PSO-TVIW algorithm. Similarly, Rs.56.90894 crore per week and Rs.184.372666 crore per month by using GA and Rs.61.752504 crore per week and Rs.259.748935 per month by using PSO respectively.

The study concludes that the total production cost of energy can be reduced by applying both GA and PSO-TVIW. It is observed that PSO-TVIW gives better results than GA. This thesis work concludes with a proposal to use ANN based scientific tools for load forecasting and the forecasted data are to be utilized for proper scheduling with intelligent techniques like PSO-TVIW. Thus, the KSEB Ltd can improve the revenue by decreasing the power purchase.

6.3 SUGGESTIONS

The research work evinced the necessity of using a scientific tool in demand forecasting of Kerala power system. The work attempted various methods for this purpose and confirmed ANN as the best tool and recommends it for demand forecasting, especially short-term load forecasting. The study concludes the requirement of proper scheduling with forecasted demand. Since Kerala power system is hydro based system, the operation and maintenance cost play an important role. The cost of imported power is one of the major factors which is to be considered for cost optimization. These are to be considered while selecting a scientific tool for scheduling and economic dispatch problem implementation. The work shows a substantial improvement in revenue considering these facts based on both GA and PSO-TVIW, which can be well utilized in implementing economic scheduling in KSEB Ltd.

6.4 RESEARCH IMPLICATIONS

This research work used ANN as the major tool for load demand prediction. It shows an abridged error compared to other scientific and statistical tools. This is an added advantage for stake holders, as the predicted demand affect the power purchase agreement and planning. Generation cost and optimized generation cost of KSEB Ltd with real data from the utility are calculated with GA and PSO algorithms. After the optimization process, a total reduction of imported power and corresponding cost savings are estimated that shows savings of crores of rupees on imported cost of power. Hence a proper economic scheduling tool as suggested in this work is required for any utility company.

6.5 RESEARCH CONTRIBUTIONS

The major contributions of the research work presented in the thesis are:

Successfully carried out the time series and multiple linear regression for load forecasting with real field data from KSEB Ltd and India Meteorological Department. The performance evaluation of time series and multiple linear regression are carried out with error reduction parameter. The error in time series model is found to be less than that of multiple linear regression.

Applied ANN and SVR for short-term, mid-term and long-term load forecasting with actual field data. ANN is found to be more suitable than SVR. Proved that the results are much useful for KSEB for load forecasting compared to the existing methods. The method can be extended for other similar industries as well.

Economic load dispatch and cost optimisation have been attempted with two major optimisation tool - Genetic Algorithm and Particle Swarm Optimisation. Application of Genetic Algorithm in cost optimisation and scheduling showed a total saving of Rs. 184.372666 crores per month with 2015 data from KSEB which is highly significant for power sector industries. Particle Swarm Optimisation is used as another major scientific optimisation tool for generation cost optimisation and the performance of GA is successfully compared and showed a total saving of Rs.259.748935 crores per month with same data.

Applied PSO-TVIW and GA based economic operation of Kerala hydro-thermal power system with forecasted demand and optimized the cost of generation. Compared GA with PSO-TVIW and found that PSO is better than GA. The actual cost of generation incurred by KSEB Ltd without using any scientific tool is much higher than that obtained by applying PSO and GA. By optimizing the cost of generation, the cost of imported power can be reduced to a great extent.

6.6 LIMITATIONS OF THE STUDY

As the generation pattern is changing gradually due to high penetration of renewable energy resources, which is intermittent in nature, a modification may be required in analysing such a power system with ANN. The study considers the transmission and distribution loss as a constant value. However, it is a variable. Improvement can be incorporated with a detailed T&D loss analysis.

Power import from various tie lines are taken as a single source as detailed data are not available. When the flood and the natural calamities occur the entire system collapses and as a result the load demand becomes very less. After immediate maintenance the system will start function and therefore the demand will also increase. Thus, the generation increases according to the demand. At this juncture the forecasted demand will not be conducive to the system.

6.7 SCOPE FOR FUTURE WORK

The present study represents an ideal scenario of cost effective and optimized economic load dispatch in Kerala power system and it is limited to the study of hydroelectric and thermal generation. Other modes of generations like, wind and solar are not under the purview of this research. The installed capacity of generators, from where the imported load is obtained, is not considered due the lack of appropriate data from KSEB Ltd. In this work the maintenance and shut down period for thermal generation is considered, but the annual maintenance period and other scheduled shut down periods are not considered for hydro generations. It is assumed that all hydro generating stations are available for generation throughout the period under consideration. A pilot project is to be implemented considering these points while implementing the proposed intelligence optimization methods.

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APPENDICES

Appendix I-A

Prediction error parameters by time series regression

TIME SERIES REGRESSION FOR 2014						
Actual	Predicted	MAPE	MAE	MSE	RMSE	MPE
2369.869	2664.58	12.43575	294.711	86854.57	294.711	-12.4358
2494.6	2491.13	0.1391	3.47	12.0409	3.47	0.1391
2402.7	2418.64	0.66342	15.94	254.0836	15.94	-0.66342
2210.2	2328.47	5.351099	118.27	13987.79	118.27	-5.3511
2385.8	2356.22	1.239836	29.58	874.9764	29.58	1.239836
2409.88	2487.24	3.210118	77.36	5984.57	77.36	-3.21012
2518.4	2772.16	10.07624	253.76	64394.14	253.76	-10.0762
2401.2	2649.55	10.34275	248.35	61677.72	248.35	-10.3427
2322.2	2627.6	13.15132	305.4	93269.16	305.4	-13.1513
2325.71	2848.27	22.46884	522.56	273069	522.56	-22.4688
2424.4	2654.17	9.477396	229.77	52794.25	229.77	-9.4774
2464.4	2840.15	15.24712	375.75	141188.1	375.75	-15.2471
2465.8	2885.05	17.0026	419.25	175770.6	419.25	-17.0026
2336.9	2852.69	22.07155	515.79	266039.3	515.79	-22.0715
2421.2	2965.93	22.49835	544.73	296730.8	544.73	-22.4983
2385.8	3002.4	25.84458	616.6	380195.6	616.6	-25.8446
2463.2	2960.9	20.20542	497.7	247705.3	497.7	-20.2054
2482.48	2755.36	10.99223	272.88	74463.49	272.88	-10.9922
2304.42	2755.36	19.56848	450.94	203346.9	450.94	-19.5685
2149.6	2755.36	28.18013	605.76	366945.2	605.76	-28.1801
2124	2755.36	29.72505	631.36	398615.4	631.36	-29.725
2044.34	2755.36	34.77993	711.02	505549.4	711.02	-34.7799
2119.3	2755.36	30.01274	636.06	404572.3	636.06	-30.0127
2255	2755.36	22.18891	500.36	250360.1	500.36	-22.1889
2518.569	2755.36	9.401807	236.791	56069.98	236.791	-9.40181
2515.222	2755.36	9.547388	240.138	57666.26	240.138	-9.54739
2766.355	2755.36	0.397454	10.995	120.89	10.995	0.397454
2245.58	2755.36	22.70148	509.78	259875.6	509.78	-22.7015
2218.53	2755.36	24.19755	536.83	288186.4	536.83	-24.1976
2220.29	2755.36	24.0991	535.07	286299.9	535.07	-24.0991
	Total	477.2177	10946.98	5312874	10946.98	-473.665
	Average	15.90726	364.8992	177095.8	364.8992	-15.7888

Appendix I-B

Prediction error parameters by time series regression

TIME SERIES REGRESSION FOR 2015						
Actual	Predicted	MAPE	MAE	MSE	RMSE	MPE
2335.98	2777.23	18.88929	441.25	194701.6	441.25	-18.8893
2515.222	2637.25	4.85158	122.028	14890.83	122.028	-4.85158
2766.355	2451.83	11.36965	314.525	98925.98	314.525	11.36965
2245.58	2686.1	19.6172	440.52	194057.9	440.52	-19.6172
2218.53	2817.75	27.00978	599.22	359064.6	599.22	-27.0098
2220.29	2690.35	21.17111	470.06	220956.4	470.06	-21.1711
2665.73	2930.93	9.948494	265.2	70331.04	265.2	-9.94849
2240.012	2572.5	14.84313	332.488	110548.3	332.488	-14.8431
2330.949	2524	8.282077	193.051	37268.69	193.051	-8.28208
2396.552	2689.97	12.24334	293.418	86094.12	293.418	-12.2433
2317.51	2800.39	20.83616	482.88	233173.1	482.88	-20.8362
2176.99	2833.1	30.1384	656.11	430480.3	656.11	-30.1384
2506.18	2727.09	8.81461	220.91	48801.23	220.91	-8.81461
2766.721	2872.63	3.827961	105.909	11216.72	105.909	-3.82796
2106.516	2722.57	29.24516	616.054	379522.5	616.054	-29.2452
2210.629	2748.16	24.31575	537.531	288939.6	537.531	-24.3157
2460.444	2778.07	12.9093	317.626	100886.3	317.626	-12.9093
2449.002	2708.38	10.59117	259.378	67276.95	259.378	-10.5912
1430	2768.67	93.61329	1338.67	1792037	1338.67	-93.6133
2013.09	2708.63	34.55086	695.54	483775.9	695.54	-34.5509
2464.492	2572.57	4.385407	108.078	11680.85	108.078	-4.38541
2188.73	2658.1	21.44486	469.37	220308.2	469.37	-21.4449
2455.29	2658.1	8.260124	202.81	41131.9	202.81	-8.26012
2581.71	2658.1	2.958892	76.39	5835.432	76.39	-2.95889
2518.569	2658.1	5.54009	139.531	19468.9	139.531	-5.54009
2515.222	2658.1	5.680532	142.878	20414.12	142.878	-5.68053
2766.355	2658.1	3.913272	108.255	11719.15	108.255	3.913272
2245.58	2658.1	18.37031	412.52	170172.8	412.52	-18.3703
2218.53	2658.1	19.81357	439.57	193221.8	439.57	-19.8136
2220.29	2658.1	19.7186	437.81	191677.6	437.81	-19.7186
	Total	527.154	11239.58	6108580	11239.58	-496.588
	Average	17.5718	374.6527	203619.3	374.6527	-16.5529

Appendix I-C

Prediction error parameters by time series regression

TIME SERIES REGRESSION FOR 2016						
Actual	Predicted	MAPE	MAE	MSE	RMSE	MPE
2274.4	2565.715	12.80843	291.315	84864.43	291.315	-12.8084
2886.717	2592.944	10.17672	293.773	86302.58	293.773	10.17672
2937.553	2589.323	11.85442	348.23	121264.1	348.23	11.85442
2810.311	2600.458	7.467252	209.853	44038.28	209.853	7.467252
2823.486	2598.523	7.967562	224.963	50608.35	224.963	7.967562
2590.666	2599.804	0.352728	9.138	83.50304	9.138	-0.35273
2591.735	2599.728	0.308403	7.993	63.88805	7.993	-0.3084
2536.566	2599.789	2.492464	63.223	3997.148	63.223	-2.49246
2643.144	2599.812	1.639411	43.332	1877.662	43.332	1.639411
2432.983	2599.81	6.856891	166.827	27831.25	166.827	-6.85689
2581.258	2599.814	0.718874	18.556	344.3251	18.556	-0.71887
2603.029	2599.814	0.12351	3.215	10.33623	3.215	0.12351
2348.91	2599.814	10.68172	250.904	62952.82	250.904	-10.6817
2425.405	2599.814	7.190923	174.409	30418.5	174.409	-7.19092
2342.721	2599.814	10.97412	257.093	66096.81	257.093	-10.9741
2527.985	2599.814	2.841354	71.829	5159.405	71.829	-2.84135
2595.357	2599.814	0.17173	4.457	19.86485	4.457	-0.17173
2453.458	2599.814	5.965295	146.356	21420.08	146.356	-5.96529
2610.019	2599.814	0.390993	10.205	104.142	10.205	0.390993
2488.72	2599.814	4.463901	111.094	12341.88	111.094	-4.4639
2714.653	2599.814	4.230338	114.839	13188	114.839	4.230338
2760.92	2599.814	5.835229	161.106	25955.14	161.106	5.835229
2766.721	2599.814	6.032659	166.9068	27857.89	166.9068	6.032659
2698.294	2599.814	3.649697	98.47954	9698.22	98.47954	3.649697
2733.042	2599.814	4.87471	133.2279	17749.67	133.2279	4.87471
2750.788	2599.814	5.488402	150.9743	22793.25	150.9743	5.488402
2446.721	2599.814	6.257048	153.0925	23437.33	153.0925	-6.25705
2638.99	2599.814	1.484523	39.17642	1534.792	39.17642	1.484523
2745.251	2599.814	5.297783	145.4375	21152.05	145.4375	5.297783
2665.297	2599.814	2.456885	65.48329	4288.061	65.48329	2.456885
	Total	151.054	3935.488	787453.8	3935.488	-473.665
	Average	5.035133	131.1829	26248.46	131.1829	0.22955

