Soft Computing Application for Similar Day based Electrical Short Term Load Forecasting

Thesis submitted in partial fulfillment of the requirements for the degree of the Doctor of Philosophy in IT in Power Systems

by

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CERTIFICATE

It is certified that the work contained in this Ph.D. Thesis titled, **“Soft Computing Application for Similar Day based Electrical Short Term Load Forecasting”**, being submitted by Santosh Kumar Kukkadapu for the award of the degree of Doctor of Philosophy, is a bonafide record of research work carried out by him under my supervision and has not been submitted elsewhere for a degree or diploma.

Date

Advisor: Dr. Amit Jain

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Nomenclature

Abbreviations	**Meaning**
AGC	Automatic Generation Control
ANN	Artificial Neural Network
AR	Auto Regressive
ARMA	Auto Regressive Moving Average
ARIMA	Auto Regressive Integrated Moving Average
a1, a3, a5, a2, a4, a6	Input Membership Function Parameter Limits of FIS
b1 – b13	Output Membership Function Parameter Limits of FIS
ΔE_H	Humidity Difference
ΔE_L	Load Difference
ΔE_T	Temperature Difference
ES	Exponential Smoothing
EP	Evolutionary Programming
EPSO	Evolutionary Particle Swarm Optimization
FIS	Fuzzy Inference System
FNN	Fuzzy Neural Networks
GA	Genetic Algorithm
HA	Heuristic Approach
MA	Moving Average
MAPE	Mean Absolute Percentage Error
NPSO	New Particle Swarm Optimization
P_A, P_f	Actual and Forecast Values of the Load
PSO	Particle Swarm Optimization
STLF	Short Term Load Forecasting

Abstract

Electrical load forecasting is a prime element for power system planning, scheduling, economic dispatch, unit commitment, maintenance, and electricity market. In practice, the electrical load is having nonlinear behavior and electrical load demand depends upon various factors like the type of day (day of the week etc.), weather variables like temperature, humidity, and the load on the previous day etc. Electrical load forecasting can become more accurate by considering these dominant factors.

Soft computing techniques have been successfully incorporated into a lot of scientific and engineering problems during recent years. Soft computing methods are capable of dealing with nonlinearity and these techniques are suitable candidates for electrical load forecasting problems. In this thesis work, soft computing techniques like fuzzy logic and bio-inspired computation techniques are chosen for similar day based electrical short term load forecasting. The fuzzy logic is able to model uncertain and ambiguous data. The fuzzy logic system gives better forms of rule expressions, reasoning logic like human thought.

This work presents fuzzy logic based Short Term Load Forecasting (STLF) by selecting similar days, which are found from previous data by using Mahalanobis distance norm. The fuzzy logic is chosen in the correction of similar days of the forecast day. The average of the corrected hourly loads of the similar days achieved through the Mahalanobis distance norm of the forecast day is then considered as the hourly load of the forecast day. The parameter limits of fuzzy membership functions are determined and optimized through different optimization techniques like Heuristic Approach, Particle Swarm Optimization (PSO), New Particle Swarm Optimization (NPSO) and Evolutionary Particle Swarm Optimization (EPSO). In the first approach, Fuzzy membership parameter values are tuned in a heuristic way. Another approach for the optimization of fuzzy parameter values is to use PSO. It simulates the bird flocking behavior where each particle fitness value can be evaluated in a search space by using the fitness function. The particle's direction of flying can be decided by its velocity and position. PSO function updates the latest particle position by using an optimization

equation based on the global best of the previous iteration provided that it is better than the previous one.

NPSO technique is also attempted for the optimization of fuzzy parameter values. Each particle tries to leave its previous worst position and the previous worst position of its group. NPSO function modifies the latest particle position using the optimization equations based on the global worst of the previous iteration provided that it is better than the previous one. The inclusion of the evolution process in PSO is providing the Evolutionary Particle Swarm Optimization (EPSO). EPSO has the properties of Replication, Mutation, Reproduction, Evaluation and Selection. In this thesis, EPSO is also used for the optimization of fuzzy parameter values.

These optimized fuzzy parameter values are incorporating in Fuzzy Inference System (FIS) and used for forecasting the load of forecast month.

It is difficult to forecast a load of anomalous days like holidays, religious days and special days because their load profile is different when compared to normal days. Load forecasting for anomalous days is also a challenging job because of small number of data availability compared to the availability of data for normal weekdays and weekends. Hence, various methodologies are developed for anomalous day load forecasting and presented in the present research work.

The short term load forecasting algorithms are developed for each optimization technique and also forecasting methodologies for various case studies of anomalous day load forecasting and these are tested by doing simulation studies on real-time data and results obtained are found good, which have been presented in this thesis.

Chapter 1

Introduction

1.1 Electrical Load Forecasting Overview

Electrical load forecasting is very significant to the power engineers, the power industry, power utilities and to the national economic development at large. In power systems load forecasting is widely used for planning, operation, unit commitment, economic dispatch and electricity market etc. The load forecasting subject is quite broad, interesting and includes usage of many engineering techniques and economic considerations. Moreover, it is directly affected by environmental and political decisions and also influenced by various regulatory commission decisions from time to time.

The matching of the network load with the system generation is a basic requirement in the power system at all times for its stable operation. For the time scale of seconds, the automatic generation control (AGC) function takes care of small and random load variations and that matches the on-line generation with the system load demand. For the time scale of minutes, with larger load fluctuations, the economic dispatch function is applied so that the system demand matching is economically allotted between the committed generating units. For the time scale of hours and days, still wider load variations exists and it may require the interchange of power with other areas or start-up or shutdown of generating units to meet the system load, This uses several generation control functions such as unit commitment, interchange evaluation and hydro-thermal coordination etc. For the time period of weeks, system load can be met with installed generating resources by using functions such that hydro, fuel and maintenance schedules are performed economically. In addition to this, at some future time, the secure operation requires the study of power system behavior under a variety of possible contingency conditions.

1.2 Classification of Load Forecasting

The Load Forecasting can be classified into four types

a. *Very Short Term Load Forecasting (VSTLF):* If the considered time period for the load forecasting is from few seconds to few minutes, it is called VSTLF. This is used for security evaluation and real time control..
b. *Short Term Load Forecasting (STLF):* The forecasting for a time frame of one day to one week is considered as STLF. This plays a very important role in determining the system security, unit commitment and economic dispatch.
c. *Medium Term Load Forecasting (MTLF):* The forecasting time span of one week to a few months is called MTLF. It is used to address the fuel management, maintenance scheduling and revenue from sales.
d. *Long Term Load Forecasting (LTLF):* The load forecasting ranging from 1 year to 5 years is considered as LTLF. It is a first step in planning the future requirements of electricity generation and network expansion.

1.3 Factors affecting Load Forecasting

The impact of meteorological parameters and economic factors on the load is negligible in very short term load forecasting and hence the near future load can be forecasted based on the past load. For short term load forecasting, economical factors are relatively stable, but the time, weather parameters and random disturbances play a vital role in STLF. The time factors include the hour of the day, the day of the week, the time of the year. Usually, the weekday's load is different compared with weekends load. The load on weekdays also behaves differently. For example, Monday and Friday, which are adjacent to the weekends, may have different loads compared to load from Tuesday to Thursday. Anomalous days like special days, holidays etc. are more difficult to forecast because the load profile is different when compared to normal days and also they occur infrequently. Forecasted weather parameters are important in STLF because these parameters influence the electrical load. Temperature and humidity are commonly used parameters in load predictors. The medium and long term forecasts take into account the number of customers in different categories, the appliance sales data, historical load, weather data, demographic and economic factors etc.

1.4 Importance of STLF

Short Term Load Forecasting (STLF) is an important element for the power system planning, control and scheduling operations and input to the power analysis functions such as load flow and contingency analysis [1]. The load dispatch center must predict the load pattern in advance to meet the load requirement with the generating units. Overestimation of the load forecasts results in the startup of additional generating units and a further rise in the operating and reserve costs. Underestimation of the load forecasts results in inability to meet the sufficient standby and spinning reserve and may also affects the stability of the system, which may cause to the power system network collapse. STLF is a very important task of the electricity sector as accurate STLF leads to optimal arrangements for power generating units economically within the start-stop time and maintenance schedules. A good STLF will have a direct favourable impact on electricity planning and operational management, fuel-efficiency and lower cost of power. STLF is very much significant in the latest trend of deregulation of electricity as in the real-time load dispatch, forecasting error leads to the extra cost due to additional purchasing of electricity or breaking-contract penalty cost to maintain the balance between generating and system load. Therefore, accurate STLF is a prime element in the power system.

1.5 Soft Computing Techniques in Load Forecasting

It is known that lot of systems are uncertain, imprecise and difficult to be modeled exactly. A flexible approach of Soft Computing techniques has emerged to deal with those models most effectively and efficiently in the present scenario. Soft computing is built based on human brain conception. These techniques can be applied to many fields.

These have the ability to provide better performance in dealing with nonlinearity, uncertainty of data and help in achieving the best results and low solution cost to real time problems. These techniques are very much suitable for applications in load forecasting problem.

Genetic Algorithm

Genetic Algorithm is a computation procedure with repeated execution on set of the population with step by step operations such as selection, crossover and mutation. First, the selection process selects the best one based on fitness assignment then new chromosomes are generated based on selected ones. The algorithm performs the mutation and recombination for new chromosomes generation. If the fitness of the new chromosome population reaches the optimal solution, the algorithm is stopped otherwise the procedure is repeated until the optimal solution is reached. Load dependent variables are given as input to the genetic algorithm for load forecasting.

Artificial Neural Networks (ANN)

ANN is based on the interconnection of nodes called artificial neurons just like a biological brain. Nodes receive a signal and then process it and transmit the signal to the nodes connected to it. ANN model is a layered structure (Input layer, Hidden layer and Output layer). The advantage of the ANN model is that it can learn non linear mapping and output to be calculated are based on the experience. The ANN based load forecasting model is divided into two processes, first one is the 'learning phase' and the second one is the 'recall phase'. In the learning phase, neurons are trained based on past input/output data and their weights are adjusting based on the learning process till reaching the desired output. In the recall phase, new input data is applied to ANN for evaluation and testing purposes.

Support Vector Machines (SVM)

SVM is supervised learning based on the statistical analysis and it non-linearly map the input space into a high-dimensional space via kernels (linear, radial base function, sigmoid and polynomial etc). It applies the structural risk minimization (SRM) principle and based on this SVM achieves an optimum network structure. SVM advantages are that does not depend on the dimensionality of input, global and unique solution, high training speed etc. Load dependent variables are given as input to a trained SVM, output is the forecasted value.

Fuzzy logic

Fuzzy logic is a mathematical tool that has the ability to model the uncertain and ambiguous data, provides better forms of rule expressions and reasoning logic like human thought. It takes uncertain and ambiguous data as input and provides the right decision as an output. Human thinking is realized with membership functions. Fuzzy systems are constructed based on the rules from the available historical load data. Then training data is applied on the constructed rule base to tune the parameters. After training the fuzzy system, it can be used to forecast the load data.

1.6 Motivation for this research work

Electricity plays an essential element in social and economic development as almost everything depends on electricity in modern age and the absence of electricity results in a standstill life. Electrical load demands are increasing day by day especially in developing countries due to the further industrialization and increase in population and standards of living.

Electrical load forecasting is a critical task in the electrical industry for effective management and efficient planning and better forecasting will make the electrical power industry significantly cost effective. Electric load demand is never steady due to the continuous change in usage of electricity by consumers all the time and the availability of a large amount of data along with changing behavior and patterns of consumers makes the electric load forecasting problem even more complex.

For the engineering systems that are dynamic and uncertain in real time and difficult to be modeled precisely with traditional techniques, soft computing techniques can deal with such models and these have been applied in many engineering fields effectively and efficiently. Therefore, a hybrid approach with soft computing techniques provides a good alternative to the load forecasting problem.

Short term load forecasting has been there for several decades and it plays a very important role in determining the system security, unit commitment and economic dispatch. In present day deregulated framework of power sector, it has become one of the foundational elements for the power system planning, control and scheduling operations. It is a challenge to forecast an accurate load of weekdays, weekends and anomalous days because of different load patterns and also due to limited data in case of anomalous days. Soft computing techniques can help in achieving the novel solutions for getting the accurate STLF and this has motivated me to do further research in this field.

1.7 Novelty and Contribution of the research work of thesis

- A Mahalanobis Distance norm is used for the selection of similar days has been proposed considering the temperature, humidity and day type as the similarity criteria parameters. The fuzzy logic is chosen in the correction of similar days of the forecast day.
- Optimization of the fuzzy input parameter limits for generation of better correction factors to improve the accuracy of the forecasted load has been done using Heuristic Approach, Particle Swarm Optimization (PSO), New Particle Swarm Optimization (NPSO) and Evolutionary Particle Swarm Optimization (EPSO).
- The short term load forecasting algorithms are developed for each optimization technique and these have been validated on real-time data.

- To overcome the small number of data availability for anomalous days, new methodologies have been proposed for anomalous day load forecasting and these have been validated on real-time data.
- The possibilities of errors in input weather parameters data are considered for week days and their impact has been analyzed.
- Impact of errors in weather variables on STLF for weekend days have been analyzed.
- In addition to weekdays and weekends, assessment of impact of error possibilities in weather parameters on STLF for anomalous days has been done in this research work.

1.8 Organization of the Thesis

The thesis is organized in eight chapters. The first chapter explained about load forecasting introduction and the classification of load forecasting and their importance. Factors affecting load forecasting and the importance of STLF were also presented.

In the second chapter, a literature review of past research is presented, which also covers the application of different techniques in STLF. In the third chapter, heuristic approach based fuzzy inference system for short term load forecasting is presented. A novel technique for selection of similar days based on Mahalanobis distance is introduced and a fuzzy inference system is formulated for short term load forecasting.

In the fourth chapter, a technique is presented for short term load forecasting which uses particle swarm optimization (PSO) based fuzzy inference system. Fifth chapter presents new particle swarm optimization (NPSO) based fuzzy inference system for short term load forecasting where fuzzy membership functions are optimized using NPSO. Sixth chapter presents a technique for short term load forecasting using fuzzy inference system where fuzzy parameters are optimized using evolutionary particle swarm optimization (EPSO). The fuzzy inference system is used to forecast the load of the forecast month.

In seventh chapter, various techniques for anomalous day load forecasting are proposed and algorithms are implemented for each proposed technique with optimization. Various case studies for anomalous day load forecasting are presented which are implemented and tested on real-time data and their results are described.

The eighth chapter concludes the research work presented in this thesis with few directions for future work.

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Chapter 2
Literature Review

In the last five decades, a lot of papers and studies have been published in the electric load forecasting field. This chapter concentrates on short term load forecasting literature published in the reputed journals and conferences. The load forecasting techniques may be broadly grouped into traditional techniques, soft computing techniques and hybrid techniques [2].

2.1 Traditional Techniques

The traditional forecasting techniques include regression, multiple regression, exponential smoothing, iterative reweighted least-squares, adaptive load forecasting and time series techniques.

2.1.1 Regression

Papalexopoulos et al [3] proposed a linear regression model for STLF. This model tested the hourly and peak load forecasts of the next 24 hours of Pacific Gas and Electric Company's (PG&E) data.

Hyde et al [4] explored a regression based procedure for STLF. The working model focused on peak load forecasting since the load graph of the next day was based on their utility company forecasted peak load in practice.

Charytonuik et al [5] forecasted the load based on a non-parametric regression approach.

The presented method was tested to forecast the load of residential, commercial and industrial customers. The model used to reflect the probability density function of the load and the affected factors on the load. The forecast was based on past load data and weather data. Past load data was grouped into two subgroups of weekdays and weekends. The temperature was considered in the load model, a cross-validation technique was applied for the calculation of a few parameters.

G. T. Heineman et al [6] proposed that the system load can be expressed as the sum of the basic load and the product of weather variable times of air-conditioning saturation coefficient. This method was tested on historical data of Public Service Electric and Gas Company by regression analysis.

2.1.2 Multiple Regression

N. Amral et al [7] proposed a multiple linear regression model for STLF. This approach was reported with testing using South Sulawesi electrical system data for hourly load prediction.

Haida et al [8] presented peak load forecasting based on multivariate linear regression, in which a transformation function was applied to observe the non-linear relationship between load and temperature. This technique was examined by comparing the forecasted results with real time load data of Tokyo Electric Power Company.

2.1.3 Exponential Smoothing

W. R. Christiaanse et al [9] explored an adaptive forecasting system with the use of general exponential smoothing based on integrated hourly demand. The developed model offers operational simplicity and better accuracy. The hourly MWH load forecasts with lead times of 24 hours are calculated at hourly intervals throughout the week.

Prajakta S [10] presented the Holt-Winters exponential smoothing that has been used when the data exhibits both seasonality and trend.

Agust´ın C et al [11] presented Exponential Smoothing (ES) based load prediction of the technological e-learning infrastructure of UNED (the largest university in Spain). This paper’s main objective is the development of algorithms to dynamically perform provisioning of resources based on the predicted loads.

2.1.4 Iterative Reweighted Least Squares

Mbamalu et al [12] presented Iteratively Reweighted Least Squares based load prediction of Nova Scotia Power Corporation’s 168 hourly loads. The presented method was used to identify the model parameters and order. The results are compared to the Box and Jenkins method based results.

2.1.5 Adaptive Load Forecasting

Lu et al [13] presented an adaptive Hammerstein model with a lattice structure and an orthogonal escalator structure for STLF. In which used a joint Hammerstein time-varying non-linear relationship between load and temperature. The developed algorithm performed better than the recursive least-square algorithm. Grady [14] further enhanced the algorithm.

2.1.6 Time Series

The time series method is considered that the data have an internal structure, such as autocorrelation, cyclic, trend, seasonal variation and irregular. Auto-Regressive (AR) technique is used to model the load profile. Liu [15] assumed that load is a linear combination of previous loads. Huang [16] and Zhao [17] presented the AR model with an optimum threshold stratification algorithm and two Periodical Auto Regressive (PAR) models for hourly load forecasting respectively.

Auto Regressive Moving Average (ARMA) model considers that the present value of the time series is in terms of its values at previous periods and previous values of white noise. Barakat et al [18] presented that monthly peak demands are decomposed into stochastic and deterministic load components, the former determined by an ARMA model. Chen et al [19] presented an adaptive ARMA model based STLF, in which the model is updated by available forecast errors and the adaptive scheme better performed compared with conventional ARMA models.

Barakat et al [20] presented a seasonal ARIMA model for load prediction based on historical data with seasonal variations, in which the model separately forecasts the static and dynamic components of the system demand.

Juberias et al [21] presented a real time ARIMA model based load forecasting that considered the meteorological influence as an explanatory variable. The model is based

on a time series analysis and considers the meteorology parameters as an explanatory variable. Information about the impact of the meteorology parameter on an hourly electrical load is given to the developed model as an explanatory variable by using the daily electrical load forecast and it is used in the Central Region Control Center in Red Electrica de Espana successfully. Amjady [22] presented the time series modeling of the ARIMA for load forecasting based on experienced human operator's knowledge.
Shilpa.G.N et al [23] presented short term electrical demand prediction based on ARMA, ARIMA and ARIMAX models. The mean absolute percentage error (MAPE) of proposed models was computed and compared on real time 2019-Karnataka State Demand Data. The forecasting accuracy of ARIMA and ARIMAX models are improved compared to ARMA model.

2.2 Soft Computing Techniques

Most of the systems are uncertain and difficult to be modeled precisely. A flexible approach called soft computing techniques is used to deal with such models effectively and efficiently in the present scenario. It is emerging as a tool to help intelligent system mimic the ability of living being which learn in uncertainty and imprecision environments and that is approximate rather than exact. It has been applied in many fields over the last few decades. The basic objective of soft computing is that certainty and precision carry a cost and that computer based intelligent systems should exploit with possible tolerance for uncertainty and imprecision.

2.2.1 Genetic Algorithms

Yang et al [24] developed a load forecasting algorithm based on Evolutionary Programming (EP) that is verified with the data of Taiwan Power (Taipower) system and substation load and temperature values.
Azadeh et al [25] explored the genetic algorithm based electricity demand function of the Iranian agriculture sector with variable parameters of price, number of customers, value-added and previous period electricity consumption.

2.2.2 Artificial Neural Networks

Park D. C. et al [26] presented electric load forecasting based on artificial neural networks (ANN) with a back propagation algorithm.

Peng T. M. et al [27] developed a model for the selection of training cases and these are similar to the forecasted inputs. M. Djukanovic et al [28] described the application of ANN in STLF, in which an algorithm is used with a supervised/unsupervised learning concept and tested on real time data of Electric Power Utility of Serbia.

Al-Fuhaid [29] presented an artificial neural network approach for STLF in Kuwait, which incorporated the temperature and humidity effects.

Khotanzad A. et al [30] presented ANNSTLF that has two ANN forecasters, which are used for prediction of the next 24 hours load. One forecaster is used to predict the base load and another one forecasts the variation in load and a combination of these two forecasts gives the final forecast. The impact of wind speed and humidity is used through a linear transformation of temperature. Hippert H. S. et al [31] presented a comprehensive review for STLF based on the ANN approach, summarizing the progress in the 1990s.

Tareq Hossen et al [32] proposed short term load forecasting based on Deep Neural Network (DNN) for residential consumers. The performance is compared using different types of recurrent neural networks (RNN).

Eduardo Machado et al [33] proposed a methodology for load forecasting based on feed forward neural network (FFNN), where this work incorporated an error correction step that involved the initial forecast error.

Chawallit et al [34] demonstrated the next day electricity demand forecasting based on genetic algorithm and neural network approach. Here, genetic algorithm is used to train the neural network and the performance was tested on real time data of the electricity generating authority of Thailand (EGAT).

2.2.3 Support Vector Machines

Support Vector Machines (SVM) is optimal margin classifiers in the context of Vapnik's statistical theory; which appeared in the early 1990s and it is a novel and promising technique for regression and data classification [35]. Mohandes M. et al [36] applied the support vector machines method for STLF, where performance is compared with the autoregressive (AR) method and the results indicated favorably for SVMs against the AR method.

Li Yuancheng [37] presented a Least Squares SVM approach to STLF and load forecasting is performed on Yan Tai Electric Power Network. Fan S [38] proposed STLF based on support vector regression, where optimally partitioning and merging the regions inside the large geographical service territory is done.

2.2.4 Fuzzy Logic

Ranaweera D. K. et al [39] developed a fuzzy logic model for STLF using a learning algorithm, in which fuzzy rules were obtained from the historical data. This model is used to forecast daily energy and daily peak load.

S.Higa et al [40] presented the application of a fuzzy logic model with similarity for next day load curve shape. This approach has the advantage of handling the non-linear curves and it is used in a situation where exact models are not easy to design. The suitability of the proposed model was tested on the Okinawa Electric Power Company, Japan's actual load data.

Wu and Lu [41] presented another kind of method instead of traditional trial and error method for finding the fuzzy membership functions that utilizes analysis of variance, recursive least-squares and cluster estimation. The presented method was illustrated on Taiwan Power Company's (Taipower) load data and the performance of this method is compared to those of artificial neural network (ANN) and Box-Jenkins (B-J) models.

Hiroyuki Mori et al [42] presented an optimal fuzzy inference to STLF, which provides the optimal fuzzy inference structure that optimizes the location and the number of fuzzy membership functions for error minimization. The proposed method is used for constructing the optimal structure of fuzzy inference with tabu search. Supervised learning was used for the optimization of the parameters. Fuzzy models are tested on actual data with different variables. Srinivas S. et al [43] explored various fuzzy logic applications.

Chenthur Pandian et al [444] developed another fuzzy logic model for STLF, in which inputs of the fuzzy logic controller are time and temperature and output is forecasted load. M.F.I. Khamis et al [45] presented a practical STLF method for Universiti Teknologi PETRONAS (UTP). The presented model was designed based on UTP 2008 electricity load data with the fuzzy logic approach and tested on January to June 2009 real time load data.

Jordan et al [46] applied the fuzzy logic method to short term load forecasting. In this work, historical data was pre-processed using a c-means method and grouped based on power levels (MW) to get the number of membership functions to the fuzzy system. The method was tested on real data of the Peruvian Electrical System.

Manish Kumar et al [47] presented short term load forecasting using a fuzzy logic approach. In this approach, fuzzy logic tool box with triangular membership functions is used for the load forecasting.

Mohd. Hasan Ali et al [48] proposed residential load forecasting based on a new fuzzy logic controller method. This method used temperature as one of the variables. It was tested on actual energy consumption data in an apartment building located in Memphis city of USA. The performance of fuzzy systems was better compared to artificial neural networks.

2.3 Hybrid Techniques

The traditional techniques are simple with rapid speed calculation, but they are linear ones. These techniques are quite difficult to model the relationship between the load and its exogenous factors because of complex, non-linear characteristics, not giving the required precision and not robust enough.

Soft Computing technique has emerged to deal with imprecise, uncertain, non linear load data. Therefore, a hybrid strategy is needed, which has ability to deal both linear and nonlinear modeling, as an alternative for load forecasting.

Hsu Y. –Y. et al [49] presented a fuzzy expert system using experienced operator's heuristic rules in the knowledge base for STLF. Tranchita C. et al [50] developed another novel method based on the use of soft computing techniques and similar day selection for short term load forecasting.

Bo Yang et al [51] presented a survey of particle swarm optimization (PSO) applications in power systems. The main theme of this paper is to provide a summary of particle swarm optimization method used in electric power system. It is a population based stochastic optimizer with simpler implementation and faster convergence speed compared to ant colony optimization and genetic algorithm. It has been successfully used in several power optimization problems such as load forecasting, economic dispatch, optimal power flow, model identification, reactive power dispatch, state estimation, generation, transmission planning, control, scheduling, unit commitment, and others.

Huang C.-M. et al [52] used particle swarm optimization technique for STLF. Chao Ming Huang et al [53] presented a PSO model to identify the autoregressive moving average with exogenous variable (ARMAX) model for hourly load forecasts with lead time of one-day to one-week. The proposed model was evaluated on the Taiwan Power (Tai power) load data and compared with the traditional time series method and the evolutionary programming (EP) algorithm. Evaluated results indicated that the presented model has high-quality solution, shorter computation time as well as superior convergence characteristics.

Li Feng et al [54] presented multi-objective PSO based electrical load classification, in which it was applied to choose the optimum rules. Yang Shang Dong et al [55] presented another hybrid PSO with an adaptive inertia weight factor (AIWF) algorithm. GwoChing Liao [56] presented PSO merged with fuzzy neural networks (FNNs).

Ning Lu et al [57] presented the work that uses the PSO algorithm with Radial Basis Function (RBF) neural network. It is a random optimization method and used in solving nonlinear optimization problems. The load prediction model which was optimized by particle swarm optimizer is more accurate than the radial base function neural network model. Azzam-ul-Asa et al [58] presented an approach for modeling STLF where swarm intelligence is used for the optimization of weights for STLF-ANN forecaster.

Sanjib Mishra et al [59] proposed a smaller MLPNN trained by PSO and genetic algorithm for STLF. The genetic algorithm training gives better performance compared with back propagation training. The particle swarm optimization training approach faster converges than a genetic algorithm and back propagation. This approach is more suitable for real-time implementation. The presented paper highlighted the suitability of PSO over GA.