Appendix II-A

Prediction error parameters by multiple linear regression

MULTIPLE LINEAR REGRESSION FOR 2014						
Actual Load	Predicted load	MAPE	MAE	MSE	RMSE	MPE
2369.869	2389.929	0.84646029	20.06	402.4036	20.06	-0.84646
2494.6	2449.818	1.79515754	44.782	2005.428	44.782	1.795158
2402.7	2452.51	2.073084447	49.81	2481.036	49.81	-2.07308
2210.2	2463.276	11.45036648	253.076	64047.46	253.076	-11.4504
2385.8	2472.697	3.642258362	86.897	7551.089	86.897	-3.64226
2409.88	2447.127	1.545595631	37.247	1387.339	37.247	-1.5456
2518.4	2432.323	3.417924079	86.077	7409.25	86.077	3.417924
2401.2	2428.285	1.127977678	27.085	733.5972	27.085	-1.12798
2322.2	2426.939	4.510335027	104.739	10970.26	104.739	-4.51034
2325.71	2436.36	4.7576869	110.65	12243.42	110.65	-4.75769
2424.4	2421.556	0.117307375	2.844	8.088336	2.844	0.117307
2464.4	2409.444	2.229995131	54.956	3020.162	54.956	2.229995
2465.8	2433.668	1.303106497	32.132	1032.465	32.132	1.303106
2336.9	2430.977	4.025717831	94.077	8850.482	94.077	-4.02572
2421.2	2439.052	0.737320337	17.852	318.6939	17.852	-0.73732
2385.8	2463.276	3.247380334	77.476	6002.531	77.476	-3.24738
2463.2	2426.939	1.472109451	36.261	1314.86	36.261	1.472109
2482.48	2400.623	3.297388096	81.857	6700.568	81.857	3.297388
2304.42	2424.248	5.199920153	119.828	14358.75	119.828	-5.19992
2149.6	2390.602	11.21148121	241.002	58081.96	241.002	-11.2115
2124	2404.06	13.18549906	280.06	78433.6	280.06	-13.1855
2044.34	2373.106	16.08176722	328.766	108087.1	328.766	-16.0818
2119.3	2381.181	12.35695749	261.881	68581.66	261.881	-12.357
2255	2410.789	6.908603104	155.789	24270.21	155.789	-6.9086
2518.569	2439.052	3.157229363	79.517	6322.953	79.517	3.157229
2515.222	2463.276	2.065265014	51.946	2698.387	51.946	2.065265
2766.355	2426.939	12.26943035	339.416	115203.2	339.416	12.26943
2245.58	2400.623	6.904363238	155.043	24038.33	155.043	-6.90436
2218.53	2424.248	9.272716619	205.718	42319.9	205.718	-9.27272
2220.29	2390.602	7.670709682	170.312	29006.18	170.312	-7.67071
	Total	157.881114	3607.156	707881.4	3607.156	-95.6313
	Average	5.262703799	120.2385	23596.05	120.2385	-3.18771

Appendix II-B

Prediction error parameters by multiple linear regression

MULTIPLE LINEAR REGRESSION FOR 2015						
Actual	Predicted	MAPE	MAE	MSE	RMSE	MPE
2335.98	2440.693	4.482623995	104.7132	10964.85	104.7132	-4.48262
2515.222	2463.276	2.065265014	51.946	2698.387	51.946	2.065265
2766.355	2426.939	12.26943035	339.416	115203.2	339.416	12.26943
2245.58	2400.623	6.904363238	155.043	24038.33	155.043	-6.90436
2218.53	2424.248	9.272716619	205.718	42319.9	205.718	-9.27272
2220.29	2390.602	7.670709682	170.312	29006.18	170.312	-7.67071
2665.73	2404.06	9.816072896	261.67	68471.19	261.67	9.816073
2240.012	2373.106	5.941664598	133.094	17714.01	133.094	-5.94166
2330.949	2381.181	2.155002104	50.232	2523.254	50.232	-2.155
2396.552	2410.789	0.594061802	14.237	202.6922	14.237	-0.59406
2317.51	2385.219	2.921627091	67.709	4584.509	67.709	-2.92163
2176.99	2378.49	9.2558992	201.5	40602.25	201.5	-9.2559
2506.18	2362.34	5.739412173	143.84	20689.95	143.84	5.739412
2766.721	2379.836	13.98352056	386.885	149680	386.885	13.98352
2106.516	2377.144	12.84718464	270.628	73239.51	270.628	-12.8472
2210.629	2385.219	7.897752178	174.59	30481.67	174.59	-7.89775
2460.444	2387.91	2.948004507	72.534	5261.181	72.534	2.948005
2449.002	2395.985	2.164841025	53.017	2810.802	53.017	2.164841
1430	2400.023	67.83377622	970.023	940944.6	970.023	-67.8338
2013.09	2402.714	19.35452464	389.624	151806.9	389.624	-19.3545
2464.492	2412.135	2.124454046	52.357	2741.255	52.357	2.124454
2188.73	2418.864	10.51449928	230.134	52961.66	230.134	-10.5145
2455.29	2405.406	2.03169483	49.884	2488.413	49.884	2.031695
2581.71	2391.948	7.350244605	189.762	36009.62	189.762	7.350245
2518.569	2425.593	3.691620122	92.976	8644.537	92.976	3.69162
2515.222	2401.369	4.526558689	113.853	12962.51	113.853	4.526559
2766.355	2420.21	12.51267462	346.145	119816.4	346.145	12.51267
2245.58	2402.714	6.997479493	157.134	24691.09	157.134	-6.99748
2218.53	2422.902	9.212045814	204.372	41767.91	204.372	-9.21205
2220.29	2424.248	9.186097312	203.958	41598.87	203.958	-9.1861
	Total	274.2658213	5857.306	2076926	5857.306	-111.818
	Average	9.142194045	195.2435	69230.85	195.2435	-3.72727

Appendix II-C

Prediction error parameters by multiple linear regression

MULTIPLE LINEAR REGRESSION FOR 2016						
Actual	Predicted	MAPE	MAE	MSE	RMSE	MPE
2274.4	2449.818	7.712707	175.4178	30771.4	175.4178	-7.71271
2886.718	2424.248	8.224777	462.4697	33942.9	462.4697	-8.22478
2937.554	2424.248	4.002619	513.3055	8704.703	513.3055	-4.00262
2810.311	2416.173	0.818718	394.1385	384.9836	394.1385	-0.81872
2823.486	2400.023	3.560416	423.4632	6808.395	423.4632	-3.56042
2590.667	2414.827	10.92504	175.8397	56566.44	175.8397	-10.925
2591.735	2410.789	3.806231	180.9462	9099.443	180.9462	3.806231
2536.567	2404.06	13.10797	132.5069	131523	132.5069	13.10797
2643.145	2408.098	14.31663	235.0468	90951.7	235.0468	-14.3166
2432.984	2418.864	9.419717	14.11975	43361.82	14.11975	-9.41972
2581.259	2443.089	0.70536	138.17	301.196	138.17	0.70536
2603.029	2459.239	0.418007	143.7902	104.7962	143.7902	-0.41801
2348.91	2429.631	69.90427	80.72079	999262.1	80.72079	-69.9043
2425.405	2459.239	22.1624	33.83379	199048.9	33.83379	-22.1624
2342.721	2453.856	0.43157	111.1348	113.1245	111.1348	0.43157
2527.985	2457.893	12.29768	70.09221	72448.72	70.09221	-12.2977
2595.358	2469.837	0.592476	125.5209	211.6152	125.5209	-0.59248
2453.459	2416.005	6.41842	37.45375	27458.15	37.45375	6.41842
2610.02	2383.705	8.708025	226.3148	36460.37	226.3148	-8.70802
2488.72	2395.817	2.975235	92.90321	5397.4	92.90321	2.975235
2714.653	2418.696	4.506939	295.9571	13031.14	295.9571	4.506939
2760.92	2456.379	0.181735	304.541	19.85594	304.541	-0.18173
2766.721	2401.2	22.96064	365.5208	201044.6	365.5208	-22.9606
2698.294	2414.659	2.848168	283.6345	4471.463	283.6345	-2.84817
2733.042	2406.584	6.952294	326.4579	32333.07	326.4579	6.952294
2750.788	2422.734	5.663865	328.0543	16864.92	328.0543	-5.66386
2446.721	2333.909	15.15773	112.8125	173864.8	112.8125	15.15773
2638.99	2395.649	3.057815	243.3414	5052.509	243.3414	-3.05782
2745.251	2364.695	2.38038	380.5565	3022.8	380.5565	-2.38038
2665.297	2340.47	4.178062	324.8273	10414.2	324.8273	4.178062
	Total	268.3959	6964.971	2213041	6964.971	-151.916
	Average	8.94653	232.1657	73768.02	232.1657	-5.06388

Appendix III-A

One day ahead actual and predicted demand values of April 02, 2015

APRIL 02, 2015								
Time	Actual	Predicted	Time	Actual	Predicted	Time	Actual	Predicted
00:30	2209.5	2033.696	08:30	2415.03	2388.371	16:30	2745.34	2753.822
01:00	2243.7	2271.381	09:00	2527.34	2492.341	17:00	2711.36	2759.224
01:30	2354.1	2367.233	09:30	2554.7	2446.488	17:30	2583.49	2471.245
02:00	2310.2	2323.702	10:00	2639.4	2552.056	18:00	2497.5	2429.706
02:30	2287.9	2331.478	10:30	2710.69	2539.408	18:30	2636.6	2486.637
03:00	2261.7	2171.718	11:00	2725.89	2740.424	19:00	3124.09	3047.274
03:30	2285.2	2163.065	11:30	2815.69	2781.773	19:30	3248.71	3034.118
04:00	2153.2	2117.885	12:00	2773.28	2620.076	20:00	3281.56	3230.121
04:30	2201	2032.778	12:30	2820.73	2814.678	20:30	3235.29	3112.72
05:00	2277.2	2306.25	13:00	2791.98	2690.743	21:00	3241.8	3248.818
05:30	2356	2381.652	13:30	2808.3	2586.708	21:30	3281.3	3222.234
06:00	2543.4	2446.439	14:00	2825.43	2640.185	22:00	3263.63	3166.554
06:30	2573.9	2372.929	14:30	2915.9	2805.21	22:30	3201.46	2995.508
07:00	2579.77	2559.888	15:00	2854.18	2890.046	23:00	2960.5	2820.93
07:30	2467.9	2495.039	15:30	2848.29	2684.141	23:30	2784.59	2753.391
08:00	2430.38	2381.668	16:00	2788.34	2820.22	24:00	2640.81	2637.785

Appendix III-B

One day ahead actual and predicted demand values of November 23, 2015

NOVEMBER 23, 2015

Time	Actual	Predicted	Time	Actual	Predicted	Time	Actual	Predicted
00:30	2028.3	2069.59	08:30	2363.908	2367.3	16:30	2451.48	2545.26
01:00	1969.3	2057.1	09:00	2172.645	2164.6	17:00	2407.38	2499.8
01:30	1988.6	2008.62	09:30	2309.249	2320.6	17:30	2419.22	2526.3
02:00	2027.7	1989.9	10:00	2352.331	2339.2	18:00	2896.92	2849.69
02:30	1888.9	1987.4	10:30	2300.672	2357.8	18:30	3160.03	3128.9
03:00	1882.2	1966.1	11:00	2395.438	2398	19:00	3043.48	3124.8
03:30	1920.5	1962.1	11:30	2434.154	2408.8	19:30	2870.23	3119.6
04:00	1849.7	1971.9	12:00	2527.367	2527.1	20:00	2924.51	3078.1
04:30	1854.5	2005.5	12:30	2486.362	2450.2	20:30	2936.92	3058.6
05:00	2045.7	2089.69	13:00	2398.77	2469.3	21:00	2992.93	3045
05:30	2165.8	2212.8	13:30	2293.971	2431.34	21:30	3026.84	3000.5
06:00	2277.6	2393.8	14:00	2513.481	2466.46	22:00	2890.86	2931.1
06:30	2532.1	2549.5	14:30	2421.482	2550.92	22:30	2655.72	2677.5
07:00	2406.9	2544.3	15:00	2353.701	2551.5	23:00	2410.13	2484.9
07:30	2432.4	2417.7	15:30	2365.471	2509.9	23:30	2223.61	2332.48
08:00	2246.6	2404.1	16:00	2500.795	2559.95	24:00	2201.72	2210.1

Appendix III-C

June 02,2013 Weekend Day

Time	Actual	Predicted	Time	Actual	Predicted
00:30	1894.5	1633.596	12:30	1496.06	1570.863
01:00	1858.65	1951.583	13:00	1472.12	1545.726
01:30	1832.77	1924.409	13:30	1492.04	1566.642
02:00	1779.54	1868.517	14:00	1454.35	1527.068
02:30	1755.81	1663.66	14:30	1467.75	1541.138
03:00	1649.11	1632.875	15:00	1457.34	1530.207
03:30	1651.92	1734.516	15:30	1503.64	1578.822
04:00	1630.02	1711.521	16:00	1499.57	1574.549
04:30	1615	1695.75	16:30	1574.75	1653.488
05:00	1645.43	1479.038	17:00	1701.27	1786.334
05:30	1725.92	1812.216	17:30	1882.57	1976.699
06:00	1778.12	1867.026	18:00	1977.32	1652.428
06:30	1874.38	1968.099	18:30	2213.94	2104.282
07:00	1845.2	1937.46	19:00	2343.64	2460.822
07:30	1802.7	1465.892	19:30	2116.01	2221.811
08:00	1745.67	1832.954	20:00	2023.89	2125.085
08:30	1745.5	1622.355	20:30	2033.99	2135.69
09:00	1768.91	1475.69	21:00	2098.87	2203.814
09:30	1660.64	1743.672	21:30	2111.96	1911.931
10:00	1603.48	1683.654	22:00	2049.12	2151.576
10:30	1616.6	1697.43	22:30	1903.88	1999.074
11:00	1545.67	1622.954	23:00	1763.34	1851.507
11:30	1556.58	1634.409	23:30	1578.8	1657.74
12:00	1547.71	1394.237	24:00	1503.7	1489.317

Appendix IV

One day ahead prediction of load demand by using SVR

APRIL 01, 2014, ONE DAY AHEAD								
Time	Actual	Predicted	Time	Actual	Predicted	Time	Actual	Predicted
00:30	2651.47	2283.5	08:30	2578.6	2293.2	16:30	2545.63	2301.8
01:00	2543.51	2269.9	09:00	2621.45	2285.1	17:00	2551.58	2315.6
01:30	2410.3	2264.3	09:30	2649.2	2276.1	17:30	2467.51	2322.3
02:00	2428.85	2259.6	10:00	2719.1	2282.8	18:00	2461.34	2390.9
02:30	2388.86	2260.1	10:30	2746.1	2266.6	18:30	2613.81	2455.3
03:00	2364.6	2254.6	11:00	2752.7	2272.8	19:00	3005.29	2448.1
03:30	2337.83	2254.8	11:30	2783.1	2275.3	19:30	3173.39	2470.4
04:00	2343.9	2248.3	12:00	2817.68	2285.3	20:00	3144.2	2449.6
04:30	2434.59	2248.4	12:30	2816.86	2277.5	20:30	3175.61	2445.9
05:00	2380.69	2256.3	13:00	2820.31	2284.1	21:00	3185.89	2443
05:30	2468.57	2287.8	13:30	2875.13	2274	21:30	3100.48	2422.8
06:00	2649.5	2333	14:00	2892.37	2275.6	22:00	3096.22	2391.9
06:30	2665.88	2352.9	14:30	2913.88	2272.4	22:30	2992.4	2355.2
07:00	2674.68	2357.9	15:00	2925.85	2284.9	23:00	2859.44	2311.6
07:30	2612.56	2352	15:30	2812.43	2278.9	23:30	2669.07	2281
08:00	2552.6	2303.3	16:00	2675.98	2294.6	24:00	2534.05	2255.5

Appendix V-A
Kerala State Electricity Board Ltd.

Date	01.04.2015	02.04.2015	03.04.2015	04.04.2015	05.04.2015	06.04.2015	07.04.2015	08.04.2015	09.04.2015	10.04.2015	11.04.2015	12.04.2015	13.04.2015	14.04.2015	15.04.2015	16.04.2015	17.04.2015	18.04.2015	19.04.2015	20.04.2015	21.04.2015	22.04.2015	23.04.2015	24.04.2015	25.04.2015	26.04.2015	27.04.2015	28.04.2015	29.04.2015	30.04.2015
Time	Hydro Gen. (MW)	Hydro Gen. (MW)	Hydro Gen. (MW)	Hydro Gen. (MW)	Hydro Gen. (MW)	Hydro Gen. (MW)	Hydro Gen. (MW)	Hydro Gen. (MW)	Hydro Gen. (MW)	Hydro Gen. (MW)	Hydro Gen. (MW)	Hydro Gen. (MW)	Hydro Gen. (MW)	Hydro Gen. (MW)	Hydro Gen. (MW)	Hydro Gen. (MW)	Hydro Gen. (MW)	Hydro Gen. (MW)	Hydro Gen. (MW)	Hydro Gen. (MW)	Hydro Gen. (MW)	Hydro Gen. (MW)	Hydro Gen. (MW)	Hydro Gen. (MW)	Hydro Gen. (MW)	Hydro Gen. (MW)	Hydro Gen. (MW)	Hydro Gen. (MW)	Hydro Gen. (MW)	Hydro Gen. (MW)
01:00	850	597	741	624	785	816	870	732	846	773	449	688	514	563	569	633	717	463	544	567	801	341	743	804	544	728	621	750	742	728
02:00	675	688	672	527	735	708	740	572	775	697	458	618	406	488	476	479	521	426	464	547	757	264	575	698	464	656	451	692	741	656
03:00	623	676	547	454	711	657	742	555	685	573	398	616	468	439	466	462	474	391	554	533	723	247	536	675	554	620	509	672	698	620
04:00	582	548	509	450	789	662	668	632	599	543	409	427	399	435	456	418	440	392	395	488	593	224	665	647	395	567	418	586	642	567
05:00	642	621	576	509	726	636	785	446	739	569	440	448	404	420	492	489	408	435	365	443	624	215	507	674	365	572	426	618	651	572
06:00	913	858	714	470	791	785	942	663	888	717	763	661	457	557	745	620	628	652	425	747	791	417	773	816	425	692	694	842	882	692
07:00	988	917	763	614	763	802	902	672	976	795	695	603	521	670	678	713	643	663	587	758	922	522	820	859	587	759	796	902	857	759
08:00	853	699	662	577	646	843	729	701	911	673	661	588	499	555	521	696	601	573	482	686	781	478	778	820	482	705	618	825	802	705
09:00	837	905	731	586	585	925	658	550	854	682	667	551	547	546	534	754	818	661	614	812	815	493	768	813	614	749	722	821	822	749
10:00	865	915	671	774	611	911	783	491	922	478	923	533	758	676	574	872	800	666	750	982	948	547	882	879	750	918	683	900	896	918
11:00	934	965	739	806	635	990	847	476	950	684	944	559	852	1016	573	815	837	710	798	1000	959	133	945	928	798	1002	760	864	729	1002
12:00	983	999	776	883	645	1136	860	564	1015	863	1033	599	958	871	611	974	1083	908	1072	974	1056	637	886	1057	1072	1062	817	1021	840	1062
13:00	1065	1031	762	938	646	1003	949	773	1021	869	1034	601	1051	930	626	917	958	914	1062	1057	1097	1157	994	1026	1062	1060	835	712	1009	1060
14:00	1116	1039	764	988	667	1102	991	721	1180	1061	1075	546	1051	1148	658	956	1004	963	1138	1084	817	1242	1019	1142	1138	1055	874	666	1030	1055
15:00	1147	1089	862	1020	712	1253	1050	821	1165	968	1129	661	1133	1000	651	1006	1124	1125	1134	1193	702	1196	1065	1207	1134	1136	1059	719	1079	1136
16:00	980	1076	826	1163	755	1110	1000	760	831	899	966	588	1101	895	703	936	1102	983	1048	1095	665	1253	1032	1087	1048	1014	921	738	1046	1014
17:00	843	1025	573	932	702	1032	633	749	731	795	759	540	999	893	671	822	968	898	957	1051	626	1093	1013	790	957	878	789	820	982	878
18:00	756	719	564	794	692	913	602	686	844	652	661	452	788	676	589	716	808	740	856	924	614	738	906	680	856	928	811	684	834	928
19:00	1289	1302	1158	1458	1229	1492	1093	1447	1196	1032	1217	948	1396	1251	1265	1177	1414	1329	1346	1203	693	1400	1388	954	1346	1131	1300	944	1335	1131
20:00	1342	1401	1287	1740	1417	1611	1279	1531	1247	1246	1261	1077	1528	1465	1345	1289	1501	1469	1482	1486	601	1536	1557	917	1482	1165	1332	967	1437	1165
21:00	1440	1547	1452	1528	1446	1402	1294	1540	1296	1380	1347	1113	1489	1443	1382	1278	1438	1477	1413	1360	645	1510	1209	811	1413	1163	1514	981	1087	1163
22:00	1255	1471	1267	1620	1435	1592	1426	1542	1317	1213	1378	958	1441	1250	1466	1335	1350	1455	1371	1405	743	1516	1507	963	1371	1178	1367	914	1112	1178
23:00	1194	1238	1194	1485	1301	1485	1074	1313	1216	1098	1256	996	1077	1246	1171	1006	1107	1287	1196	1263	645	1264	1260	857	1196	1085	1203	899	1157	1085
24:00	821	919	778	1026	881	999	880	1038	871	707	854	689	781	761	804	780	749	986	840	945	454	825	933	669	840	747	865	825	852	747
	22992	23246	19587	21964	20303	24863	21795	19973	23075	19967	20776	16061	20616	20193	18029	20147	21494	20564	20891	22603	18072	19246	22760	20770	20891	21571	20383	19363	22264	21571
	957.9908333	968.5683333	816.12375	915.14875	845.9433333	1035.958333	908.145	832.2208333	961.455	831.9683333	865.6541667	669.2266667	859.0066667	841.3608333	751.1958333	839.4604167	895.6020833	856.8475	870.44	941.81	752.985	801.8970833	948.3170833	865.41625	870.44	898.78625	849.2845833	806.7958333	927.6679167	898.78625
	Dy Chief Engineer(Grid)		Dy Chief Engineer(Grid)	Dy Chief Engineer(Grid)	Dy Chief Engineer(Grid)	Dy Chief Engineer(Grid)	Dy Chief Engineer(Grid)	Dy Chief Engineer(Grid)	Dy Chief Engineer(Grid)	Dy Chief Engineer(Grid)	Dy Chief Engineer(Grid)	Dy Chief Engineer(Grid)	Dy Chief Engineer(Grid)	Dy Chief Engineer(Grid)	Dy Chief Engineer(Grid)	Dy Chief Engineer(Grid)	Dy Chief Engineer(Grid)	Dy Chief Engineer(Grid)	Dy Chief Engineer(Grid)	Dy Chief Engineer(Grid)	Dy Chief Engineer(Grid)	Dy Chief Engineer(Grid)	Dy Chief Engineer(Grid)	Dy Chief Engineer(Grid)	Dy Chief Engineer(Grid)	Dy Chief Engineer(Grid)	Dy Chief Engineer(Grid)	Dy Chief Engineer(Grid)	Dy Chief Engineer(Grid)	Dy Chief Engineer(Grid)