Carolina et al [60] proposed another approach for STLF based on the application of soft computing techniques. Proposed method validated on Colombian city load and meteorological data.

Senthil Kumar [61] discussed different soft computing techniques such as genetic algorithms, neural networks, fuzzy logic for short term load forecasting. Soft computing techniques can provide better forecasting results with less computation time and error for the non linear time series data sets.

Kuruge et al [62] proposed short term load forecasting based on hybrid particle swarm optimization with GA to train artificial neural networks. In this work, performance was evaluated on real time data of the Electricity Generating Authority of Thailand.

Zaahra Shaafiei Chafi et al [63] proposed a neural network and particle swarm optimization algorithms to short term load forecasting. PSO algorithm is used for determining the learning rate and the number of hidden layers. The proposed approach has been tested on real time data of the Iranian power grid.

Ruixuan et al [64] presented a similar day approach to forecasting the 24h ahead electricity usage and incorporated long short term memory (LSTM) and wavelet transform.

Ref [65] – [66] provides the details about the application of Euclidean distance norm based similarity in forecasting. Ref [67] – [70] have provided the details about availability of one day ahead of weather variables.

2.4 Anomalous days forecasting

Hasan H. Çevik et al [71] presented STLF for holidays by using fuzzy logic without considering weather factors. He explained that the normal days and holidays load are having different trends and holiday’s classification is done according to their historical load shapes and their characteristics. The fuzzy model is developed with three inputs and one output. The historical load data between the years 2009 and 2011 is taken and also used to develop the forecasting model. The performance was tested with real time data of the year 2012. This paper presented that fuzzy logic is able to give better results for the holiday short term load forecast.

Siddharth Arora et al [72] demonstrated anomalous load by using a rule based triple seasonal Holt-Winters-Taylor (HWT) exponential smoothing and singular value decomposition (SVD) based exponential smoothing, ANN and triple seasonal ARMA. The demonstrated method is used for modeling of normal and anomalous loads. The performance was evaluated on Great Britain's half–hourly load data of nine years.

Song K B et al [73] presented a paper on fuzzy linear regression method based STLF for the holidays. He analyzed from the historical load data that the load profile of the same type of holiday follows a similar trend of the previous year's load profile. Relative coefficients are also introduced in the proposed algorithm for the case of holidays that are falling on Monday or Saturday for the betterment of accuracy. Model of fuzzy linear regression is made from the previous three years load data and load forecasting is done for the holidays of the years of 1996-1997 with an average maximum error of 3.57%.

Kwang-Ho Kim et al [74] presented STLF for the special days in anomalous load conditions by using a hybrid approach of fuzzy inference and ANN method. Public holidays, days proceeding and following holidays and consecutive holidays are included in special days. In this, days are divided into five different types. For each day type, five ANN models and two fuzzy inference models are developed for minimum and maximum loads. This method was tested with real time load data of 1996-1997 year's special days.

Qia Ding et al [75] presented that holiday load is influenced by weather conditions and increases with long time. The proposed method uses a hybrid method of fuzzy inference method for holiday load level forecast and to obtain a scaled load curve using similar days. Load annual increase and weather information are also considered. Test results showed better results on weather change days.

Bichupuriya et al [76] presented holiday load forecasting in the Indian context. Holidays are classified as Public holidays, Sunday and regional holidays. This paper presented two different models for Sunday and other holiday's that are public holidays and regional holidays. Proposed model is tested on load data of urban distribution utilities.

Srinivasan et al [77] presented a demand forecasting of weekends and public holidays by using fuzzy neural computation. In this paper, combined fuzzy logic and fuzzy set theory with neural network modeling are used. Better results are shown on Weekdays, Saturdays, Sundays and public holidays based on the forecasted weather information.

Florian [78] addressed the issue of public holidays in electrical load forecasting. A large load forecasting study for Germany was analyzed that compared the techniques using standard performance and significance measures. General recommendations have been included for the improvement of forecasting accuracy. Miggue Lopez et al [79] introduced classifications of special day's algorithm for short term load forecasting. The classifications have been tested with the benchmark used at the Transmission System Operator in Spain.

2.5 Conclusions

A number of papers have been published in the area of short term load forecasting (STLF) in the past few decades. Literature survey provided thorough knowledge of the past works in this area and helped in understanding the challenges to do STLF where the different weather variables also have impacts on the performance of the STLF techniques. The papers discussed in this chapter have contributed their part to the enhancement of the load forecasting models.

It has been observed that the soft computing techniques have performed better than conventional methods for the complex non-linear time series data sets, which is usually the case for load data and weather variable. It is understood that mean absolute percentage error (MAPE) is used popularly for the validation of STLF models.

Accurate short term load forecasting with historical data, changing weather, holidays and other parameters remains a challenging task. Soft computing techniques have emerged to deal with imprecise, uncertain, non-linear load data and employing the advancement in the soft computing algorithms make it possible to improve the short term load forecasting results. Therefore, soft computing technique based methodologies are needed, which have the ability to deal with the nonlinear nature of data sets for short term load forecasting for weekdays, weekends as well as holidays.

Chapter 3
Heuristic Approach based Fuzzy Inference System for Short Term Load Forecasting

3.1 Introduction

The electrical load is having nonlinear behavior and electrical load demand depends upon the various factors like the load on the previous day, the type of day and weather variables like temperature and humidity. This chapter presents fuzzy logic based short term load forecasting by selecting similar days. Mahalanobis distance norm is introduced in the selection of similar days. The fuzzy logic is used for the correction of similar days of the forecast day.

It is important to determine the parameters of the fuzzy membership functions. The parameters limit of fuzzy membership functions are optimized through heuristic approach. The heuristic approach is a general way of solving a problem, which is used to find the close to best possible optimal solution by rules of thumb, guesses, intuitive judgments or common sense and it is used as part of a global procedure to find the optimum solution of a problem. The solution can be approached by the reasonable computational effort by using the heuristic approach and fuzzy membership parameters are tuned.

The average of the corrected hourly loads of the similar days of the forecast day is then considered as the hourly load of the forecast day. The accuracy of forecast results can be expressed in the form of the Mean Absolute Percentage Error (MAPE). MAPE is provided as:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{\left|P_A^i - P_F^i\right|}{P_A^i} * 100 \tag{1}$$

Where

P_A - actual value of the Load

P_F - forecast value of the load

N - number of the hours of the day (24 hours and in this case i= 1, 2….24).

In general, performance metrics for short term load forecasting can be divided into two groups namely scale-dependent and scale-independent measures. The mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE), and median absolute error (MdAE) belong to the scale-dependent group. These can be used when comparing forecasting methods to data with the same scale only. In case of load forecasting for different time and days, there are large differences in the values of loads for different time and days and when comparing the forecasted results with actual values it becomes somewhat difficult to judge the effectiveness of forecasting technique as there are significant differences in the values of errors between forecasting and actual values by these scale-dependent performance metrics.

The performance metrics Mean Absolute Percentage Error (MAPE) is scale-independent as its estimated error is in terms of absolute percentage and normalized on a common scale. Moreover, the problem of positive values and the negative values canceling each other is also not there and MAPE is easy to understand as all errors are in terms of percentage of the actual values. It has been found that MAPE is most widely used performance metrics for STLF and it helps in judging the effectiveness of the forecasting techniques in very easy manner. Therefore, MAPE has been used in the present thesis as the error performance criteria for judging the effectiveness of the proposed STLF techniques.

3.2 Mahalanobis Distance based Selection of Similar Days

To evaluate the similarity between the forecast day and the searched previous days, Mahalanobis distance norm is proposed in the present work.

In 1936, Mahalanobis distance was introduced by Mahalanobis P.C. It is superior to other classical statistical techniques because

- In its calculation, it takes into account of correlation between the variables.
- It is very sensitive, there are inter variable changes in the reference data.
- It is independent of the dimensionality of the dataset.

Distance d_{ij} between any two points in n-dimensional space may be expressed as:

$$d_{ij} = \left[\sum_{i=1}^{n} \left| X_{ik} - X_{jk} \right|^{p} \right]^{\frac{1}{p}} \tag{2}$$

Where p is the type of distance, k is the index of coordinates

- p = 1, this distance is called Manhattan distance or City block distance.
- p =1, this distance is called Hamming distance for binary data. The Hamming distance defines the number of common “1” bits of two binary values.
- p = 2, this distance is called a well-known Euclidean distance.

The various distances do not account for different metrics of the individual coordinates. If the coordinates span has different ranges, the largest range coordinate will dominate the results. Therefore, one has to scale the data before calculating the distances. Any correlations between variables (coordinates) will also distort the distances. To overcome these drawbacks, Mahalanobis distance is used, which takes care of correlation and different scaling.

For example, consider the case of Euclidean distance, even though Euclidean distance is simple to code and speed to calculate, but it has two basic drawbacks:

i. It is sensitive to the scales of the variables and these are not comparable. Variables are measured in the same units of length such as age, weight, height etc.
ii. It is blind to correlated variables. Suppose a data set is having ‘n’ variables where some variables are an exact duplicate one of others and these are completely correlated. Therefore, Euclidean distance has no means of taking into account these duplicate variables does not bring any new information and may weight these variable more heavily in its computations than the other variables.

The Mahalanobis distance norm takes into account that covariance among the variables in calculating distances. Therefore, inherent problems of scale and correlation in the

Euclidean distance are no longer an issue with reference to the Mahalanobis distance norm.

Correlation measures the relationship strength between two variables. It does not have units and the range of values is [-1,1] where the correlation magnitude indicates its strength and sign represents the type of relationship: positive sign means direct association (when one variable increases, the other also does) and negative sign means inverse association. Therefore, it is a similarity measure. A bigger weight to noisy component is given by covariance and is very useful for checking the similarity between two datasets.

In Euclidean distance, all points that are equidistant from a given location are a sphere and this sphere is stretched by Mahalanobis distance with respect to scales and correlation among variables. The region forms an ellipse when two variables are used and an ellipsoid or hyper ellipsoid when more than two variables are used. It can be shown that the surfaces are ellipsoids with center on the average of the sample space where Mahalanobis distance is a constant. If all the characteristics are not correlated, those surfaces are spheroids as found in the Euclidian distance case.

The Mahalanobis distance can be used to measure the similarity between the two vectors $\vec{x}$ and $\vec{y}$ and the dissimilarity can be expressed as

$$d(\vec{x},\vec{y}) = \sqrt{(\vec{x}-\vec{y})^T \mathrm{S}^{-1}(\vec{x}-\vec{y})} \tag{3}$$

Where

$\vec{x}$, $\vec{y}$ are vectors and S is the covariance matrix

Smaller the Mahalanobis distance means that the achieved similar days are better i.e. the days are more similar to the forecast day.

In literature, an approach based on Euclidean distance norm has been used for similar day selection for STLF. In this thesis, the Mahalanobis distance norm is proposed to be used for selection of similar day for STLF instead of Euclidean distance norm. The STLF is done for the days of a week and MAPE (%) of forecasting results using Euclidean distance and Mahalanobis distance are shown in the Table 1.

TABLE 1
Comparison of MAPE of STLF results using Euclidean distance and Mahalanobis distance

Day	MAPE of STLF using Euclidean Distance	MAPE of STLF using Mahalanobis Distance
8th Jan 2003 (Wed)	3.304	3.083
9th Jan 2003 (Thu)	2.935	4.049
10th Jan 2003 (Fri)	3.897	2.583
11th Jan 2003 (Sat)	2.520	4.825
12th Jan 2003 (Sun)	6.275	2.455
13th Jan 2003 (Mon)	7.731	3.390
14th Jan 2003 (Tue)	8.543	2.887

It can be seen that the quality of STLF results using Mahalanobis distance norm are better than the STLF results using the Euclidean distance norm. Therefore, the Mahalanobis distance norm is chosen for selection of similar days for STLF throughout this thesis.

3.3 Formation of Fuzzy Inference System

In the Fuzzy Inference System (FIS), applying difference of the previous day of the forecast day and its similar days Load, Temperature and Humidity are given to the FIS as input that generates the correction factors as output. These are used to correct the similar days of the forecast day and then the corrected loads of the similar days are averaged to obtain the load of the forecast day. The parameters of the FIS used for the load forecast are calculated using the history data.

The input limits of FIS are a1, a2, a3, a4, a5 and a6. All the inputs are triangular membership functions. The limits for a1 to a6 are taken from a history of 3 years of data from the year 2000 to the year 2002.

Now a FIS is defined with three inputs (Load Difference, Temperature Difference and Humidity Difference) and one output (Correction Factor). Each input uses three triangular membership functions, namely Low (L), Medium (M), High (H) and the output uses seven triangular membership functions. Limits for the membership functions are obtained from the history of the load data and shown in the Table 2.

The basic working of the FIS is based on 27 predefined rules. The rules specify the mapping of the three inputs (Load difference, Temperature difference and humidity difference) to the output (Correction factor). Rules of the fuzzy inference system are given in the Table 3.