Appendix V-B

Operating Cost per Unit on each Generating Station

		Cost/kWHr (Paise)											
Stn.wise generator No.	No.	Apr-15	May-15	Jun-15	Jul-15	Aug-15	Sep-15	Oct-15	Nov-15	Dec-15	Jan-16	Feb-16	Mar-16
Kuyyiadi	1	10.45	13.55	23.24	31.21	33.17	23.89	19.65	24.76	21.65	16.51	15.67	11.12
"	2	10.45	13.55	23.24	31.21	33.17	23.89	19.65	24.76	21.65	16.51	15.67	11.12
"	3	10.45	13.55	23.24	31.21	33.17	23.89	19.65	24.76	21.65	16.51	15.67	11.12
KES	4	9.79	12.85	20.14	27.36	29.45	19.72	23.6	19.12	18.35	14.77	15.49	12.08
KAES	5	9.79	12.85	20.14	27.36	29.45	19.72	23.6	19.12	18.35	14.77	15.49	12.08
"	6	9.79	12.85	20.14	27.36	29.45	19.72	23.6	19.12	18.35	14.77	15.49	12.08
Sholayar	7	17.27	15.38	19.35	20.02	23.67	18.32	22.14	16.87	16.29	13.29	14.45	11.26
"	8	17.27	15.38	19.35	20.02	23.67	18.32	22.14	16.87	16.29	13.29	14.45	11.26
"	9	17.27	15.38	19.35	20.02	23.67	18.32	22.14	16.87	16.29	13.29	14.45	11.26
Poringal	10	12.37	11.78	15.36	17.32	20.59	21.43	23.45	14.22	17.49	13.51	11.49	10.65
"	11	12.37	11.78	15.36	17.32	20.59	21.43	23.45	14.22	17.49	13.51	11.49	10.65
"	12	12.37	11.78	15.36	17.32	20.59	21.43	23.45	14.22	17.49	13.51	11.49	10.65
"	13	12.37	11.78	15.36	17.32	20.59	21.43	23.45	14.22	17.49	13.51	11.49	10.65
PLBE	14	10	15.23	8.88	9.98	11.28	13.65	14.23	12.32	12.44	10.33	9.32	9.87
Pallivasal	15	16.48	14.97	16.73	19.66	20.51	17.09	22.71	20.04	17.77	13.52	16.22	10.48
"	16	16.48	14.97	16.73	19.66	20.51	17.09	22.71	20.04	17.77	13.52	16.22	10.48
"	17	16.48	14.97	16.73	19.66	20.51	17.09	22.71	20.04	17.77	13.52	16.22	10.48
"	18	16.48	14.97	16.73	19.66	20.51	17.09	22.71	20.04	17.77	13.52	16.22	10.48
"	19	16.48	14.97	16.73	19.66	20.51	17.09	22.71	20.04	17.77	13.52	16.22	10.48
"	20	16.48	14.97	16.73	19.66	20.51	17.09	22.71	20.04	17.77	13.52	16.22	10.48
Sengulam	21	18.18	19.76	16.99	21.29	24.76	26.26	21.65	19.39	17.49	16.66	15.95	13.34
"	22	18.18	19.76	16.99	21.29	24.76	26.26	21.65	19.39	17.49	16.66	15.95	13.34
"	23	18.18	19.76	16.99	21.29	24.76	26.26	21.65	19.39	17.49	16.66	15.95	13.34
"	24	18.18	19.76	16.99	21.29	24.76	26.26	21.65	19.39	17.49	16.66	15.95	13.34
Panniar	25	20.25	19.17	17.35	18.88	19.07	21.31	23.67	22.03	18.26	17.55	14.19	21.22
"	26	20.25	19.17	17.35	18.88	19.07	21.31	23.67	22.03	18.26	17.55	14.19	21.22
Nrmglm+NES	27	15.04	18.61	18.31	16.67	18.42	12.39	20.18	22.04	14.43	15.32	13.32	12.68
"	28	15.04	18.61	18.31	16.67	18.42	12.39	20.18	22.04	14.43	15.32	13.32	12.68
"	29	15.04	18.61	18.31	16.67	18.42	12.39	20.18	22.04	14.43	15.32	13.32	12.68
"	30	15.04	18.61	18.31	16.67	18.42	12.39	20.18	22.04	14.43	15.32	13.32	12.68
Sabirigiri	31	15.59	17.45	20.01	24.21	26.01	19.87	19.77	19.98	12.09	18.38	12.32	10.04
"	32	15.59	17.45	20.01	24.21	26.01	19.87	19.77	19.98	12.09	18.38	12.32	10.04
"	33	15.59	17.45	20.01	24.21	26.01	19.87	19.77	19.98	12.09	18.38	12.32	10.04
"	34	15.59	17.45	20.01	24.21	26.01	19.87	19.77	19.98	12.09	18.38	12.32	10.04
"	35	15.59	17.45	20.01	24.21	26.01	19.87	19.77	19.98	12.09	18.38	12.32	10.04
"	36	15.59	17.45	20.01	24.21	26.01	19.87	19.77	19.98	12.09	18.38	12.32	10.04
													Table Continued---
Idukki	37	16.63	18.74	26.15	14.67	28.39	26.13	19.65	26.89	18.83	16.44	11.42	9.35

"	38	16.63	18.74	26.15	14.67	28.39	26.13	19.65	26.89	18.83	16.44	11.42	9.35
"	39	16.63	18.74	26.15	14.67	28.39	26.13	19.65	26.89	18.83	16.44	11.42	9.35
"	40	16.63	18.74	26.15	14.67	28.39	26.13	19.65	26.89	18.83	16.44	11.42	9.35
"	41	16.63	18.74	26.15	14.67	28.39	26.13	19.65	26.89	18.83	16.44	11.42	9.35
"	42	16.63	18.74	26.15	14.67	28.39	26.13	19.65	26.89	18.83	16.44	11.42	9.35
Idamalayar	43	18.38	18.99	24.65	17.67	24.54	27.19	18.65	24.87	19.82	18.45	13.16	11.62
"	44	18.38	18.99	24.65	17.67	24.54	27.19	18.65	24.87	19.82	18.45	13.16	11.62
Lower Periyar	45	18.41	16.23	21.46	16.69	23.33	25.54	20.67	22.32	18.66	14.4	12.67	12.02
"	46	18.41	16.23	21.46	16.69	23.33	25.54	20.67	22.32	18.66	14.4	12.67	12.02
"	47	18.41	16.23	21.46	16.69	23.33	25.54	20.67	22.32	18.66	14.4	12.67	12.02
Kakkad	48	14.32	17.92	23.65	19.06	22.68	24.44	22.13	17.66	20.55	15.88	13.55	10.45
"	49	14.32	17.92	23.65	19.06	22.68	24.44	22.13	17.66	20.55	15.88	13.55	10.45
Kallada	50	18.91	24.82	27.11	26.32	28.99	27.56	29.43	19.65	19.99	14.94	16.31	17.45
"	51	18.91	24.82	27.11	26.32	28.99	27.56	29.43	19.65	19.99	14.94	16.31	17.45
Malankara	52	16.63	20.63	22.22	17.74	23.45	16.97	22.94	21.13	17.98	13.37	12.33	11.21
	53	16.63	20.63	22.22	17.74	23.45	16.97	22.94	21.13	17.98	13.37	12.33	11.21
	54	16.63	20.63	22.22	17.74	23.45	16.97	22.94	21.13	17.98	13.37	12.33	11.21
Kuthungal	55	17.09	16.07	21.27	19.94	10.76	19.62	23.11	25.18	16.88	14.04	13.85	13.23
"	56	17.09	16.07	21.27	19.94	10.76	19.62	23.11	25.18	16.88	14.04	13.85	13.23
"	57	17.09	16.07	21.27	19.94	10.76	19.62	23.11	25.18	16.88	14.04	13.85	13.23

Appendix V-C

MW Capacity and Cost coefficients of 57 Generators

Generator No.	Capacity MW		Cost coefficients		
	Min(Pi)	Max(Pi)	α Rs/Hr	β Rs/MWhr	γ Rs/MWhr²
1	50	130	1094.56833	370.55747	10.815462
2	50	130	1094.56833	370.55747	10.815462
3	50	130	1094.56833	370.55747	10.815462
4	50	130	1094.56833	370.55747	10.815462
5	50	130	1094.56833	370.55747	10.815462
6	50	130	1094.56833	370.55747	10.815462
7	25	55	284.811081	40.930728	0.6070053
8	25	55	284.811081	40.930728	0.6070053
9	25	55	284.811081	40.930728	0.6070053
10	25	55	284.811081	40.930728	0.6070053
11	30	60	261.076825	40.930728	0.6621876
12	30	60	261.076825	40.930728	0.6621876
13	2	7	86.6747364	16.571331	0.0141532
14	2	7	86.6747364	16.571331	0.0141532
15	2	7	86.6747364	16.571331	0.0141532
16	2	3.5	90.3512669	12.121285	0.0307435
17	2	3.5	90.3512669	12.121285	0.0307435
18	2	3.5	90.3512669	12.121285	0.0307435
19	12	60	286.076825	18.159747	0.0876487
20	12	60	286.076825	18.159747	0.0876487
21	12	60	286.076825	18.159747	0.0876487
22	5	12	41.4667938	78.079869	0.0073327
23	5	12	41.4667938	78.079869	0.0073327
24	5	12	41.4667938	78.079869	0.0073327
25	5	25	152.465895	18.06544	0.0023702
26	7.5	37.5	171.332303	25.317845	0.0013344
27	7.5	37.5	171.332303	25.317845	0.0013344
28	2	5	62.1339642	10.711081	0.0035296
29	2	5	62.1339642	10.711081	0.0035296
30	2	5	62.1339642	10.711081	0.0035296
31	2	7.5	41.4226428	10.867111	0.0052944
32	2	7.5	41.4226428	10.867111	0.0052944
33	2	7.5	41.4226428	10.867111	0.0052944
34	3	12	13.6206439	6.0950452	0.0006553
35	3	12	13.6206439	6.0950452	0.0006553
36	3	12	85.150954	13.785603	0.0085024
37	3	12	85.150954	18.881842	0.0022503
38	4	16	31.332722	23.102416	0.0053236
39	4	16	31.332722	23.102416	0.0053236
40	2	9	-8731.2619	-12.610634	-0.2298792
41	2	9	-8731.2619	-12.610634	-0.2298792
42	2	9	-8731.2619	-12.610634	-0.2298792
43	2	9	-8731.2619	-12.610634	-0.2298792
44	4	16	-1899.2215	8.4555742	-0.5644961
45	4	18	20.822944	11.71707	0.0055074
46	4	18	20.822944	11.71707	0.0055074
47	4	18	20.822944	11.71707	0.0055074
48	5	25	63.8373356	54.762392	0.007235
49	5	25	63.8373356	54.762392	0.007235
50	5	25	63.8373356	54.762392	0.007235
51	10	50	319.186678	54.762392	0.01447
52	10	50	319.186678	54.762392	0.01447
53	10	50	319.186678	54.762392	0.01447
54	5	25	66.9044152	51.746857	0.0476392
55	5	25	66.9044152	51.746857	0.0476392
56	2	7.5	61.3405285	17.517469	0.0015295
57	2	7.5	61.3405285	17.517469	0.0015295

Appendix V-D
Optimized cost per unit

α Rs/Hr	β Rs/MWhr	γ Rs/MWhr²	Opt.Pi	Cost Rs/hr
1094.57	370.55747	10.8154619	128.5408	227427.2822
1094.57	370.55747	10.8154619	128.9529	228727.8704
1094.57	370.55747	10.8154619	128.6181	227671.0432
1094.57	370.55747	10.8154619	128.8447	228385.8699
1094.57	370.55747	10.8154619	128.598	227607.5156
1094.57	370.55747	10.8154619	128.832	228345.7846
284.811	40.930728	0.60700533	54.14718	4280.784354
284.811	40.930728	0.60700533	53.56101	4218.467764
284.811	40.930728	0.60700533	54.14796	4280.867248
284.811	40.930728	0.60700533	53.59873	4222.46544
261.077	40.930728	0.66218763	59.2521	5011.123771
261.077	40.930728	0.66218763	58.96842	4977.305523
86.6747	16.571331	0.01415321	1.615383	113.4807154
86.6747	16.571331	0.01415321	1.615383	113.4807154
86.6747	16.571331	0.01415321	1.615383	113.4807154
90.3513	12.121285	0.0307435	0.807692	100.1615817
90.3513	12.121285	0.0307435	0.807692	100.1615817
90.3513	12.121285	0.0307435	0.807692	100.1615817
286.077	18.159747	0.08764874	59.22405	1668.997594
286.077	18.159747	0.08764874	58.95277	1661.261105
286.077	18.159747	0.08764874	59.29412	1670.997898
41.4668	78.079869	0.00733272	4.038458	356.9086179
41.4668	78.079869	0.00733272	4.038458	356.9086179
41.4668	78.079869	0.00733272	4.038458	356.9086179
152.466	18.06544	0.00237021	23.7485	582.8297679
171.332	25.317845	0.00133436	35.93175	1082.769563
171.332	25.317845	0.00133436	36.1269	1087.729108
62.134	10.711081	0.00352958	4.30307	108.2898449
62.134	10.711081	0.00352958	4.176857	106.9341936
62.134	10.711081	0.00352958	3.391218	98.4981701
41.4226	10.867111	0.00529436	6.00804	106.9037829
41.4226	10.867111	0.00529436	6.645812	113.8772495
41.4226	10.867111	0.00529436	6.410365	111.3023498
13.6206	6.0950452	0.00065535	3.692304	36.13433827
13.6206	6.0950452	0.00065535	3.692304	36.13433827
85.151	13.785603	0.00850243	1.846152	110.6302519
85.151	18.881842	0.00225033	1.846152	120.0173733
31.3327	23.102416	0.00532364	6.410216	179.6429446
31.3327	23.102416	0.00532364	6.599218	184.022448
-8731.3	-12.61063	-0.2298792	2.769228	-8767.94648
-8731.3	-12.61063	-0.2298792	2.769228	-8767.94648
-8731.3	-12.61063	-0.2298792	2.769228	-8767.94648
-8731.3	-12.61063	-0.2298792	2.769228	-8767.94648
-1899.2	8.4555742	-0.5644961	3.692304	-1875.69681
20.8229	11.71707	0.00550737	4.153842	69.58882863
20.8229	11.71707	0.00550737	4.153842	69.58882863
20.8229	11.71707	0.00550737	4.153842	69.58882863
63.8373	54.762392	0.00723502	23.71418	1366.551414
63.8373	54.762392	0.00723502	24.33319	1400.664861
63.8373	54.762392	0.00723502	24.20259	1393.467141
319.187	54.762392	0.01447003	48.74295	3022.845969
319.187	54.762392	0.01447003	48.49598	3008.973952
319.187	54.762392	0.01447003	49.26159	3051.983881
66.9044	51.746857	0.04763919	23.49671	1309.086951
66.9044	51.746857	0.04763919	23.89957	1330.843017
61.3405	17.517469	0.00152949	1.730768	91.66377545
61.3405	17.517469	0.00152949	1.730768	91.66377545

Appendix V-E

Cost Coefficient of Thermal Generation

Gen. No.	Min(Pi)	Max(Pi)	α Rs/Hr	β Rs/MWhr	γ Rs/MWhr^2
1	21.32	21.32	92.2777	9.646381	-0.00092
2	21.32	21.32	92.2777	9.646381	-0.00092
3	21.32	21.32	92.2777	9.646381	-0.00092
4	16	16	622.4186	7.37367	8.46E-04
5	16	16	622.4186	7.37367	8.46E-04
6	16	16	622.4186	7.37367	8.46E-04
7	16	16	622.4186	7.37367	8.46E-04
8	16	16	622.4186	7.37367	8.46E-04
9	16	16	622.4186	7.37367	8.46E-04
10	30	116.6	151.8691	4.780732	3.83E-04
11	30	116.6	151.8691	4.780732	3.83E-04
12	35	126.38	164.6074	4.780732	3.53E-04

Appendix V-F

One day Optimized Power Output (Thermal) By GA

00:00	00:30	01:00	01:30	02:00	02:30	03:00	03:30	04:00	04:30	05:00	05:30	06:00	06:30	07:00	07:30	08:00	08:30	09.00
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

09:30	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30
2.0882	2.611	3.0737	3.2908	3.3528	3.3528	3.9766	3.4797	1.5616	0	0
2.0882	2.611	3.0737	3.2908	3.3528	3.3528	3.9766	3.4797	1.5616	0	0
2.0882	2.611	3.0737	3.2908	3.3528	3.3528	3.9766	3.4797	1.5616	0	0
1.5672	1.9595	2.3067	2.4696	2.5162	2.5162	2.5627	2.6114	1.1719	0	0
1.5672	1.9595	2.3067	2.4696	2.5162	2.5162	2.5627	2.6114	1.1719	0	0
1.5672	1.9595	2.3067	2.4696	2.5162	2.5162	2.5627	2.6114	1.1719	0	0
1.5672	1.9595	2.3067	2.4696	2.5162	2.5162	2.5627	2.6114	1.1719	0	0
1.5672	1.9595	2.3067	2.4696	2.5162	2.5162	2.5627	2.6114	1.1719	0	0
1.5672	1.9595	2.3067	2.4696	2.5162	2.5162	2.5627	2.6114	1.1719	0	0
11.421	14.28	16.81	17.997	18.337	18.337	18.876	19.031	8.5403	0	0
11.421	14.28	16.81	17.997	18.337	18.337	18.876	19.031	8.5403	0	0
12.379	15.477	18.22	19.507	19.875	19.875	21.5278	20.627	9.2566	0	0
50.8888	63.627	74.9013	80.191	81.7046	81.7046	86.5858	84.7965	38.0534		

15:00	15:30	16:00	16:30	17:00	17:30	18:00	18:30	19:00
0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0

Appendix V-G

One day Optimized Power Output (Thermal) By PSO

00:00	00:30	01:00	01:30	02:00	02:30	03:00	03:30	04:00	04:30	05:00	05:30	06:00	06:30	07:00	07:30	08:00
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

08:30	09:00	09:30	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00	15:30	16:00	16:30	17:00	17:30	18:00	18:30	19:00
0	0	0.061	1.0378	3.205	3.4797	3.4797	3.6629	3.9986	4.0291	1.5567	0	0	0	0	0	0	0	0	0	0	0
0	0	0.061	1.0378	3.205	3.4797	3.4797	3.6629	3.9986	4.0291	1.5567	0	0	0	0	0	0	0	0	0	0	0
0	0	0.061	1.0378	3.205	3.4797	3.4797	3.6629	3.9986	4.0291	1.5567	0	0	0	0	0	0	0	0	0	0	0
0	0	0.0458	0.7789	2.405	2.6114	2.6114	2.7489	3.0008	3.0238	1.1683	0	0	0	0	0	0	0	0	0	0	0
0	0	0.0458	0.7789	2.405	2.6114	2.6114	2.7489	3.0008	3.0238	1.1683	0	0	0	0	0	0	0	0	0	0	0
0	0	0.0458	0.7789	2.405	2.6114	2.6114	2.7489	3.0008	3.0238	1.1683	0	0	0	0	0	0	0	0	0	0	0
0	0	0.0458	0.7789	2.405	2.6114	2.6114	2.7489	3.0008	3.0238	1.1683	0	0	0	0	0	0	0	0	0	0	0
0	0	0.0458	0.7789	2.405	2.6114	2.6114	2.7489	3.0008	3.0238	1.1683	0	0	0	0	0	0	0	0	0	0	0
0	0	0.0458	0.7789	2.405	2.6114	2.6114	2.7489	3.0008	3.0238	1.1683	0	0	0	0	0	0	0	0	0	0	0
0	0	0.3339	5.6758	17.53	19.031	19.031	20.032	21.869	22.036	8.5138	0	0	0	0	0	0	0	0	0	0	0
0	0	0.3339	5.6758	17.53	19.031	19.031	20.032	21.869	22.036	8.5138	0	0	0	0	0	0	0	0	0	0	0
0	0	0.3619	6.1519	19	20.627	20.627	21.713	23.703	23.884	9.2279	0	0	0	0	0	0	0	0	0	0	0

Appendix V-H
Optimized Power by GA (Hydro)

Sl.No.	Optimized power by GA-Hydro (One Week)						
1	127.73	127.74	127.73	127.73	127.72	127.74	127.76
2	127.71	127.77	127.71	127.72	127.72	127.72	127.73
3	127.73	127.71	127.73	127.73	127.72	127.73	127.73
4	127.72	127.72	127.76	127.79	127.74	127.75	127.74
5	127.71	127.74	127.73	127.73	127.73	127.73	127.71
6	127.76	127.72	127.75	127.72	127.75	127.73	127.71
7	52.733	52.751	52.742	52.715	52.712	52.751	52.728
8	52.74	52.72	52.714	52.726	52.752	52.734	52.711
9	52.715	52.737	52.749	52.714	52.742	52.734	52.72
10	52.733	52.714	52.722	52.732	52.724	52.749	52.726
11	57.72	57.718	57.739	57.723	57.72	57.735	57.731
12	57.717	57.712	57.747	57.717	57.719	57.74	57.739
13	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154
14	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154
15	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154
16	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769
17	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769
18	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769
19	57.734	57.794	57.714	57.724	57.734	57.737	57.738
20	57.73	57.714	57.724	57.723	57.711	57.726	57.748
21	57.721	57.715	57.727	57.738	57.741	57.724	57.77
22	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385
23	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385
24	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385
25	22.722	22.714	22.727	22.744	22.718	22.718	22.722
26	35.213	35.214	35.236	35.217	35.268	35.216	35.217
27	35.255	35.23	35.218	35.234	35.214	35.234	35.218
28	2.7293	2.7128	2.732	2.7329	2.7222	2.7119	2.7386
29	2.7447	2.7188	2.7341	2.7538	2.7384	2.7182	2.7382
30	2.7129	2.7277	2.7181	2.7457	2.7416	2.7247	2.7235
31	5.2199	5.2222	5.2138	5.2536	5.2221	5.2185	5.2595
32	5.2448	5.2133	5.2203	5.2542	5.2238	5.2153	5.2225
33	5.212	5.2366	5.218	5.2264	5.2633	5.2176	5.2113
34	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923
35	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923
36	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462
37	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462
38	5.7323	5.7156	5.7534	5.7516	5.721	5.7211	5.7308
39	5.7229	5.7914	5.7235	5.7419	5.7444	5.7173	5.7151
40	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692
41	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692
42	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692
43	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692
44	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923
45	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538
46	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538
47	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538
48	22.718	22.715	22.732	22.711	22.714	22.72	22.724
49	22.792	22.715	22.719	22.725	22.714	22.715	22.74
50	22.734	22.739	22.711	22.726	22.712	22.731	22.713
51	47.728	47.744	47.736	47.736	47.751	47.734	47.724
52	47.72	47.781	47.713	47.716	47.714	47.717	47.711
53	47.723	47.744	47.724	47.782	47.743	47.771	47.719
54	22.713	22.719	22.717	22.733	22.72	22.744	22.771
55	22.733	22.728	22.729	22.712	22.729	22.848	22.712
56	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308
57	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308