TABLE 2

PARAMETERS OF MEMBERSHIP FUNCTIONS OF FUZZY VARIABLES

Fuzzy variables	**Input membership parameters**
(a1,a2)	(-5000,5000)
(a3,a4)	(-50, 50)
(a5,a6)	(-55,55)
Fuzzy variables	**Output membership parameters**
(b1,b2,b3)	(-0.3,-0.225,-0.15)
(b2,b3,b4)	(-0.225,-0.15,-0.075)
(b3,b4,b5)	(-0.15,-0.075,0)
(b4,b5,b6)	(-0.075,0,0.15)
(b5,b6,b7)	(0,0.15,0.075)
(b6,b7,b8)	(0.15,0.075,0.225)
(b7,b8,b9)	(0.075,0.225,0.3)

TABLE 3

RULES OF THE FUZZY INFERENCE SYSTEM

Rule No	ΔE_L	ΔE_T	ΔE_H	Output Value
R1	L	L	L	PS3
R2	M	M	M	ZE
R3	H	H	H	NS3
R4	H	H	L	NS1
R5	H	H	M	NS2
R6	H	L	L	PS1
R7	H	L	M	NS2
R8	H	L	H	NS1
R9	H	M	L	PS3
R10	H	M	M	PS2
R11	H	M	H	PS1
R12	M	L	L	ZE
R13	M	L	M	NS1
R14	M	L	H	PS1
R15	M	M	L	ZE
R16	M	M	H	NS1
R17	L	L	M	PS2
R18	L	L	H	PS1
R19	L	M	L	PS1
R20	L	M	M	NS3
R21	L	M	H	PS3
R22	L	H	L	PS1
R23	L	H	M	PS1
R24	L	H	H	PS1
R25	M	H	L	PS1

R26	M	H	M	PS1
R27	M	H	H	PS2

Where

ΔE_L-Load Difference; ΔE_T-Temperature Difference; ΔE_H-Humidity Difference; L-Low; M-Medium; H-High; PS3-Positive Small 3; PS2-Positive Small 2; PS1-Positive Small 1; ZE-Zero; NS1-Negative Small 1; NS2-Negative Small 2; NS3-Negative Small 3

FIS is developed using fuzzy logic toolbox in MATLAB and step by step procedure is as follows:

Step 1: Compile the list of input and output variable.

Three inputs (Load Difference-ΔE_L, Temperature Difference-ΔE_T and Humidity Difference- ΔE_H) and one output (Correction Factor).

Step 2: Each input uses three triangular membership functions, namely Low (L), Medium (M), High (H) and the output uses seven triangular membership functions. Input and Output membership functions are shown in the Fig 1-4.

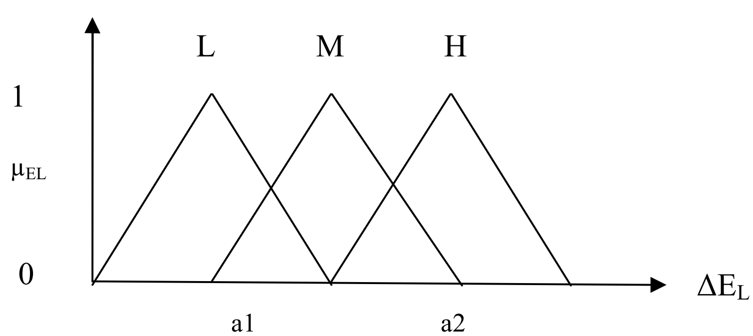

Fig. 1 Input membership functions for Load Difference

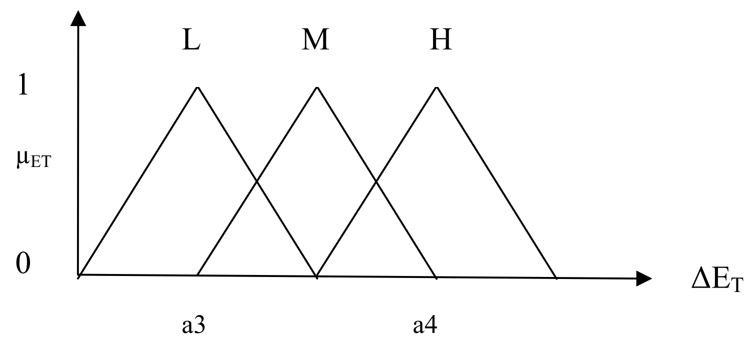

Fig. 2 Input membership functions for Temperature Difference

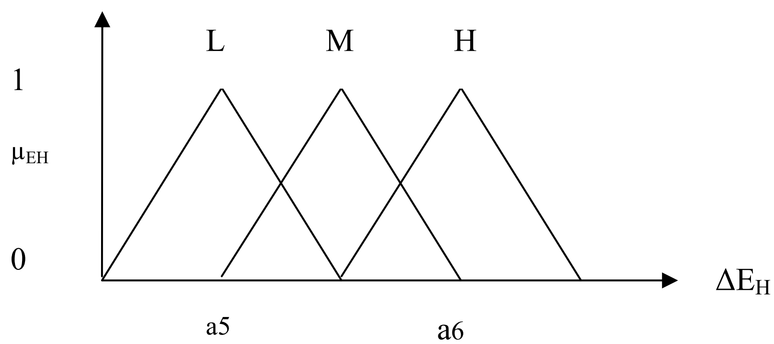

Fig. 3 Input membership functions for Humidity Difference

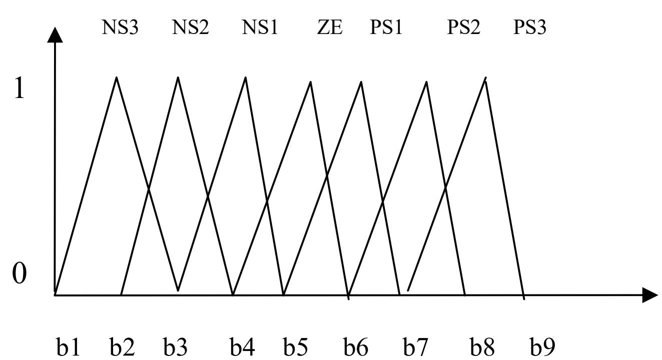

Fig. 4 Output membership functions for Correction factor

Where, ΔE_L-Load Difference; ΔE_T-Temperature Difference; ΔE_H-Humidity difference; L-Low; M-Medium; H-High; PS3-Positive Small 3; PS2-Positive

Small 2; PS1-Positive Small 1; ZE-Zero; NS1-Negative Small 1;NS2-Negative Small 2; NS3-Negative Small 3

a1 to a6 are input fuzzy membership parameters,

b1 to b9 are output fuzzy membership parameters.

The graphical representation of input and output membership functions are shown in the Fig 5-6.

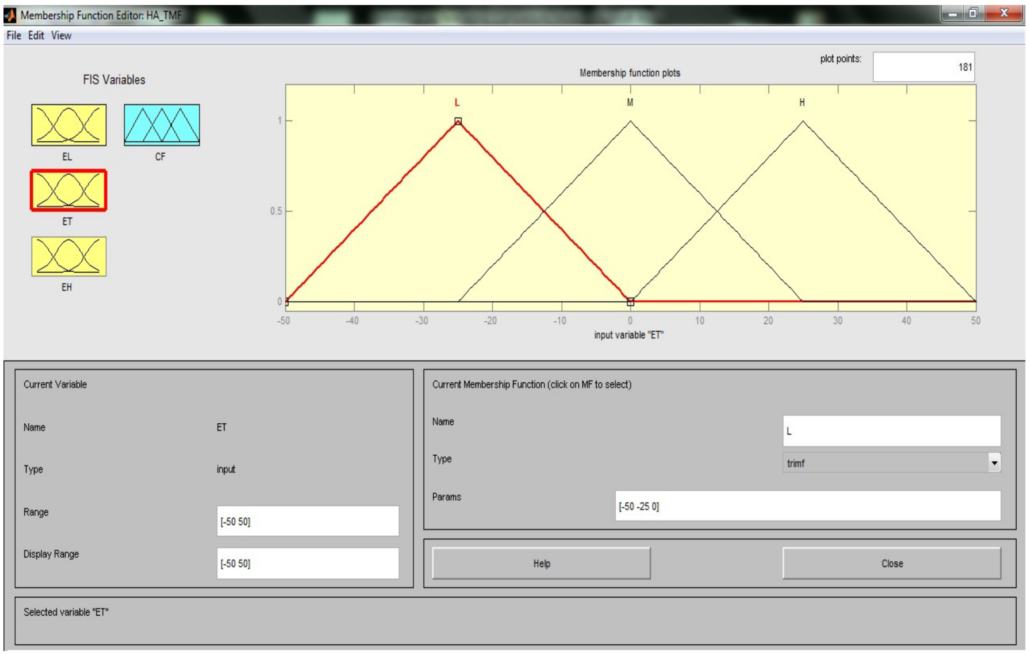

Fig. 5 Input membership functions

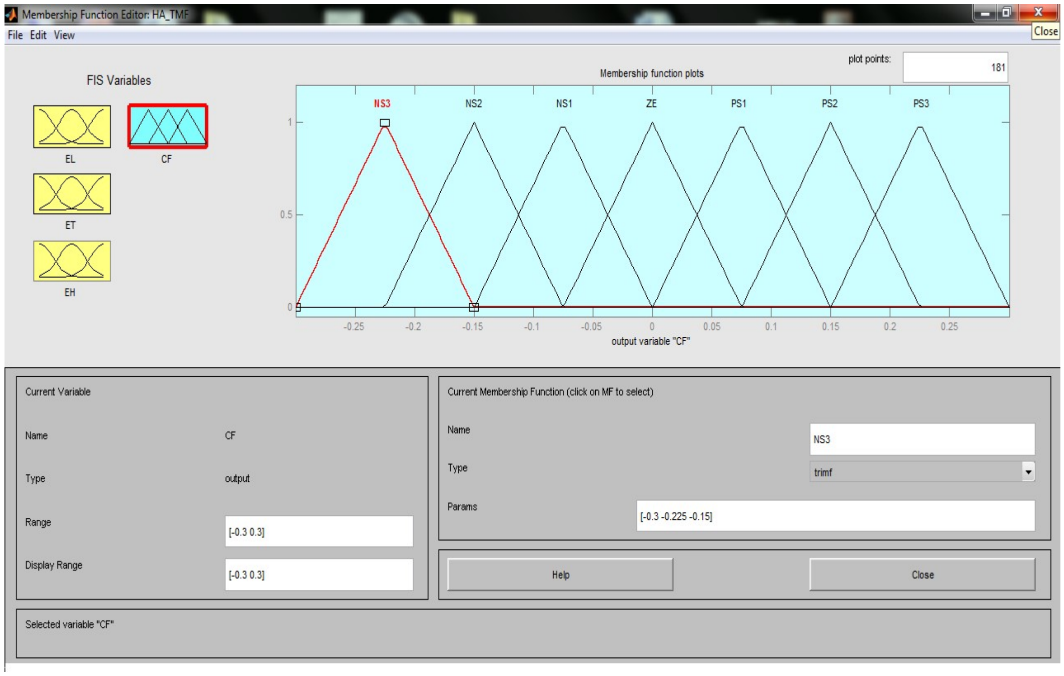

Fig. 6 Output membership functions for Correction factor

Step 3: Limits of membership functions are obtained from the history of load data.

a1, a2----Load Difference Limits

a3, a4----Temperature Difference Limits

a5, a6----Humidity Difference Limits

Step 4: Construct the fuzzy rules from input and output pairs, there are 3 inputs, so the number of combination rules can be generated are 27 (3*3*3). The rules specify the mapping of the three input values of load, temperature and humidity differences to the output which is the correction factor.

For example

Rule 1: IF 'Load difference' is Low and 'Temperature Difference' is Low and 'Humidity difference' is Low *THEN* 'Correction factor' is Positive Small 3.

Rule 2: *IF* 'Load difference' is Medium and 'Temperature Difference' is Medium and 'Humidity difference' is Medium *THEN* 'Correction factor' is Zero.

Rule 3: *IF* 'Load difference' is High and 'Temperature Difference' is High and 'Humidity difference' is High *THEN* 'Correction factor' is Negative Small 3.

Rule 4: *IF* 'Load difference' is High and 'Temperature Difference' is High and 'Humidity difference' is Low *THEN* 'Correction factor' is Negative Small 2.

………………….

Similarly construct 27 Rules.

The graphical representation of fuzzy rules is shown in the Fig 7.

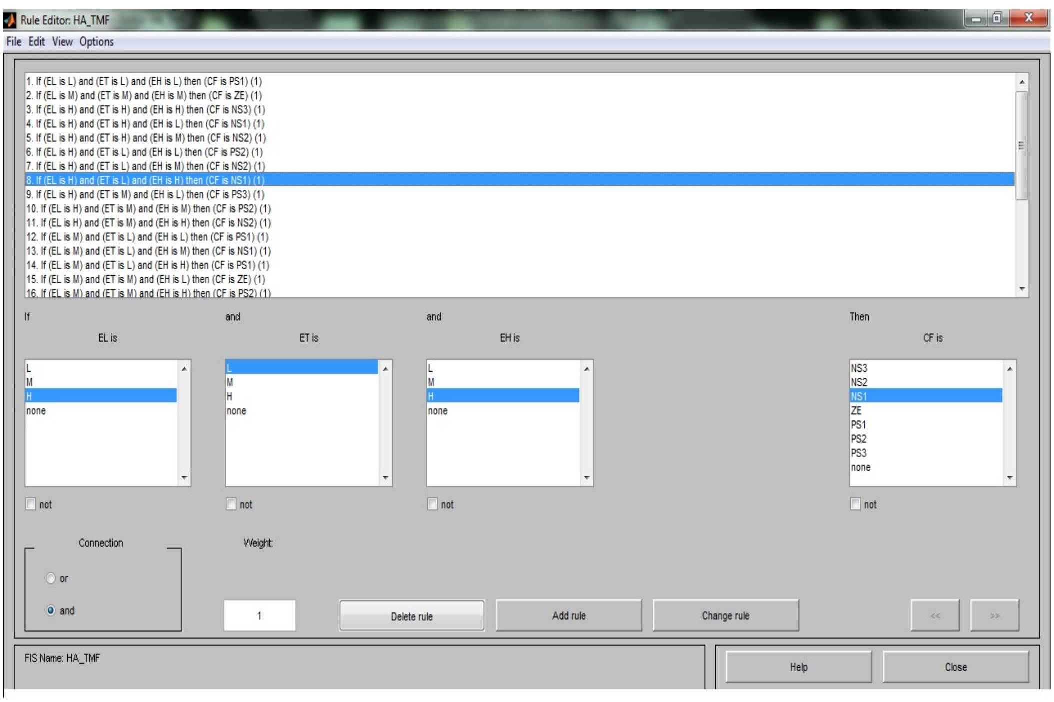

Fig. 7 Fuzzy rules

Step 5: The correction factor generates based on fuzzy input parameter values and firing of the rules as shown in the Fig 8.