Appendix V-I

One day Optimized Power Output (Hydro) By PSO

Sl.NO.	00:00	00:30	01:00	01:30	02:00	02:30	03:00	03:30	04:00	04:30	05:00	05:30	06:00	06:30	07:00	07:30	08:00
1	128.5408	128.6609	129.2751	129.0113	129.0479	128.4939	129.3087	128.7729	129.3135	129.1336	128.7853	128.8141	129.022	128.6919	128.9171	128.4952	129.0217
2	128.9529	128.9281	128.4592	128.5967	128.9262	128.457	128.6639	128.5682	128.6687	128.873	128.5241	128.9856	128.6885	128.5182	128.737	129.2471	128.7135
3	128.6181	128.3829	128.7231	129.1451	128.4719	129.2223	129.2269	129.0144	128.5494	128.8257	129.0393	129.1236	128.9093	128.6839	128.609	128.9515	128.9306
4	128.8447	128.5412	128.408	129.1524	129.2295	128.4831	129.3294	128.5761	129.0617	128.9842	128.5349	128.56	128.8376	128.9599	128.5962	128.7677	129.1858
5	128.598	128.4147	128.933	128.5309	129.0729	129.1898	128.9412	128.7211	128.9432	128.5296	128.5136	128.9198	129.2128	128.5032	128.8223	129.3155	128.9822
6	128.832	128.4433	128.4643	128.9929	128.4274	128.9994	129.3309	129.2065	128.6689	128.8497	128.4046	129.295	128.8565	128.9637	128.3778	128.5102	129.323
7	54.14718	53.65609	54.05128	53.68444	54.06826	53.95152	53.60517	53.4477	54.34828	53.86055	53.73726	54.05183	53.67335	53.81295	53.506	53.94199	53.88204
8	53.56101	53.7236	53.61916	54.08451	54.18689	53.39131	54.1902	54.34814	54.04768	53.59014	53.62169	53.78648	53.98548	54.08704	54.08783	53.83783	53.69275
9	54.14796	54.12604	53.67545	53.70785	53.47	54.07207	53.91477	54.32951	54.00594	53.60457	53.35622	53.43123	53.72471	53.70463	54.15011	53.49615	54.09197
10	53.59873	53.54464	53.98678	53.95342	53.4193	54.08021	54.17644	54.23038	53.99358	53.99314	53.47309	53.66017	53.39747	53.61937	54.33731	53.61176	53.50728
11	59.2521	59.18088	58.82969	59.03028	58.53527	58.83963	58.71255	59.14498	58.92403	58.95554	59.21812	58.68314	59.10278	59.10032	59.06259	58.70756	59.01346
12	58.96842	58.91007	58.97475	59.30125	58.83973	58.48864	59.08937	58.9285	58.51876	59.03099	59.28241	58.99227	58.94562	58.75699	59.19417	58.92656	58.79465
13	1.615383	1.615383	1.615383	1.615383	1.615383	1.615383	1.615383	1.615383	1.615383	1.615383	1.615383	1.615383	1.615383	1.615383	1.615383	1.615383	1.615383
14	1.615383	1.615383	1.615383	1.615383	1.615383	1.615383	1.615383	1.615383	1.615383	1.615383	1.615383	1.615383	1.615383	1.615383	1.615383	1.615383	1.615383
15	1.615383	1.615383	1.615383	1.615383	1.615383	1.615383	1.615383	1.615383	1.615383	1.615383	1.615383	1.615383	1.615383	1.615383	1.615383	1.615383	1.615383
16	0.807692	0.807692	0.807692	0.807692	0.807692	0.807692	0.807692	0.807692	0.807692	0.807692	0.807692	0.807692	0.807692	0.807692	0.807692	0.807692	0.807692
17	0.807692	0.807692	0.807692	0.807692	0.807692	0.807692	0.807692	0.807692	0.807692	0.807692	0.807692	0.807692	0.807692	0.807692	0.807692	0.807692	0.807692
18	0.807692	0.807692	0.807692	0.807692	0.807692	0.807692	0.807692	0.807692	0.807692	0.807692	0.807692	0.807692	0.807692	0.807692	0.807692	0.807692	0.807692
19	59.22405	59.25538	58.43614	59.08268	58.8738	59.25335	59.0147	59.28797	58.35987	59.22396	58.74207	58.4248	59.28677	58.78766	58.97937	59.16685	59.20926
20	58.95277	58.55554	58.54798	58.78917	59.00716	58.97402	58.77914	58.97182	58.45539	58.94088	58.76449	59.30423	58.58738	58.64195	58.62745	58.57055	58.80362
21	59.29412	59.13462	58.95167	58.70547	58.81742	58.82708	58.56049	59.248	58.90287	58.95107	59.09862	58.82653	58.43343	58.46081	58.8771	58.50886	58.86709
22	4.038458	4.038458	4.038458	4.038458	4.038458	4.038458	4.038458	4.038458	4.038458	4.038458	4.038458	4.038458	4.038458	4.038458	4.038458	4.038458	4.038458
23	4.038458	4.038458	4.038458	4.038458	4.038458	4.038458	4.038458	4.038458	4.038458	4.038458	4.038458	4.038458	4.038458	4.038458	4.038458	4.038458	4.038458
24	4.038458	4.038458	4.038458	4.038458	4.038458	4.038458	4.038458	4.038458	4.038458	4.038458	4.038458	4.038458	4.038458	4.038458	4.038458	4.038458	4.038458
25	23.7485	23.51378	24.13483	23.62666	23.44527	23.96985	23.54539	23.51095	23.7658	23.53608	23.98576	23.43012	23.98862	24.13381	24.34838	23.83947	23.6512
26	35.93175	36.01474	35.87876	36.56847	36.29583	36.5876	36.72012	36.33362	36.42469	36.31404	35.90884	36.10855	36.12012	36.17891	36.2297	36.84217	36.16652
27	36.1269	36.17876	36.67347	35.95349	36.029	35.99979	36.8004	36.27592	36.45572	36.71598	36.11836	36.34407	36.307	36.16385	35.86974	36.008	36.45783
28	4.30307	3.597814	4.196144	4.205621	3.677814	3.948443	3.795128	3.942481	4.258728	3.537005	4.276823	4.20302	4.112926	3.378974	3.592709	3.612386	4.149715
29	4.176857	4.190258	3.5418	3.896793	3.984795	3.64417	4.189986	3.463414	4.178951	3.993876	3.442485	4.195567	3.443727	3.575255	4.216721	3.575944	4.212461
30	3.391218	4.231338	3.834274	3.721024	4.171942	4.302852	4.235301	3.630428	4.206484	3.787983	4.047669	3.520707	4.350761	3.513089	3.486347	4.0695	3.653629
31	6.00804	6.781456	6.46025	6.140703	6.621376	6.564805	6.40149	5.985702	6.548641	6.717089	6.722755	5.872578	6.537901	6.206278	6.027754	5.929429	5.970858
32	6.645812	5.887557	6.429944	6.452816	6.290996	6.210962	6.134523	5.963952	6.260553	6.542862	6.238325	6.297415	6.023993	6.214645	6.537577	6.26239	6.651606
33	6.410365	6.218625	6.806416	6.705134	6.403605	6.053226	6.250659	5.968606	6.343939	6.723194	6.823935	5.875024	6.352851	6.390423	6.494573	6.246577	6.498188
34	3.692304	3.692304	3.692304	3.692304	3.692304	3.692304	3.692304	3.692304	3.692304	3.692304	3.692304	3.692304	3.692304	3.692304	3.692304	3.692304	3.692304
35	3.692304	3.692304	3.692304	3.692304	3.692304	3.692304	3.692304	3.692304	3.692304	3.692304	3.692304	3.692304	3.692304	3.692304	3.692304	3.692304	3.692304
36	1.846152	1.846152	1.846152	1.846152	1.846152	1.846152	1.846152	1.846152	1.846152	1.846152	1.846152	1.846152	1.846152	1.846152	1.846152	1.846152	1.846152
37	1.846152	1.846152	1.846152	1.846152	1.846152	1.846152	1.846152	1.846152	1.846152	1.846152	1.846152	1.846152	1.846152	1.846152	1.846152	1.846152	1.846152
38	6.410216	7.263212	6.745704	6.797112	7.258818	6.730268	7.176416	6.589979	7.002499	6.846334	7.122393	6.636045	6.540216	6.889868	6.65233	6.843167	6.987322
39	6.599218	6.804328	7.244053	6.47675	6.948314	7.232448	6.87673	7.350434	7.034527	7.342371	6.680805	7.260505	7.125313	7.258848	7.342603	6.37201	6.390986
40	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228
41	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228
42	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228
43	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228	2.769228
44	3.692304	3.692304	3.692304	3.692304	3.692304	3.692304	3.692304	3.692304	3.692304	3.692304	3.692304	3.692304	3.692304	3.692304	3.692304	3.692304	3.692304
45	4.153842	4.153842	4.153842	4.153842	4.153842	4.153842	4.153842	4.153842	4.153842	4.153842	4.153842	4.153842	4.153842	4.153842	4.153842	4.153842	4.153842
46	4.153842	4.153842	4.153842	4.153842	4.153842	4.153842	4.153842	4.153842	4.153842	4.153842	4.153842	4.153842	4.153842	4.153842	4.153842	4.153842	4.153842
47	4.153842	4.153842	4.153842	4.153842	4.153842	4.153842	4.153842	4.153842	4.153842	4.153842	4.153842	4.153842	4.153842	4.153842	4.153842	4.153842	4.153842
48	23.71418	23.89247	23.76842	23.4539	23.96045	23.54622	23.50329	23.80319	24.30383	24.32083	24.16138	23.76145	24.34579	23.63044	23.46098	24.12346	24.34527
49	24.33319	23.47322	23.69245	23.52614	24.15459	23.96219	23.78332	23.78808	24.34936	23.81015	23.82717	24.21317	23.98089	23.92478	24.13203	23.82377	23.75355
50	24.20259	24.04605	23.64521	23.59156	23.83096	24.32854	24.29629	24.06941	23.4363	23.45462	23.48654	24.29338	23.82682	23.722	23.41583	23.48948	23.48016
51	48.74295	48.37276	48.54792	49.1272	49.13262	48.8073	49.27455	49.02497	48.50226	48.68432	48.96286	48.99127	48.9867	48.97241	48.86184	49.22071	48.66121
52	48.49598	49.21106	49.07318	48.38314	48.42915	48.47119	49.31052	49.33215	48.38978	49.195	49.02718	48.89057	48.61321	48.43092	48.5895	49.3411	48.89314
53	49.26159	48.49479	48.82137	48.94612	48.73483	49.14902	49.32454	48.62448	48.83813	48.89569	49.19075	48.70936	48.95976	48.79431	48.91367	48.70512	48.40928
54	23.49671	23.99565	23.92385	24.21125	24.24714	23.99165	24.11589	24.00655	24.10137	24.19965	23.75548	24.34093	24.0591	23.75775	23.50894	23.85143	23.45235
55	23.89957	24.21141	23.95755	23.44146	23.84726	23.60718	24.31597	24.11023	23.91879	23.82464	23.45945	23.80337	24.22643	23.87906	24.30984	24.14896	24.03442
56	1.730768	1.730768	1.730768	1.730768	1.730768	1.730768	1.730768	1.730768	1.730768	1.730768	1.730768	1.730768	1.730768	1.730768	1.730768	1.730768	1.730768
57	1.730768	1.730768	1.730768	1.730768	1.730768	1.730768	1.730768	1.730768	1.730768	1.730768	1.730768	1.730768	1.730768	1.730768	1.730768	1.730768	1.730768

Contd…..