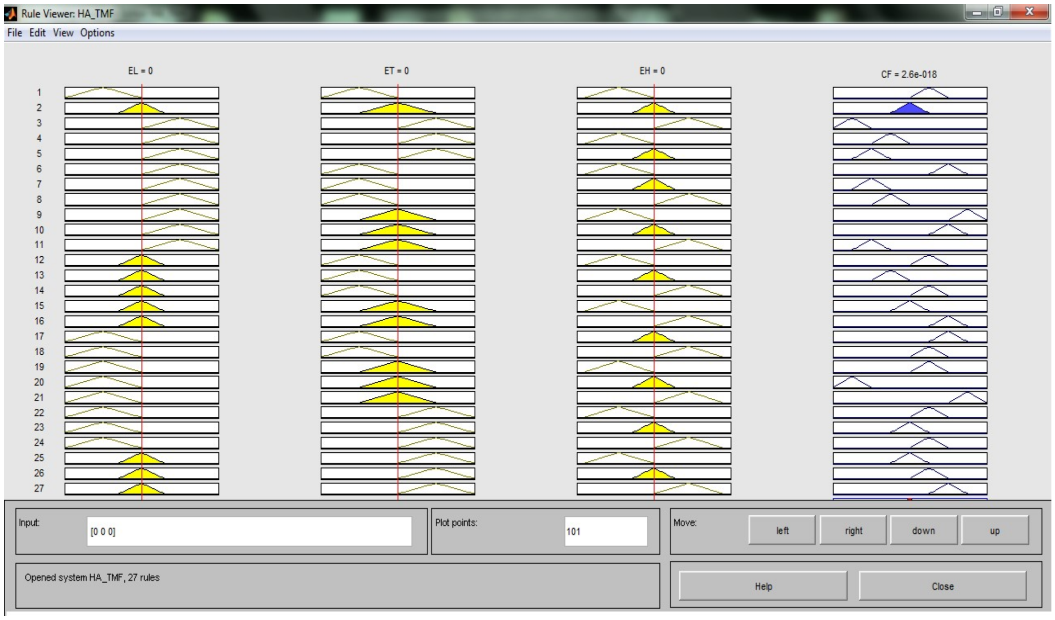

Fig. 8 Correction factor generation

3.4 Implementation

Research work has been done on real time data of ISO New England load data.

Input Data:

ISO New England: Dec-2002, Nov-2002
Jan-2002, Dec-2001, Nov-2001
Jan-2001, Dec-2000, Nov-2000

The input data file consists of 24 hours of load, 24 hours of Temperature, 24 hours of humidity and one day type.

Testing Data:

ISO New England: Jan-2003
(31 Days)

Testing data file consists of 24 hours of load, 24 hours of Temperature, 24 hours of humidity and 1 Day type

Day type values are taken as

Sunday: 1

Saturday: 2

Monday: 3

Weekdays: 4 (Tuesday - Friday)

Monday is accounted as different to other weekdays because this is adjacent and immediately after the weekend and load behavior is different than the other weekdays.

Data considered is for 9 months and out of it, 8 months data is used as dataset to develop the forecasting system and 9^{th} month data is used for testing data.

The forecasting system is developed based on the previous month to test month (in this case previous month to testing month is Dec-2002, testing month is Jan 2003)

Five similar days are found from previous data based on 24 hours of Load, 24 hours of Temperature, 24 hours of Humidity and Day type of a given Dec-2002 day. Mahalanobis distance norm is applied for the selection of similar days. For example, similar days of Dec 1 are found from the input data of Nov 2002, Nov 2001 and Nov 2000 (Total 90 days).

Now select the similar days of the previous day of the forecast day of Dec 2002. For example, Dec 2 is our forecast day, so select the similar days for Dec 1. Next, calculate the correction factors with the difference of Load, Temperature and Humidity for five similar days of the previous day of forecast day i.e. Dec 1. Fuzzify the values of correction factors by sending it to FIS and get the defuzzify values. These are fuzzy correction factors. Take the average of applied fuzzy correction factors on forecasted similar days, which is the forecasted load value. Similarly, calculate for all the days of Dec 2002. Compare the forecasted load values with actual load values of Dec 2002. Now apply the heuristic approach on the fuzzy membership parameters. Step by step procedure of fuzzy membership parameters a1….a6 tuning in a heuristic way is as follows:

Step 1: Initial parameters of fuzzy inference system are obtained from the history data set then calculate the Fuzzy Correction Factors, compare the forecasted load value with actual load values of Dec 2002, calculate the Mean Absolute Percentage Error (MAPE).

Step 2: Parameter ‘ $\mathbf{a_i}$ ’ is increased by ‘ $\boldsymbol{\delta a_i}$ ’ as shown in the Fig 9, where i=1,2…..6 parameters. Calculate the MAPE.

If the MAPE of step 2 is less than the previous step, repeat it otherwise go to step 3.

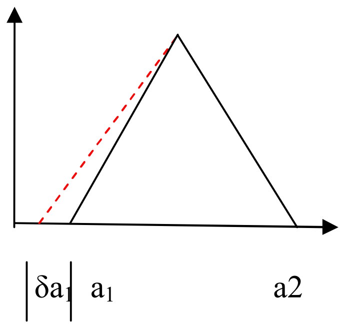

Fig. 9 **'a1'** is increased by **'δa1 '**

Step 3: Parameter ' $\mathbf{a_i}$ ' is decreased by ' $\boldsymbol{\delta a_i}$ ' as shown in the Fig 2, calculate the MAPE.

If the MAPE of step 3 is less than step 2, repeat it otherwise go to step 4.

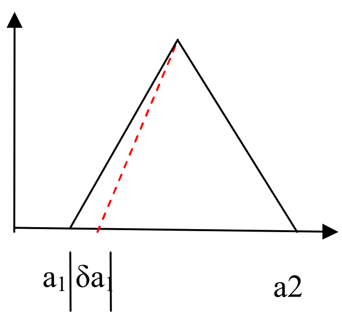

Fig. 10 **'a1'** is decreased by **'δa$_1$ '**

Step 4: If all the parameters are optimized and MAPE of Dec 2002 is as minimum as possible, go to step 5, otherwise, take the next parameter, and repeat steps 2 to 3.

Step 5: Store the updated the fuzzy parameters in the fuzzy inference system

The parameters obtained with the Heuristic Approach are set as input parameter limits of the fuzzy inference system and it is used to forecast the load of the test forecast month (Jan 2003).

3.5 Results and Discussion

In this section, the heuristic approach based fuzzy inference system for STLF is used and results for seven different days of the testing month (Jan 2003) are presented. Hourly forecasted load results are shown in the Table 4-7. Summary of daily forecast MAPE results are shown in the Table 8 it also shows the results of with and without optimization techniques. It can be seen that the results from this technique is not giving as reasonable results because the MAPE is higher than 3% for few days. In the Table 9, the variation of fuzzy membership parameter limits with and without optimization techniques are shown.

TABLE 4
Hourly results of 8th Jan 2003 and 9th Jan 2003 using Heuristic Approach

	8th Jan 2003		**9th Jan 2003**	
Hour	**Actual Load (MW)**	**Forecasted Load (MW)**	**Actual Load (MW)**	**Forecasted Load (MW)**
1	12606	12702	13033	13619
2	12146	12229	12569	13209
3	11932	12030	12350	12979
4	11927	12037	12328	12943
5	12252	12377	12605	13045
6	13446	13502	13727	14353
7	15835	15599	16038	16559
8	17297	17083	17527	17982
9	17470	17664	17730	18350
10	17465	17943	17722	18455
11	17464	18087	17701	18440
12	17389	18042	17592	18274
13	17197	17860	17275	17978
14	17120	17712	17124	17773
15	16975	17525	16864	17544
16	17083	17602	16844	17623
17	18223	18836	17892	18170
18	19640	20174	19213	19856
19	19582	20044	19049	19939
20	19147	19520	18519	19364
21	18450	18767	17760	18562
22	17226	17579	16469	17142
23	15495	15928	14777	15172
24	14007	14381	13255	13968
MAPE (%): **2.155**			MAPE (%): **4.023**	

TABLE 5
Hourly results of 10th Jan 2003 and 11th Jan 2003 using Heuristic Approach

	10th Jan 2003		**11th Jan 2003**	
Hour	**Actual Load (MW)**	**Forecasted Load (MW)**	**Actual Load (MW)**	**Forecasted Load (MW)**
1	12271	12458	12177	12926
2	11803	12104	11652	12343
3	11552	11634	11425	12058
4	11490	11557	11372	11994
5	11750	11781	11638	12221
6	12903	12632	12735	13076
7	15239	14323	15113	14795
8	16654	15523	16619	16055
9	16866	16075	16892	16650
10	16890	16369	16956	17015
11	16958	16478	16985	17145
12	16864	16427	16858	17116
13	16669	16200	16606	16894
14	16541	16017	16478	16717
15	16344	15838	16301	16545
16	16405	15958	16324	16653
17	17428	17250	17216	17945
18	18756	18618	18551	19281
19	18677	18442	18391	19114
20	18235	17903	17864	18589
21	17527	17251	17235	17961
22	16334	16919	16334	16970
23	14657	15007	15068	15581
24	13170	13690	13749	14124
MAPE (%):**2.577**			MAPE (%):**3.231**	

TABLE 6
Hourly results of 12th Jan 2003 and 13th Jan 2003 using Heuristic Approach

	12th Jan 2003		13th Jan 2003	
Hour	**Actual Load (MW)**	**Forecasted Load (MW)**	**Actual Load (MW)**	**Forecasted Load (MW)**
1	12793	12600	12610	12058
2	12280	12056	12070	11526
3	12033	11793	11759	11246
4	11955	11727	11633	11147
5	12076	11894	11680	11262
6	12512	12421	11955	11722
7	13376	13481	12495	12644
8	14295	14299	13132	13451
9	15377	15262	14115	14247
10	16058	15926	14805	14813
11	16249	16211	15113	15074
12	16177	16243	15249	15145
13	15911	16069	15200	15021
14	15584	15798	14950	14801
15	15331	15586	14715	14603
16	15322	15652	14819	14711
17	16246	16979	15992	15917
18	17636	18444	17625	17324
19	17527	18270	17702	17248
20	16995	17655	17273	16776
21	16443	16979	16671	16165
22	15703	16146	15607	15280
23	14652	15038	14259	14085
24	13563	13934	13061	12943
	MAPE (%):**1.972**		MAPE (%):**1.960**	

TABLE 7
Hourly results of 14th Jan 2003 using Heuristic Approach

	14th Jan 2003	
Hour	**Actual Load (MW)**	**Forecasted Load (MW)**
1	12300	12968
2	11971	12465
3	11870	12254
4	11911	12230
5	12278	12539
6	13540	13563
7	16047	15525
8	17543	16909
9	17700	17470
10	17719	17760
11	17769	17884
12	17640	17798
13	17434	17567
14	17270	17380
15	17091	17203
16	17189	17310
17	18167	18668
18	19541	20166
19	19449	19992
20	18969	19396
21	18169	18638
22	16950	17552
23	15303	16071
24	13881	14643
MAPE (%):**2.420**		

The graphical representations of the forecasted load and actual load curves by using optimization with heuristic approach are shown in the Fig 11-17.