Appendix V-J

One day Optimized Power Output (Hydro) By GA

00.00	00.30	01.00	01.30	02.00	02.30	03.00	03.30	04.00	4.30	05.00	5.30	06.00	6.30	07.00	7.30	08.00	8.30	09.00	9.30	10.00	10.30	11.00
128.64	128.51	128.66	128.53	127.94	128.7	127.76	128.12	128.46	127.75	128.71	127.85	127.74	128.22	128.6	127.79	127.77	128.11	128.67	128.44	127.81	128.19	128.46
127.9	127.77	127.73	128.39	128.21	128.04	127.86	127.78	128.67	128.47	127.74	127.77	127.72	128.37	128.45	127.9	128.37	127.83	128.58	127.99	128.39	128.68	128.61
128.53	128.59	128.61	127.84	128.19	128.15	128.28	127.76	128.62	128.49	128.44	127.82	127.79	128.29	127.79	127.77	128.48	128	128.69	128.7	127.92	127.95	128.17
128.31	128.38	128.33	128.42	128.05	128.23	127.84	128.49	128.66	128.15	128.1	128.06	127.84	128.59	128.68	127.77	128.69	128.55	128.25	128.42	127.87	128.71	128.08
128.24	128	128.12	128.02	128.12	128	128.48	127.97	127.71	128.3	127.89	128.6	127.72	128.17	128.51	128.18	128.04	128.56	127.97	127.75	128.55	128.53	128.5
128.64	127.91	128.24	127.98	127.91	128.53	127.97	128.68	128.69	128.66	127.78	128.36	128.33	128.31	128.48	128.69	128.06	128.67	127.95	128.04	127.88	127.77	127.76
53.354	52.91	53.601	52.946	53.681	52.718	53.478	52.743	53.115	53.436	53.659	53	53.025	53.514	53.238	53.687	53.633	53.211	53.01	53.005	52.896	53.593	52.894
52.862	53.657	53.057	52.821	53.613	52.836	53.146	53.478	53.492	53.652	53.49	52.762	52.908	53.435	53.208	53.07	53.252	53.668	53.402	53.551	53.179	53.707	53.06
52.8	53.129	53.201	53.547	53.003	53.226	52.822	53.196	53.043	53.255	52.807	53.376	53.178	53.039	53.126	52.869	53.208	53.38	53.55	53.275	53.57	53.055	52.897
53.674	53.251	52.735	53.357	52.92	52.932	53.678	53.127	53.115	53.061	53.316	52.779	52.81	53.2	52.834	52.982	53.021	52.964	52.719	53.087	52.938	53.223	53.155
58.511	57.839	57.799	58.313	58.619	57.962	58.22	57.764	57.983	57.761	57.773	58.305	58.008	57.894	57.786	58.611	58.134	57.836	58.497	57.806	57.752	58.585	58.559
58.644	58.334	58.087	57.857	57.912	58.084	57.719	57.959	58.097	57.942	57.897	58.031	58.136	58.139	58.347	57.992	58.472	57.939	58.343	58.432	57.947	57.896	57.917
1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154
1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154
1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154
0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769
0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769
0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769
58.627	58.111	58.213	57.965	57.851	58.603	57.949	58.101	58.441	58.421	58.043	57.921	57.72	58.711	58.213	58.574	57.718	57.762	58.703	58.001	57.738	57.904	57.715
57.923	58.3	57.738	58.423	58.387	57.919	58.496	58.515	58.494	58.486	57.818	58.591	58.439	57.894	57.75	58.502	58.637	58.309	58.023	58.536	57.939	57.973	57.807
58.244	57.966	58.236	58.184	57.726	58.693	57.914	58.557	58.141	58.51	58.032	57.882	58.106	58.631	58.184	58.649	58.333	57.781	58.609	57.875	58.158	57.973	58.374
4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385
4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385
4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385
22.833	23.032	23.064	23.369	22.81	23.25	23.602	23.17	22.773	23.184	23.547	23.208	23.437	23.588	23.579	23.028	23.266	23.335	23.068	23.329	22.981	23.591	22.868
35.415	35.364	35.279	35.599	35.496	35.514	36.196	35.234	35.944	35.636	36.062	35.308	36.12	35.305	35.627	35.937	35.244	35.582	35.744	36.123	35.534	35.604	35.717
35.962	35.514	35.322	35.87	35.886	35.719	35.354	35.997	35.439	35.347	35.245	35.223	35.564	35.721	36.201	35.22	35.802	35.892	35.427	35.865	35.571	35.85	36.096
3.0852	3.5348	3.4984	2.7594	3.6026	2.7459	3.6029	3.3884	3.5628	3.2233	3.3657	3.6905	2.8998	2.7378	3.0766	3.2879	3.4276	2.8996	3.6477	2.8394	2.9555	3.0392	2.9667
2.9643	3.6627	2.8142	3.4208	3.6731	3.5281	3.6111	3.3567	3.6467	2.9844	2.7853	2.7716	2.8959	3.4661	2.945	3.1394	3.5061	3.3957	2.7209	3.3719	3.6091	3.2523	2.7621
2.8045	2.7492	2.9053	3.1034	3.1277	3.0147	3.3813	3.241	2.9181	2.9041	3.5175	3.1164	3.4839	2.8149	2.7728	3.2602	3.5869	3.1102	3.2974	3.0518	3.0021	2.8429	3.0736
5.2936	5.7115	5.4604	5.2382	5.8267	5.8469	6.1086	5.9058	5.6076	5.6653	6.1808	5.3576	6.1301	6.1975	5.3504	5.7351	5.4678	5.3229	5.7372	5.5872	6.055	5.5357	6.0382
6.0817	6.1243	5.7842	6.113	5.6851	6.0013	5.5872	5.4024	5.4746	6.0191	5.5243	5.4641	5.6783	5.3314	5.8338	5.8358	5.8139	5.3859	5.245	5.9928	6.084	6.0383	5.8213
6.0217	5.3124	5.6996	5.679	5.3381	5.5209	5.7735	5.4485	6.1329	5.6751	5.322	5.5411	5.9017	5.6847	6.1054	5.5167	5.5968	5.6659	5.4335	6.0314	6.139	5.4969	5.4811
3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923
3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923
1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462
1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462
6.3851	6.0064	6.3169	6.4901	6.2473	6.346	5.9266	6.3022	5.8119	6.0807	5.759	6.0455	6.081	6.293	6.1825	6.2718	5.8328	6.1865	6.1716	6.5352	6.3791	6.0197	5.774
6.3125	6.0353	6.2613	5.9553	6.2842	6.4515	6.01	6.0641	6.2569	6.6774	6.2936	6.2068	6.4531	6.4098	5.9016	6.601	6.5108	6.6795	6.7101	6.7051	6.5915	6.503	6.6873
2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692
2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692
2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692
2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692
3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923
4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538
4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538
4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538
23.219	23.644	23.318	23.554	23.481	23.037	23.048	23.645	23.44	23.552	23.699	23.2	23.439	23.22	23.332	22.85	23.572	23.295	23.217	23.122	23.405	23.597	23.215
22.912	23.453	23.639	22.953	23.07	22.974	22.867	22.94	22.902	23.313	22.754	23.38	23.191	23.679	23.093	23.294	23.282	23.65	23.69	23.539	23.609	22.926	23.535
23.13	23.195	23.538	23.495	22.846	23.7	22.993	22.868	23.35	23.409	23.029	23.576	22.875	23.364	23.059	23.081	23.327	23.046	23.027	22.886	23.391	23.434	23.703
48.087	47.857	48.593	48.651	48.603	48.662	48.377	48.567	48.23	48.245	47.759	48.451	48.484	47.835	48.633	48.367	48.003	48.05	48.203	48.09	48.551	48.323	47.771
48.426	47.955	47.83	48.575	48.578	48.597	48.192	48.382	48.15	48.379	48.59	48.58	47.889	48.162	48.283	48.544	48.49	48.615	47.862	48.043	48.329	47.821	48.424
48.695	47.887	47.746	48.632	47.954	48.529	48.555	47.976	48.013	48.61	48.556	48.102	48.332	47.982	48.636	47.794	48.59	47.743	48.382	48.672	47.715	48.167	48.183
23.623	23.278	23.141	23.501	23.201	23.313	23.118	22.838	23.069	23.385	22.795	23.059	23.375	23.65	23.542	23.083	23.225	23.692	23.698	23.478	23.004	23.443	23.56
23.187	23.407	22.823	23.4	23.567	23.068	23.423	23.021	23.018	23.548	22.763	23.006	23.366	23.602	23.075	23.666	23.191	23.467	23.627	23.302	22.821	22.842	23.251
1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308
1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308
1730.49	1727.533	1726.544	1730.105	1728.563	1729.595	1728.492	1727.141	1729.624	1731.335	1726.196	1725.547	1726.22	1730.604	1729.578	1728.702	1730.707	1728.737	1731.028	1730.626	1727.417	1729.219	1728.039

11.30	12.00	12.30	13.00	13.30	14.00	14.30	15.00	15.30	16.00	16.30	17.00	17.30	18.00	18.30	19.00	19.30	20.00	20.30	21.00	21.30	22.00	22.30	23.00	23.30
127.8	128.18	128.08	128.11	127.74	128.25	128.67	127.92	128.11	128.11	128.03	128.08	128	128.67	127.71	127.91	128.5	128.64	127.77	128.23	128.4	127.82	128.55	128.6	127.81
127.93	128.44	128.48	127.94	128.5	127.91	128.15	127.8	128.4	128.61	128.24	128.2	127.8	127.89	128.63	128.56	128.25	128.57	127.83	128.26	128.17	128.48	127.95	128.01	127.75
128.19	128.01	128.08	128.4	127.82	127.84	128.11	128.47	128.41	128.57	128.33	128.28	127.86	128.57	127.74	128.36	128.15	128.58	128.61	127.85	128.53	128.44	128.46	127.81	128.1
127.91	127.91	128.3	127.84	128.63	128.1	128.64	128.45	127.87	128.02	128.36	127.75	128.2	128.23	128.13	128.05	128.4	127.97	127.99	128.67	128.7	128.5	127.88	128.12	128.21
128.46	127.85	128.63	127.72	128.28	128.32	128.47	127.78	127.93	128.51	128.46	128.67	127.75	128.01	128.54	127.8	128.55	127.95	127.93	127.95	127.98	128.28	128.28	127.8	127.75
127.99	128.63	127.78	128	128.65	128.31	128.36	127.92	128.56	127.72	127.73	128.04	128.69	128.16	127.74	127.99	128.27	128.39	128.3	127.9	128.38	127.91	128.29	127.78	128.3
53.355	53.362	53.617	53.599	53.422	53.477	53.644	52.787	53.574	53.478	52.857	52.936	53.557	53.513	52.86	52.823	53.27	52.73	53.227	53.387	53.336	53.463	53.567	53.194	52.859
53.131	52.848	52.744	53.108	52.94	52.781	52.898	53.357	52.995	53.558	53.574	53.115	53.235	53.069	53.177	52.885	53.286	53.155	53.219	52.977	53.657	53.295	52.956	52.862	52.802
53.506	52.713	53.574	53.702	52.917	52.797	52.724	53.662	53.686	53.359	53.291	53.08	53.07	53.645	53.288	53.105	52.975	52.906	53.483	53.029	53.395	52.976	53.397	53.474	53.079
52.865	53.384	52.891	53.319	53.457	53.303	53.015	52.943	53.455	53.283	53.055	52.854	53.678	53.058	53.174	53.449	52.867	52.947	53.589	53.429	53.041	53.061	52.885	52.775	53.267
58.234	57.919	58.41	57.817	58.645	58.293	58.687	58.305	58.231	58.671	58.625	58.097	57.947	58.7	58.189	57.729	57.772	58.171	58.707	58.601	58.326	58.515	58.396	57.751	58.209
58.344	58.095	58.137	58.347	57.903	58.381	58.595	58.127	58.255	57.861	58.492	58.127	58.264	58.158	58.348	57.754	58.532	58.417	58.552	58.547	58.697	58.546	58.094	58.347	57.806
1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154
1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154
1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154	1.6154
0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769
0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769
0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769	0.80769
58.151	58.154	58.686	58.602	57.96	58.401	58.256	58.386	58.006	57.749	57.866	57.733	57.958	57.932	57.77	58.004	58.081	58.293	58.686	57.716	58.346	57.976	58.489	57.879	58.421
58.319	58.61	58.199	57.968	57.794	58.167	58.198	58.437	57.959	57.753	58.27	57.939	57.715	58.618	58.456	58.632	57.974	58.194	58.607	58.238	58.206	58.704	57.995	58.679	58.065
57.87	57.72	58.365	58.134	58.043	58.458	58.56	57.859	57.715	58.048	58.519	58.084	58.537	58.669	57.854	57.948	58.617	57.714	58.574	58.474	57.999	58.291	58.269	58.003	58.18
4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385
4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385
4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385	4.0385
23.035	23.391	23.664	23.296	23.577	23.313	23.082	23.208	22.711	23.458	23.71	23.13	23.409	23.052	23.633	22.816	23.466	23.365	23.503	22.959	23.278	22.76	23.246	23.397	23.66
35.373	35.473	35.508	36.016	35.547	36.077	35.784	35.514	36.175	35.779	35.77	36.194	35.212	35.289	35.729	36.072	35.905	35.337	35.919	35.465	35.806	35.801	36.135	35.221	35.534
35.749	35.307	35.427	35.874	36.048	36.12	35.323	35.491	35.394	35.335	35.801	35.445	35.486	36.169	36.074	36.015	35.283	35.387	36.116	35.823	35.865	35.529	35.928	35.636	35.489
3.4475	3.0484	2.7683	3.2383	2.9122	3.0203	3.1339	3.0762	3.4182	3.1349	3.0857	3.5278	3.0721	2.8967	3.1042	3.5081	3.599	3.6654	3.5067	2.9684	3.6003	3.3292	2.8122	2.7396	2.7759
3.6987	2.7281	3.5066	3.2322	2.8336	2.8719	3.5335	3.4296	3.1461	3.0332	3.2527	2.7328	3.3006	3.5807	3.6442	3.0521	2.9234	2.8896	3.4563	3.5281	3.5674	2.7716	2.8213	3.4163	2.7964
3.4977	2.8905	3.4962	3.2809	3.3119	2.7472	3.2103	3.261	2.8691	3.3756	3.5804	3.3049	3.6075	3.4969	2.9972	2.8651	3.4678	3.0469	3.4245	2.7338	3.0182	3.1378	3.5476	3.4513	2.8486
6.0741	5.6098	5.4924	5.7536	6.0642	6.2049	6.0182	5.7727	5.2218	5.6548	5.5887	5.3975	6.0626	6.1215	5.8958	6.0122	5.6251	5.4617	5.2713	5.9213	5.8223	5.9772	5.6235	6.0338	5.9706
5.3366	5.7902	5.4968	5.7735	5.7897	5.9154	5.7734	5.671	5.4121	5.9069	6.0608	5.607	5.6151	5.8178	5.7784	6.0653	5.8324	6.0912	6.0693	6.144	5.7738	5.8394	6.1752	5.5437	5.2808
6.0301	5.2788	6.0003	5.9614	5.5217	5.3631	5.3431	6.1725	5.8483	5.3743	5.5996	5.5768	5.5887	5.331	5.73	6.0197	5.6409	5.5264	5.7238	5.3384	5.6721	5.8221	6.0723	5.508	5.5116
3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923
3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923
1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462
1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462	1.8462
6.4502	5.866	6.2569	6.0237	6.229	5.8615	6.154	6.6109	6.263	5.8456	6.2102	5.9561	6.6146	5.7431	6.1431	5.9508	6.5822	6.2277	5.8663	6.0727	5.8531	5.8014	6.6863	6.3622	6.1814
5.8471	6.2073	6.4623	6.5581	6.1458	6.4	6.5006	5.8892	6.1793	6.4618	6.367	6.2214	5.8115	6.168	6.366	6.3825	5.875	6.4969	6.0312	6.2799	5.8413	6.652	6.1437	6.5777	6.1023
2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692
2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692
2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692
2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692	2.7692
3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923	3.6923
4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538
4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538
4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538	4.1538
23.636	23.398	23.684	23.391	23.294	22.964	23.68	23.007	23.111	22.841	23.506	23.206	22.977	23.155	23.194	23.114	23.665	23.233	23.616	23.176	22.83	22.954	23.362	23.675	23.111
23.612	22.984	22.941	23.154	23.171	23.383	22.805	23.628	23.399	23.71	23.046	22.968	23.011	23.224	23.451	22.995	23.585	23.048	23.47	23.641	23.532	22.777	22.991	23.525	23.621
22.954	23.074	23.441	23.594	23.445	22.976	23.611	22.884	23.239	23.419	23.353	23.518	22.811	23.711	22.757	23.286	22.928	23.162	23.295	23.212	23.669	23.212	23.13	23.133	23.311
47.983	48.488	48.489	48.346	48.304	48.556	47.722	48.049	47.745	48.321	48.353	47.82	47.84	48.155	48.526	47.777	48.197	48.404	48.668	48.338	48.625	47.973	48.267	48.533	48.146
48.263	48.041	48.074	48.296	48.514	48.627	48.626	48.133	48.114	48.168	48.586	48.034	48.383	48.606	48.401	47.952	48.197	48.611	48.099	47.832	48.123	47.766	48.258	47.805	48.466
47.766	48.51	48.46	48.426	48.53	48.255	47.886	48.151	48.475	48.501	48.434	48.405	48.63	47.934	47.804	47.877	47.722	48.337	47.727	48.056	48.023	48.304	48.665	47.856	48.15
23.35	23.576	23.09	23.584	23.323	23.073	23.089	22.931	23.491	22.86	23.654	23.709	23.631	23.083	23.149	22.748	22.81	23.322	23.605	23.446	22.975	22.954	23.67	23.179	23.057
23.236	22.912	23.249	22.803	22.931	23.678	22.899	23.312	23.152	23.458	22.991	23.14	23.039	23.637	22.731	23.556	22.971	23.683	23.247	23.202	23.004	22.875	23.387	23.486	22.741
1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308
1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308	1.7308
1728.548	1725.552	1730.634	1730.362	1729.347	1729.348	1730.305	1727.548	1727.674	1729.091	1731.802	1726.032	1727.517	1731.217	1727.868	1726.217	1728.923	1729.076	1732.842	1728.548	1731.195	1727.647	1731.533	1727.316	1724.515

Appendix VI-A

Details of generation, consumption, expenditure and rate/unit of KSEB Ltd.