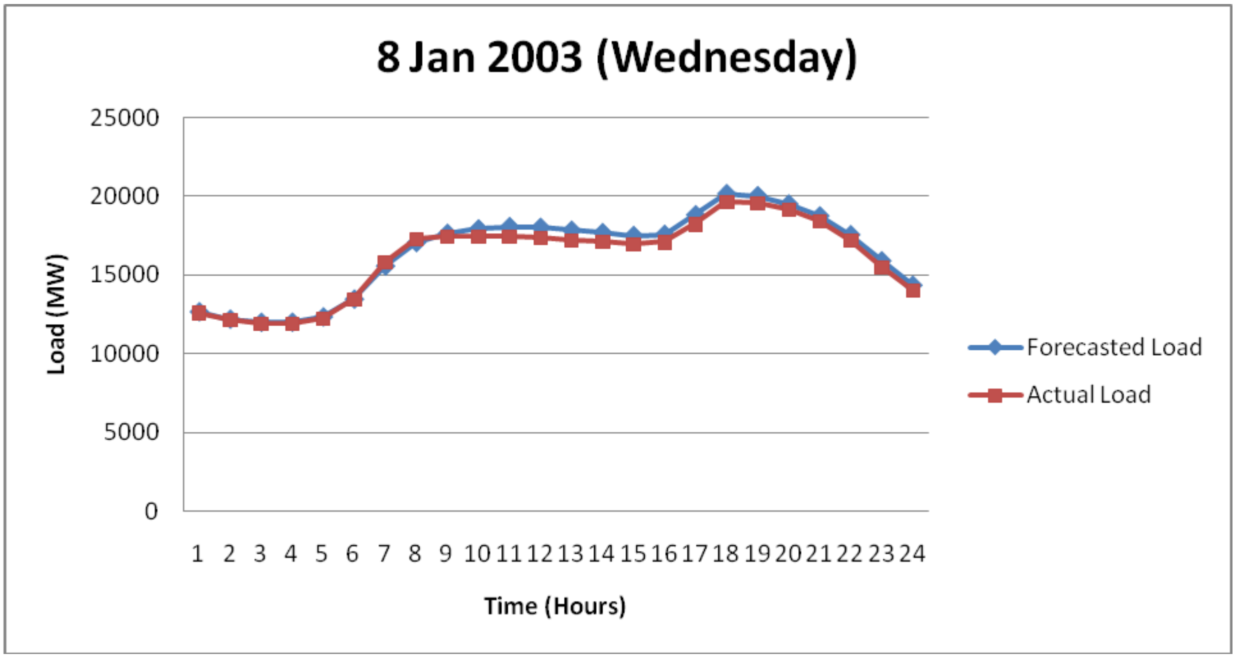

Fig. 11 Forecasted Load and Actual Load curves for 8th January 2003 (Wednesday)

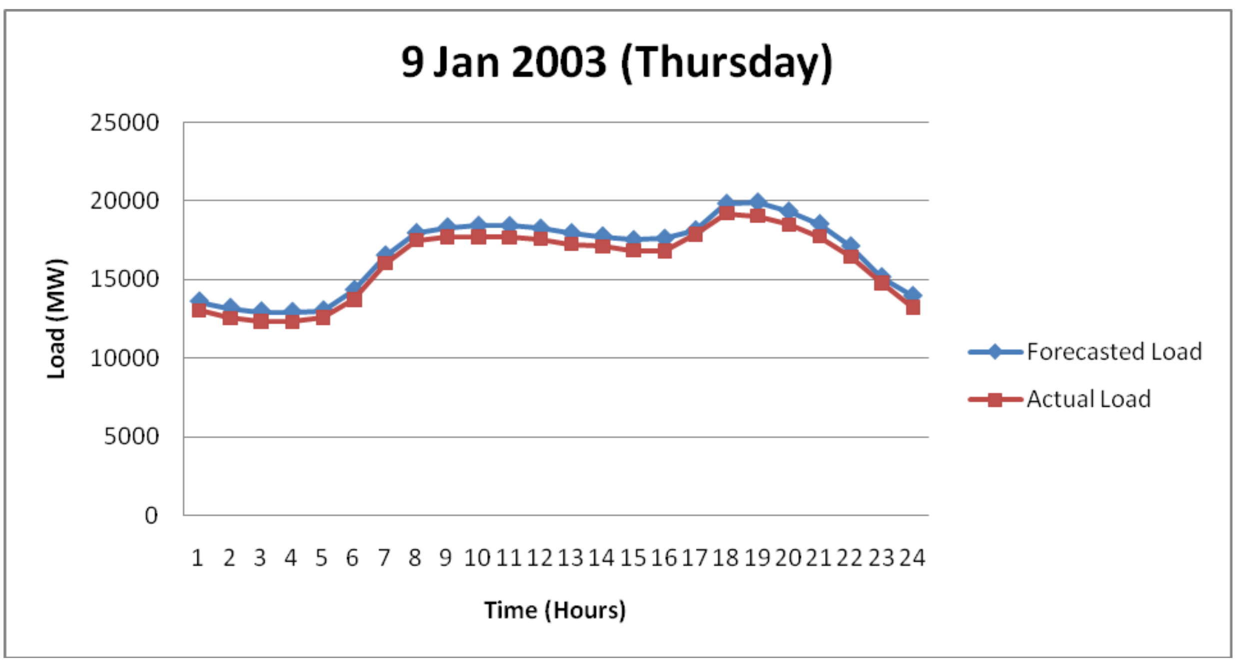

Fig.12 Forecasted Load and Actual Load curves for 9th January 2003 (Thursday)

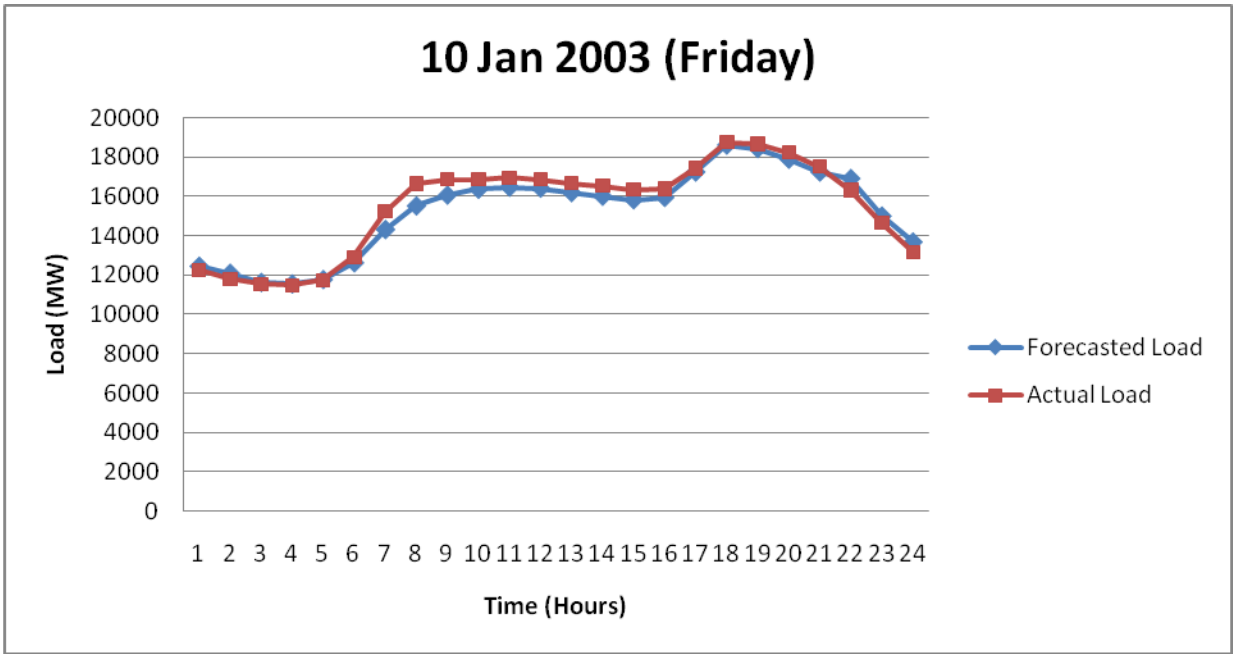

Fig.13 Forecasted Load and Actual Load curves for 10th January 2003 (Friday)

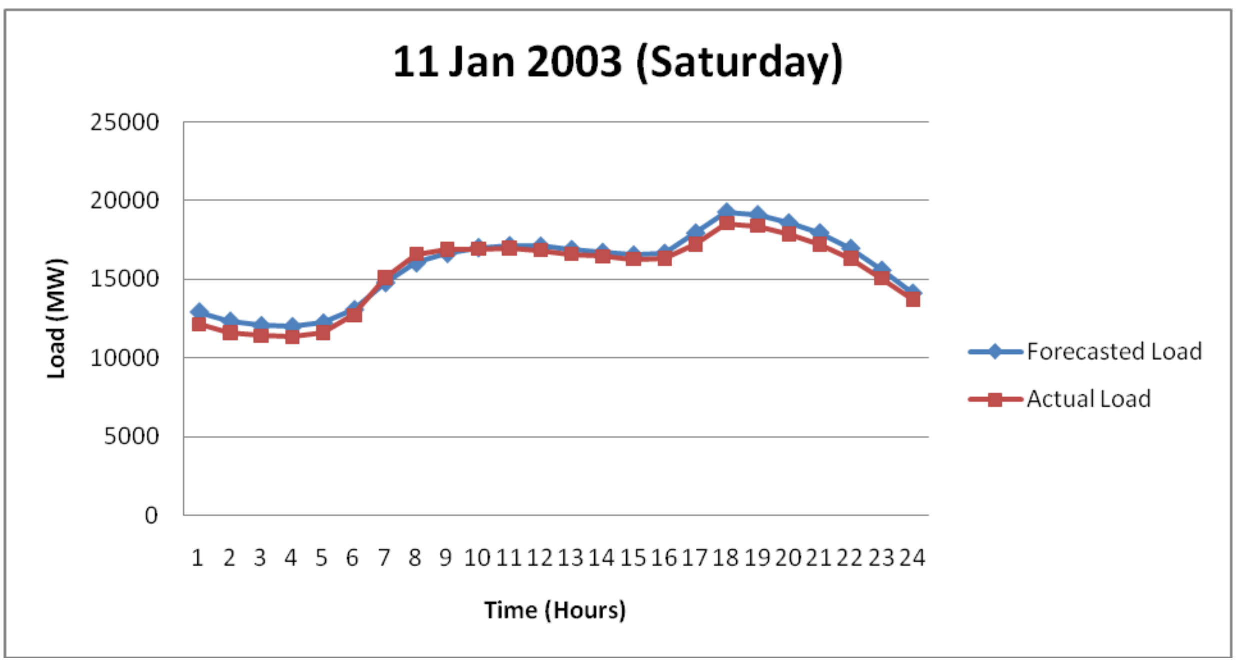

Fig.14 Forecasted Load and Actual Load curves for 11th January 2003 (Saturday)

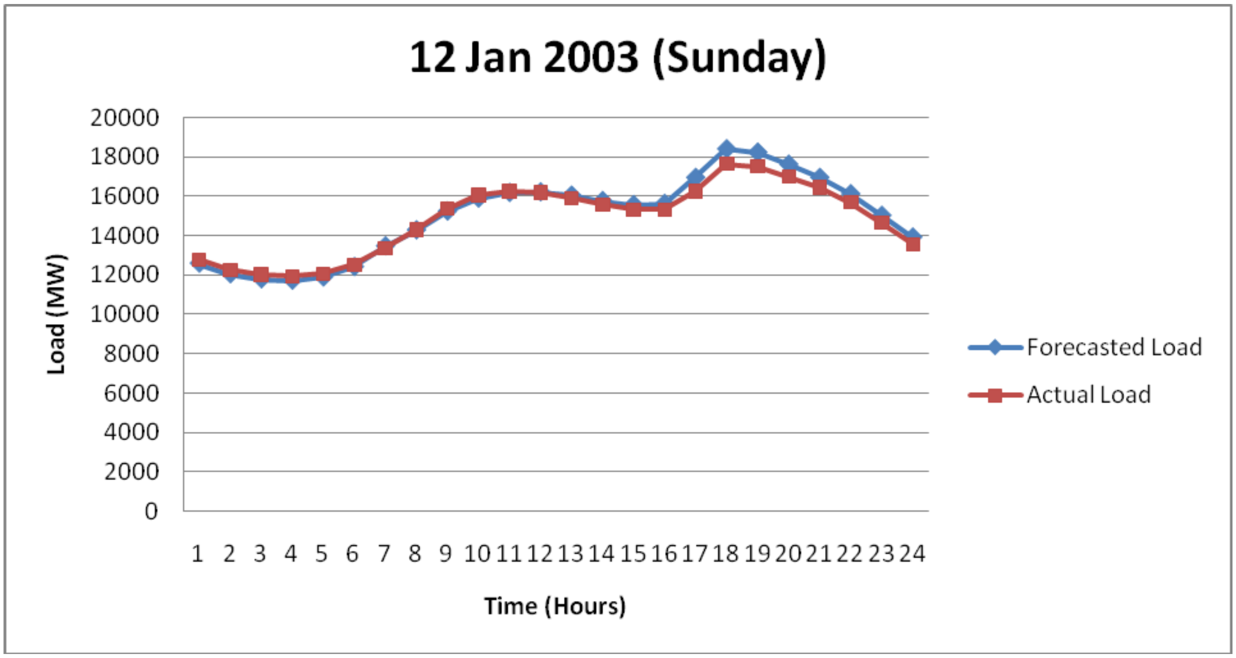

Fig.15 Forecasted Load and Actual Load curves for 12th January 2003 (Sunday)

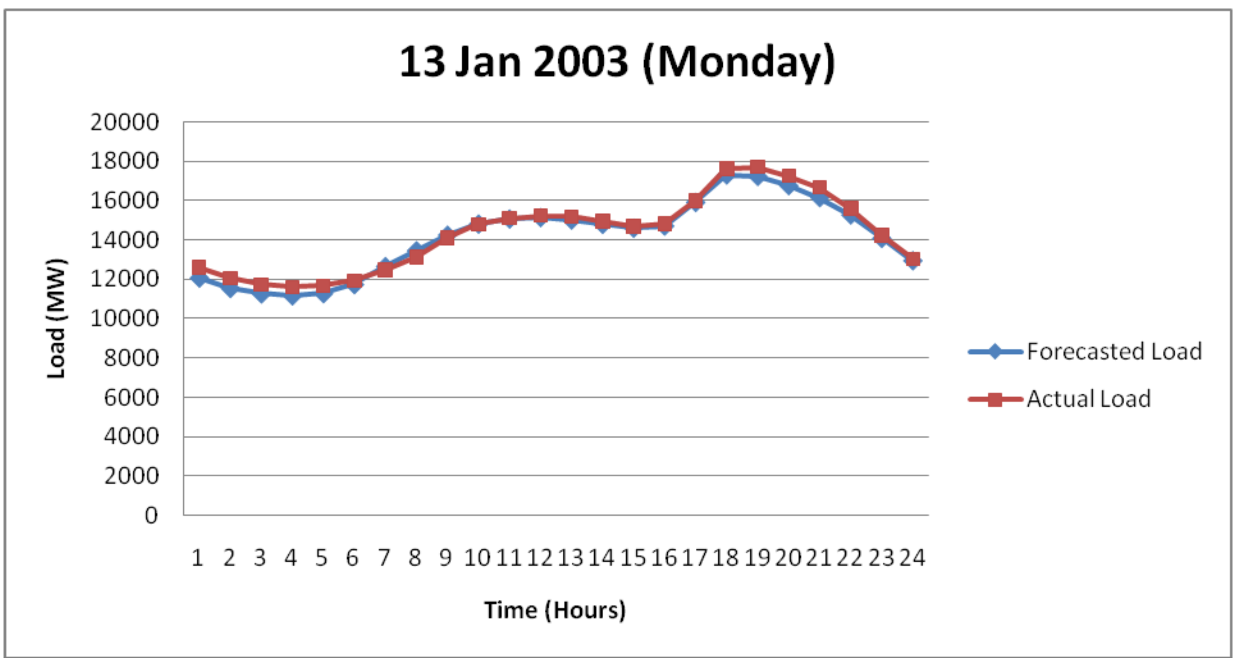

Fig.16 Forecasted Load and Actual Load curves for 13th January 2003 (Monday)