		MU at Kerala Periphery			Expenditure in Rs.			Total Exp		Exchange + Traders (Units)			Rate Rs/Unit		
Month	Consumption in MU	Hydro generation in kWhr	CGS+IPP+Traders+ Exchng+UI (net import)	BDPP+KDPP	Hydro @ .93 Rs/Unit	CGS+IPP+Traders +UI+exchng	BDPP+KDPP	Hydro+CGS+IPP+UI+ Traders+Internal thermal	Rate/unit at KSEB peri.	Exchange + Traders (Units)	Amount	Rate	Hydro @ .93 Rs/Unit	CGS+IPP+ Traders+UI	BDPP +KDPP
Apr-15	1871.37	626564866.20	1237166446.50	23445891.25	582705326	5094491653	197089724	5874286703	3.14	200355080.5	983474992.3	4.91		4.12	8.41
May-15	1946.18	762520668.00	1167882489.00	17337350.39	709144221	4736326283	162029660	5607500163	2.88	139909629	726499056	5.19		4.06	9.35
Jun-15	1757.79	525356418.00	1206032626.00	15438168.70	488581469	4768779285	144789611	5402150364	3.07	212087777	856493287.5	4.04		3.95	9.38
Jul-15	1840.37	712385869.00	1107788747.00	10003726.06	662518858	4454937437	87547617	5205003912	2.83	164430224	821376305	5.00		4.02	8.75
Aug-15	1885.95	678275351.00	1187968288.00	11251735.76	630796076	4996511479	85099017	5712406572	3.03	215523691	949398393	4.41		4.21	7.56
Sep-15	1840.99	594825057.00	1225182341.61	33900662.03	553187303	5302820701	245066176	6101074181	3.31	217564414.5	1011623123	4.65		4.33	7.23
Oct-15	1893.06	539594220.00	1345596413.05	11608109.08	501822625	5437611207	83550117	6022983949	3.18	289029126	1308863301	4.53		4.04	7.20
Nov-15	1806.12	411986677.00	1378296861.00	5731326.88	383147610	5461235282	41722270	5886105162	3.26	364737905	1612677293	4.42		3.96	7.28
Dec-15	1903.94	409863750.03	1472261276.00	2784933.00	381173288	5911174147	18590990	6310938425	3.31	478828098	2011214237	4.20		4.02	6.68
Jan-16	1913.52	405671185.00	1492452903.00	2841533.00	377274202	6385613648	16888109	6779775959	3.54	492766284	2494460533	5.06		4.28	5.94
Feb-16	1922.76	456605349.9	1429025187.00	179873.00	424642975	5507431876	962885	5933037737	3.09	454037952	2054812777	4.53		3.85	5.35
Mar-16	2254.30	597234472.1	1617389032.00	19887983.51	555428059	6067273507	118684576	6741386142	2.99	625986094	2861604253	4.57		3.75	5.97
total	**22836.34**	6720883883.25	15867042610.16	154411292.67	6250422011	64124206504.74	1202020753.29	71576649269.45	**3.13**	**3855256275.00**	**17692497550.82**	4.59		48.59	89.09
			15867.04261	154.4112927											7.4241

Appendix VI-B

Optimized cost by using GA

Month	Optimized hydro generation MW	Optimized hydro cost in RS.	Optimized thermal generation MW	Optimized cost of Thermal generation	Total optimized cost	Total expenditure by KSEB in Rs.	Savings in Rs.
Apr-15	43937.607	980687388.7	1493.0833	291688760	1272376149	779795049.7	492581099
May-15	45401.6702	1013365278	1493.0833	291688760	1305054038	871173880.7	433880157.7
Jun-15	43936.2316	980656688.9	1493.0833	291688760	1272345449	633371079.6	638974369.3
Jul-15	45399.7614	1013322674	1120.5	218900880	1232223554	750066475.6	482157078.8
Aug-15	45402.114	1013375185	1120.5	218900880	1232276065	715895093.3	516380972.1
Sep-15	43937.7281	980690090.5	1120.5	218900880	1199590971	798253479.1	401337491.4
Oct-15	45400.9018	1013348127	1120.5	218900880	1232249007	585372741.9	646876265.2
Nov-15	45400.8561	1013347109	1120.5	218900880	1232247989	424869880	807378109.1
Dec-15	42471.5702	947965446.4	1120.5	218900880	1166866326	399764278	767102048.5
Jan-16	45401.6667	1013365200	8165.5	1595212080	2608577280	394162310.6	2214414970
Feb-16	43936.1526	980654926.7	8165.5	1595212080	2575867007	425605860.8	2150261146
Mar-16	45402.2526	1013378279	8850.8333	1729098800	2742477079	674112635.5	2068364443
Total	536028.512	11964156394	36384.083	7107994520	1.9072E+10	7452442765	11619708150

Appendix VI-C

Optimized cost by using PSO

Month	Optimized hydro generation (PSO) MW	Optimized hydro generation cost in RS.	Optimized Thermal generation MW	Optimized cost of thermal generation Rs.	Total optimized cost in Rs.	Total expenditure by KSEB in Rs.	Savings
Apr-15	51375.6365	1146704207	1534.66667	299812480.1	1446516687	779795049.69	666721637.06
May-15	53088.30677	1184931007	1534.66667	299812480.1	1484743487	871173880.75	613569606.42
Jun-15	51375.4606	1146700281	1534.66667	299812480.1	1446512761	633371079.62	813141681.04
Jul-15	53089.13287	1184949446	1151.66667	224989600.1	1409939046	750066475.62	659872570.11
Aug-15	53087.99467	1184924041	1151.66667	224989600.1	1409913641	715895093.29	694018547.81
Sep-15	51375.1785	1146693984	1151.66667	224989600.1	1371683584	798253479.13	573430105.06
Oct-15	53087.76897	1184919003	1151.66667	224989600.1	1409908603	585372741.87	824535861.60
Nov-15	51375.4647	1146700372	1151.66667	224989600.1	1371689972	424869879.96	946820092.20
Dec-15	53087.55867	1184914310	1151.66667	224989600.1	1409903910	399764277.95	1010139631.62
Jan-16	53087.87297	1184921325	8393.33333	1639721600	2824642925	394162310.55	2430480614.08
Feb-16	47950.91576	1070264440	8393.33333	1639721600	2709986040	425605860.81	2284380178.89
Mar-16	53088.21427	1184928943	9096.66667	1777124800	2962053743	674112635.48	2287941107.09
TOTAL	625069.5053	13951551357	37397.3333	7305943041	21257494398	7452442764.71	13805051632.99

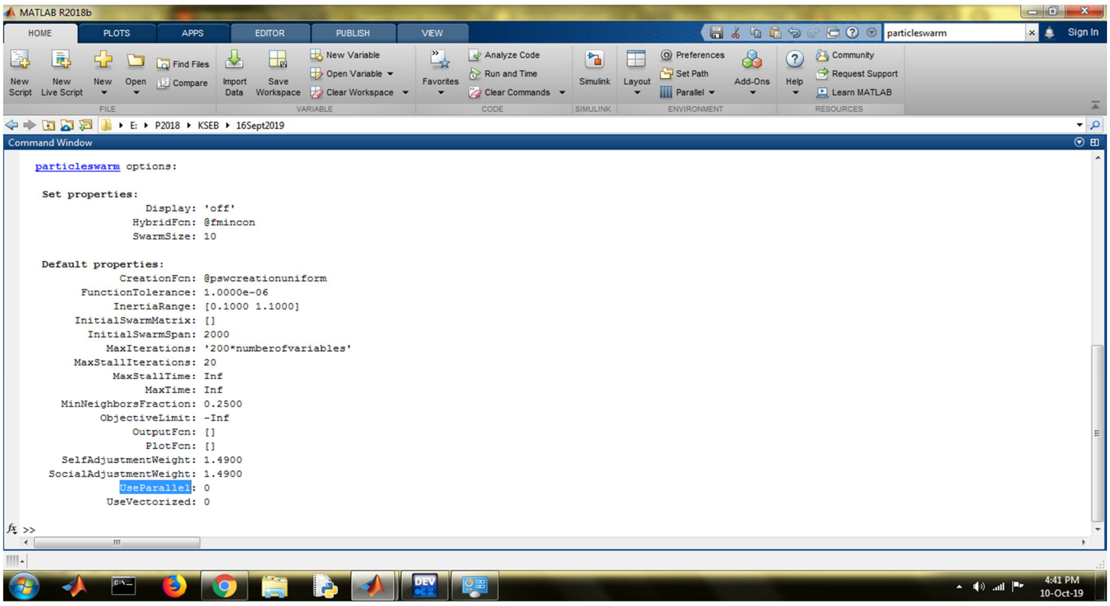
Appendix VI-D

Per unit cost under Kerala (KSEB Ltd) Periphery

Month	Hydro (kWhr)	Hydro generation in MW	Generation(Hydro) cost in Rs.	Thermal generation (MW)	Cost of thermal generation(Rs.)
Apr-15	626564866.20	26106.8694	582705325.6	976.91214	197089724.1
May-15	762520668.00	31771.6945	709144221.2	722.3896	162029659.5
Jun-15	525356418.00	21889.8508	488581468.7	643.25703	144789610.9
Jul-15	712385869.00	29682.7445	662518858.2	416.82192	87547617.45
Aug-15	678275351.00	28261.473	630796076.4	468.82232	85099016.86
Sep-15	594825057.00	24784.3774	553187303	1412.5276	245066176.1
Oct-15	539594220.00	22483.0925	501822624.6	483.67121	83550117.27
Nov-15	411986677.00	17166.1115	383147609.6	238.80529	41722270.35
Dec-15	409863750.03	17077.6563	381173287.5	116.03888	18590990.43
Jan-16	405671185.00	16902.966	377274202.1	118.39721	16888108.5
Feb-16	456605349.9	19025.2229	424642975.4	7.4947083	962885.4
March	597234472.1	24884.7697	555428059.1	828.66598	118684576.4
		280036.828	6250422011	6433.8039	1202020753

Appendix VII-A

PSO and GA Parameters



LIST OF PAPERS SUBMITTED ON THE BASIS OF THIS THESIS

I. REFEREED JOURNALS

1. K. Pramelakumari, Dr. V. P. Jagathy Raj and Dr. P. S. Sreejith, "Particle Swarm Optimization Based Economic Dispatch of Kerala Power System", *International Journal of Computer Applications*, vol. 181(27), pp.25-30, 2018.
2. K. Pramelakumari, Dr. V. P. Jagathy Raj and Dr. P. S. Sreejith, "Error Reduction Based Demand Forecasting : An Appraisal of Kerala Power System" , *International Journal of Computer Applications*, vol. 182(11), pp. 10-15, 2018.

II. PRESENTATIONS IN CONFERENCES

1. K. Pramelakumari, Dr. V. P. Jagathy Raj, S. R. Anand and E. A. Jasmine, "Short –term Load Forecast of a Low Load Factor Power System for Optimization of Merit Order Dispatch Using Adaptive Learning Algorithm, in *Power, Signals, Controls and Computation (EPSCICON), International Conference on*, pp. 1-7, 2012 IEEE.

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