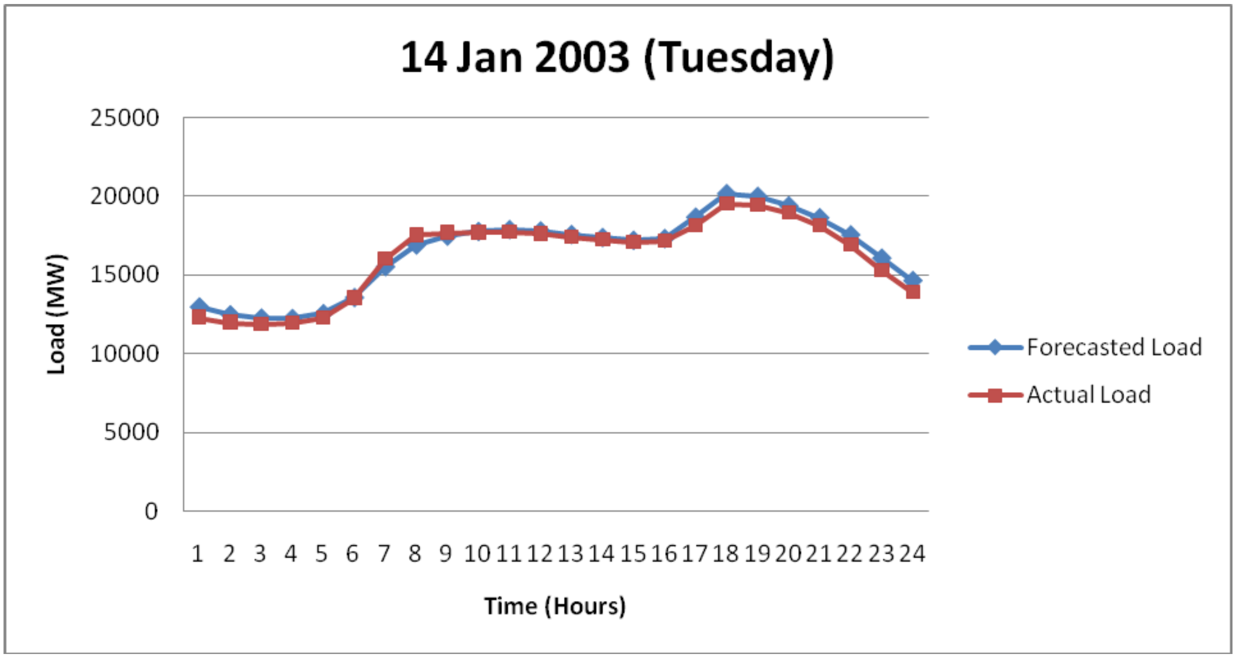

Fig.17 Forecasted Load and Actual Load curves for 14th January 2003 (Tuesday)

The graphical representations of fuzzy membership parameters using a heuristic approach are shown in the Fig 18-20.

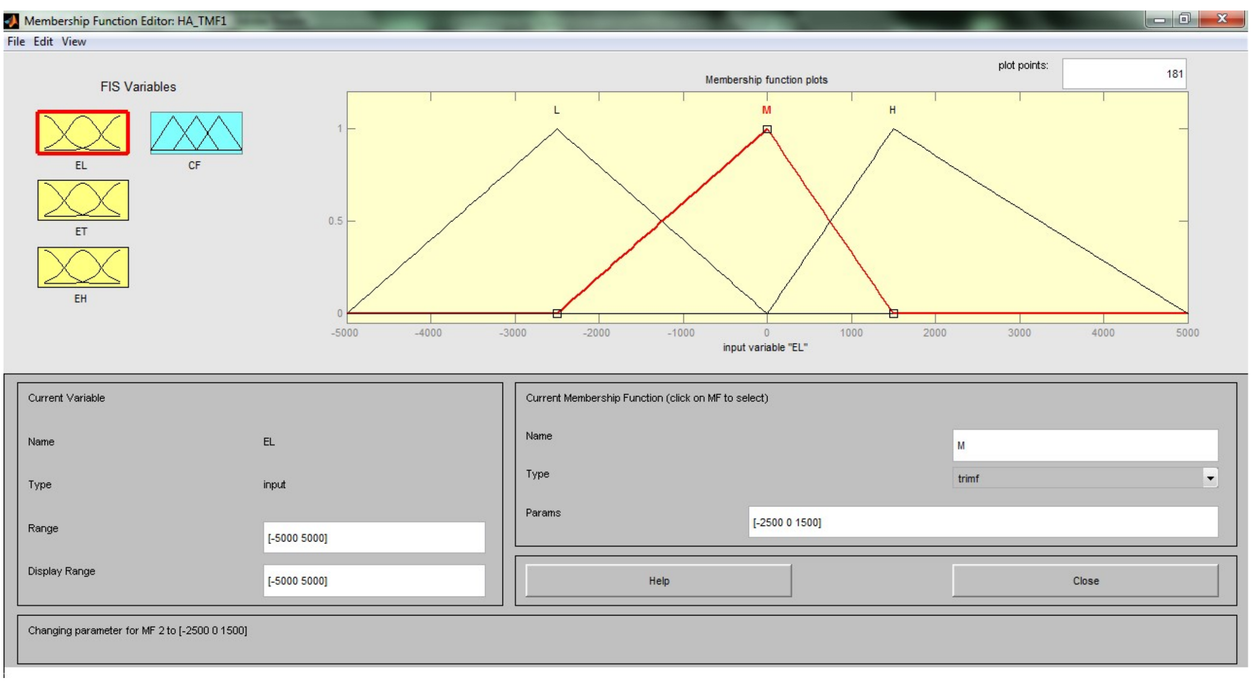

Fig. 18 Fuzzy membership parameters (a1, a2) using Heuristic Approach

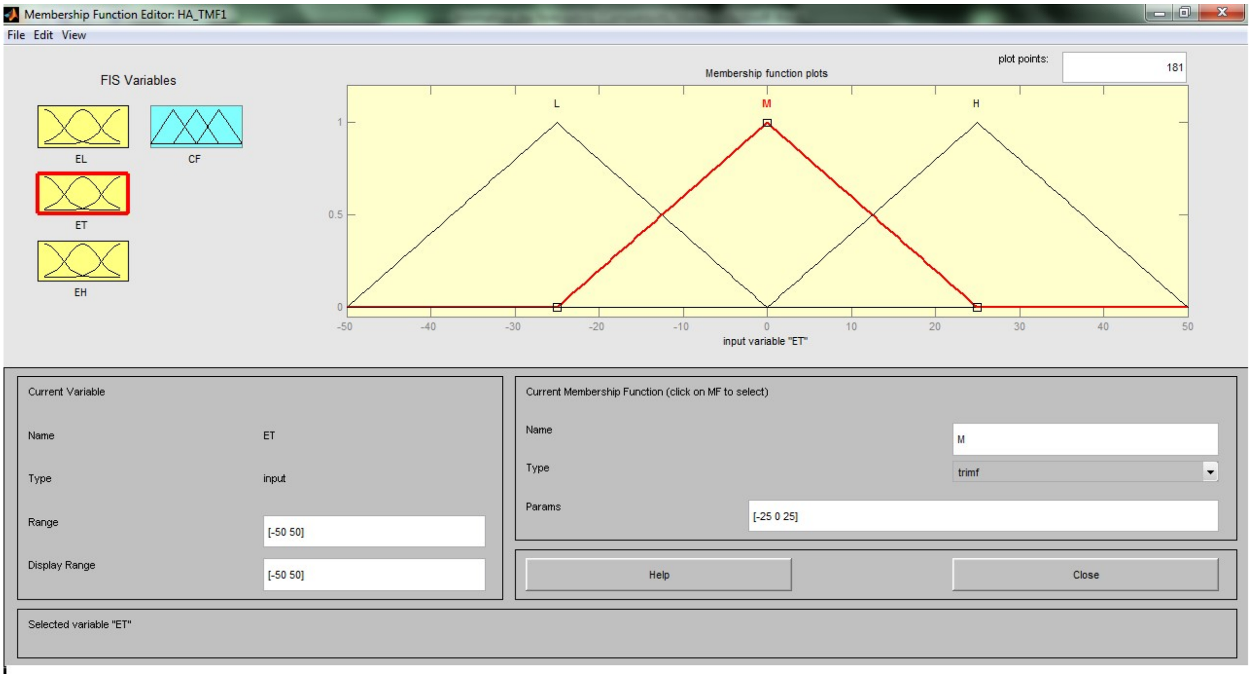

Fig. 19 Fuzzy membership parameters (a3, a4) using Heuristic Approach

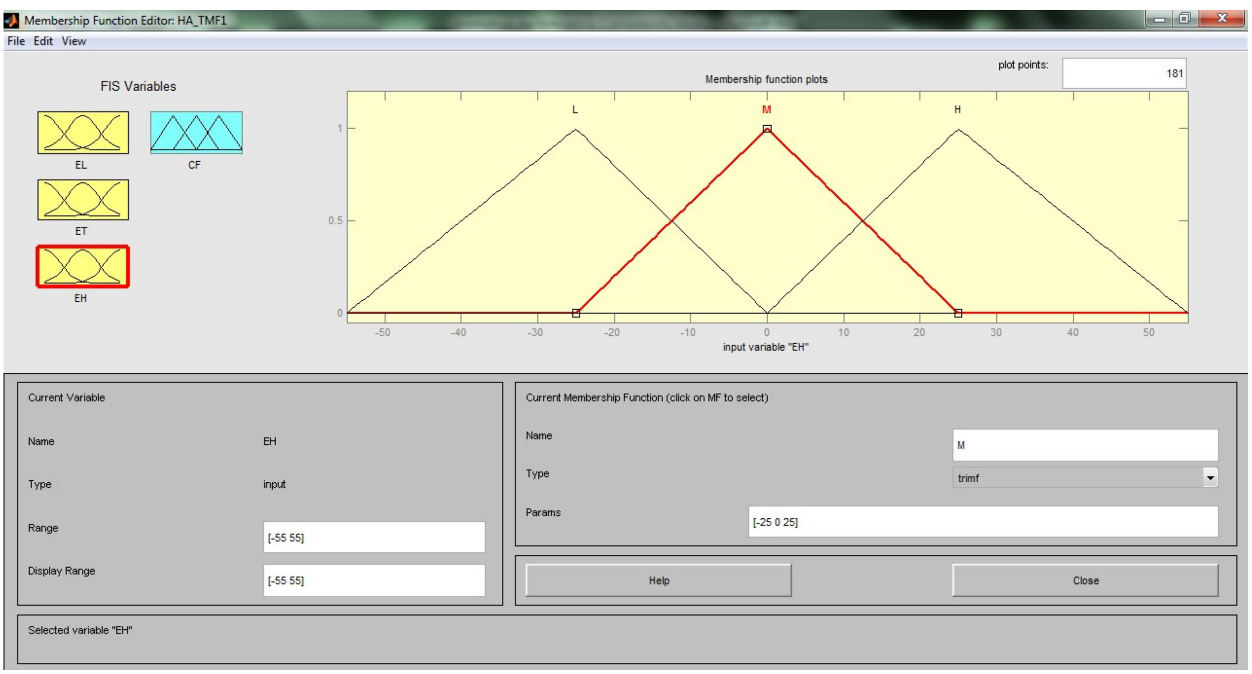

Fig. 20 Fuzzy membership parameters (a5, a6) using Heuristic Approach

TABLE 8

DAILY FORECAST RESULTS BY USING HEURISTIC APPROACH

Day	MAPE (%) Without optimization	MAPE (%) With optimization
8th Jan 2003 (Wednesday)	3.083	2.155
9th Jan 2003 (Thursday)	4.049	4.023
10th Jan 2003 (Friday)	2.583	2.577
11th Jan 2003 (Saturday)	4.825	3.231
12th Jan 2003 (Sunday)	2.455	1.972
13th Jan 2003 (Monday)	3.390	1.960
14th Jan 2003 (Tuesday)	2.887	2.420

TABLE 9

MEMBERSHIP PARAMETER VALUES BY USING OPTIMIZATION WITH HEURISTIC APPROACH

Membership Parameters	Without Optimization	With Optimization
(a1,a2)	(-5000,5000)	(-2500,1500)
(a3,a4)	(-50,50)	(-25,25)
(a5,a6)	(-55,55)	(-25,25)

3.6 Impact of Error in Weather Variables on STLF using Heuristic Approach

For forecasting of next day load, next day data of temperature and humidity is used and these temperatures and humidity themselves are forecasted and may have some errors. If the next day Temperature T (provided by weather forecast) has a possible error ‘X’ and the next day Humidity H (provided by weather forecast) has a possible error ‘Y’. The next day load forecasting is done by two case studies: (i) Temperature as ‘T+X’ and Humidity as ‘H+Y’. (ii) Temperature as ‘T-X’ and Humidity as ‘H-Y’. The literature relating to one day ahead forecasted temperature and humidity provided the reasonable range of errors of less than 1% and 3% respectively [80-84]. Case studies with X=1% and Y=3% have been done for studying the impact of forecasted temperature and forecasted humidity errors for next day load forecasting.

Variations in MAPE (%) of Heuristic approach with and without weather forecast errors are shown in the Table 10. Where (T+1%) is Temperature with 1% noise (addition), (H+3%) is Humidity with 3% noise (addition), (T-1%) is Temperature with 1% noise (subtraction), (H-3%) is Humidity with 3% noise (subtraction) and percentage error in temperature is applied on Kelvin scale.

TABLE 10

COMPARATIVE MAPE (%) OF DAILY FORECAST RESULTS WITH AND WITHOUT WEATHER FORECAST ERROR USING HEURISTIC APPROACH

Day	Heuristic Approach		
	Without Weather Forecast Error	With Weather Forecast Error	
		T+ 1%, H+3%	T-1%, H-3%
8th Jan 2003 (Wednesday)	2.155	2.284	2.430
9th Jan 2003 (Thursday)	4.023	5.100	5.878
10th Jan 2003 (Friday)	2.577	3.035	2.370
11th Jan 2003 (Saturday)	3.231	3.059	4.108
12th Jan 2003 (Sunday)	1.972	2.950	2.664
13th Jan 2003 (Monday)	1.960	2.096	2.726
14th Jan 2003 (Tuesday)	2.420	2.294	2.121

3.7 Summary and Observations

Results for the heuristic approach based fuzzy inference system for STLF are presented for different days and these included weekdays and weekends also. MAPE results are compared with and without optimization techniques. Heuristic Approach based optimization technique shows better results and MAPE has been less than 3% for most of the days. The graphical representation of Forecasted and Actual load curves shows that optimization technique based forecasted load curve followed a similar pattern to the actual load curve. Variations in MAPE (%) of heuristic approach with and without weather forecast errors are also shown.

Chapter 4
Particle Swarm Optimization based Fuzzy Inference System for Short Term Load Forecasting

4.1 Introduction

Particle Swarm Optimization technique was developed by Dr. Kennedy and Dr.Eberhart in 1995, which is inspired by bird flocking [85]. PSO is a velocity-location search model and used to solve the optimization problems. Each particle fitness value can be evaluated in a search space by using the fitness function. The particle direction of flying can be decided by its velocity and position. PSO function tunes the latest particle position by using the optimization equation.

PSO has some similarities with evolutionary approaches like a genetic algorithm. The system is randomly initialized with a group of solutions and searches for the optimal solution by updating generations; it has no evolution operators such as crossover and mutation as in the case of genetic algorithm.

Compared to the genetic algorithm, PSO has several benefits e.g its implementation is easy and there are only a few parameters to tune. It has been implemented successfully in many fields like artificial neural network training, function optimization and fuzzy system control etc.

PSO is initialized with a group of solutions (particles) randomly and then searches for an optimal solution by updating generations. In each of the iteration, each particle is updated with the two "best" values of Pbest and Gbest. Pbest is the best fitness (solution) that has been achieved so far. Gbest is the best fitness (solution) that is tracked by the particle swarm optimizer it is the best value, obtained so far by any particle in the complete population and it is called a global best.

After obtaining the two best values, the particle updates its velocity and positions with equations (3) and (4).

$$v_i^{k+1} = v_i^k + c1 * rand() * (pbest_i^k - present_i^k) + c2 * rand() * (gbest_i^k - present_i^k) \quad (3)$$

$$present_i^{k+1} = present_i^k + v_i^{k+1} \quad (4)$$

where

v_i^k is the velocity of ith particle in kth iteration

$c1$, $c2$ are learning factors. Usually $c1 = c2 = 1$

$rand(\ )$ is a random number between (0,1)

$pbest_i^k$ and $gbest_i^k$ are defined as stated before

$present_i^k$ is the ith particle position in kth iteration

The pseudo-code of the PSO implementation procedure is given in the flowchart as shown in the Fig 21.

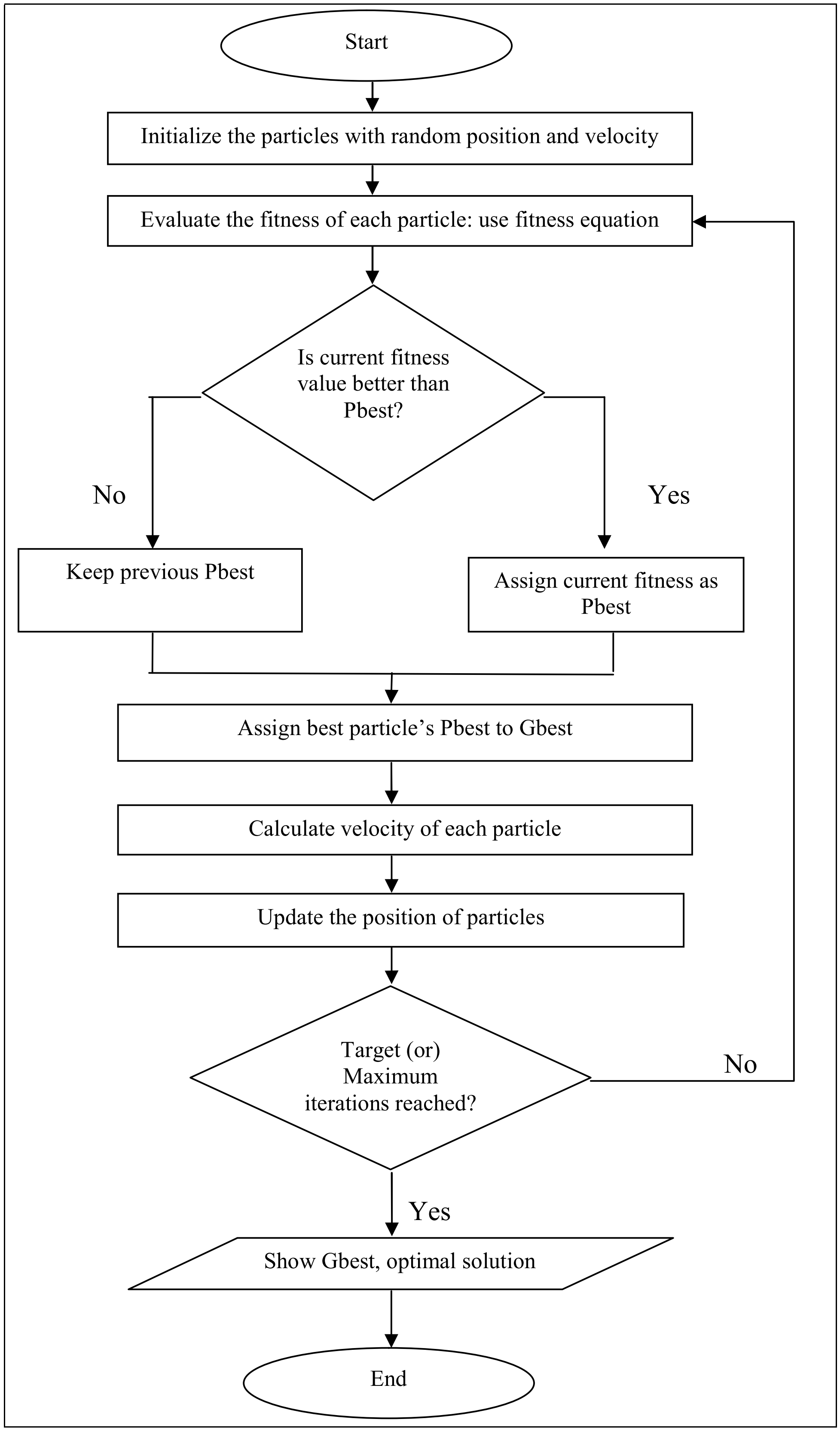

Fig. 21 Particle Swarm Optimization Algorithm

4.2 PSO Implementation for FIS

Optimization of the fuzzy parameters a1, a2, a3, a4, a5 and.a6 is done using the PSO technique as discussed in section 4.1. For the considered data set the FIS has been optimized for six parameters (minima and maxima of each of the inputs ΔE_L, ΔE_T and ΔE_H) considering 49 particles. The initial parameter values of the FIS are obtained from the historical data set. These are incorporated into the FIS to obtain the forecast errors of the previous month of test forecast month (in the present case, previous month to the test forecast month is Dec 2002). The PSO function accepts the training data (90 days) and the objective is to reduce the forecast MAPE of the 30 days of the previous month (Dec 2002) of the test forecast month (Jan 2003) using the 90 days historical data of the previous to the previous month of test forecast month (Jan 2003) for last three years (i.e. Nov-2000, Nov-2001 and Nov-2002). Particle swarm optimizer function is run for 50 iterations or until MAPE comes as less than 3% (here MAPE is considered as a fitness function). After each of the iterations, the particle swarm optimizer tunes the latest particle position and velocity using the fitness equations, which are based on the "Pbest" and "Gbest" of the previous iteration if the fitness function value is better than the previous one. The final parameters obtained from PSO are input parameter limits of FIS and used to forecast the load of the test forecast month (Jan 2003).

4.3 Results and Discussion

In this section, the results of particle swarm optimization based fuzzy inference system for STLF for few different days of the testing month (Jan 2003) are presented. Hourly forecasted load results are shown in the Tables 11-14. The comparison of MAPE for forecasting with and without optimization techniques is shown in the Table 15. It can be seen that the proposed technique is giving the good quality results with MAPE less than 3% showing the suitability of the proposed technique. The variation of fuzzy membership parameter limits of with and without optimization technique is shown in the Table 16.

TABLE 11
Hourly results of 8th Jan 2003 and 9th Jan 2003 using PSO

	8th Jan 2003		**9th Jan 2003**	
Hour	**Actual Load (MW)**	**Forecasted Load (MW)**	**Actual Load (MW)**	**Forecasted Load (MW)**
1	12606	12520	13033	13152
2	12146	12053	12569	12663
3	11932	11857	12350	12440
4	11927	11864	12328	12403
5	12252	12199	12605	12688
6	13446	13307	13727	13737
7	15835	15375	16038	15831
8	17297	16839	17527	17190
9	17470	17411	17730	17554
10	17465	17686	17722	17665
11	17464	17828	17701	17655
12	17389	17783	17592	17497
13	17197	17604	17275	17211
14	17120	17458	17124	17014
15	16975	17274	16864	16791
16	17083	17351	16844	16864
17	18223	18568	17892	18053
18	19640	19887	19213	19472
19	19582	19758	19049	19357
20	19147	19242	18519	18901
21	18450	18500	17760	18228
22	17226	17329	16469	17062
23	15495	15700	14777	15470
24	14007	14175	13255	13941
MAPE (%):**1.298**			MAPE (%):**1.360**	

TABLE 12
Hourly results of 10th Jan 2003 and 11th Jan 2003 using PSO

	10th Jan 2003		**11th Jan 2003**	
Hour	**Actual Load (MW)**	**Forecasted Load (MW)**	**Actual Load (MW)**	**Forecasted Load (MW)**
1	12271	12555	12177	12747
2	11803	11997	11652	12172
3	11552	11726	11425	11891
4	11490	11649	11372	11827
5	11750	11876	11638	12051
6	12903	12730	12735	12895
7	15239	14425	15113	14589
8	16654	15629	16619	15831
9	16866	16190	16892	16417
10	16890	16487	16956	16775
11	16958	16593	16985	16903
12	16864	16540	16858	16875
13	16669	16310	16606	16656
14	16541	16123	16478	16481
15	16344	15943	16301	16311
16	16405	16065	16324	16417
17	17428	17877	17216	17693
18	18756	19156	18551	19013
19	18677	18979	18391	18850
20	18235	18041	17864	18334
21	17527	17889	17235	17715
22	16334	16694	16334	16738
23	14657	15133	15068	15369
24	13170	13801	13749	13932
MAPE (%):**2.505**			MAPE (%):**2.275**	

TABLE 13
Hourly results of 12th Jan 2003 and 13th Jan 2003 using PSO

	12th Jan 2003		13th Jan 2003	
Hour	**Actual Load (MW)**	**Forecasted Load (MW)**	**Actual Load (MW)**	**Forecasted Load (MW)**
1	12793	12485	12610	12235
2	12280	11947	12070	11694
3	12033	11687	11759	11098
4	11955	11622	11633	10922
5	12076	11788	11680	11041
6	12512	12312	11955	11711
7	13376	13766	12495	12821
8	14295	14177	13132	13637
9	15377	15131	14115	14446
10	16058	15788	14805	15023
11	16249	16070	15113	15291
12	16177	16100	15249	15367
13	15911	15927	15200	15244
14	15584	15658	14950	15022
15	15331	15447	14715	14822
16	15322	15512	14819	15132
17	16246	16825	15992	16159
18	17636	18276	17625	18186
19	17527	18103	17702	17503
20	16995	17492	17273	16819
21	16443	16822	16671	16196
22	15703	15996	15607	15904
23	14652	14900	14259	14412
24	13563	13808	13061	13449
MAPE (%):**1.958**			MAPE (%):**2.414**	

TABLE 14
Hourly results of 14th Jan 2003 using PSO

	14th Jan 2003	
Hour	**Actual Load (MW)**	**Forecasted Load (MW)**
1	12300	12751
2	11971	12257
3	11870	12049
4	11911	12025
5	12278	12330
6	13540	13337
7	16047	15266
8	17543	16628
9	17700	17180
10	17719	17466
11	17769	17588
12	17640	17503
13	17434	17275
14	17270	17091
15	17091	16916
16	17189	17022
17	18167	18358
18	19541	19831
19	19449	19661
20	18969	19074
21	18169	18330
22	16950	17261
23	15303	15804
24	13881	14398
MAPE (%):**1.856**		

The graphical representations of the forecasted load and actual load curves by using PSO are shown in the Fig 22-28.

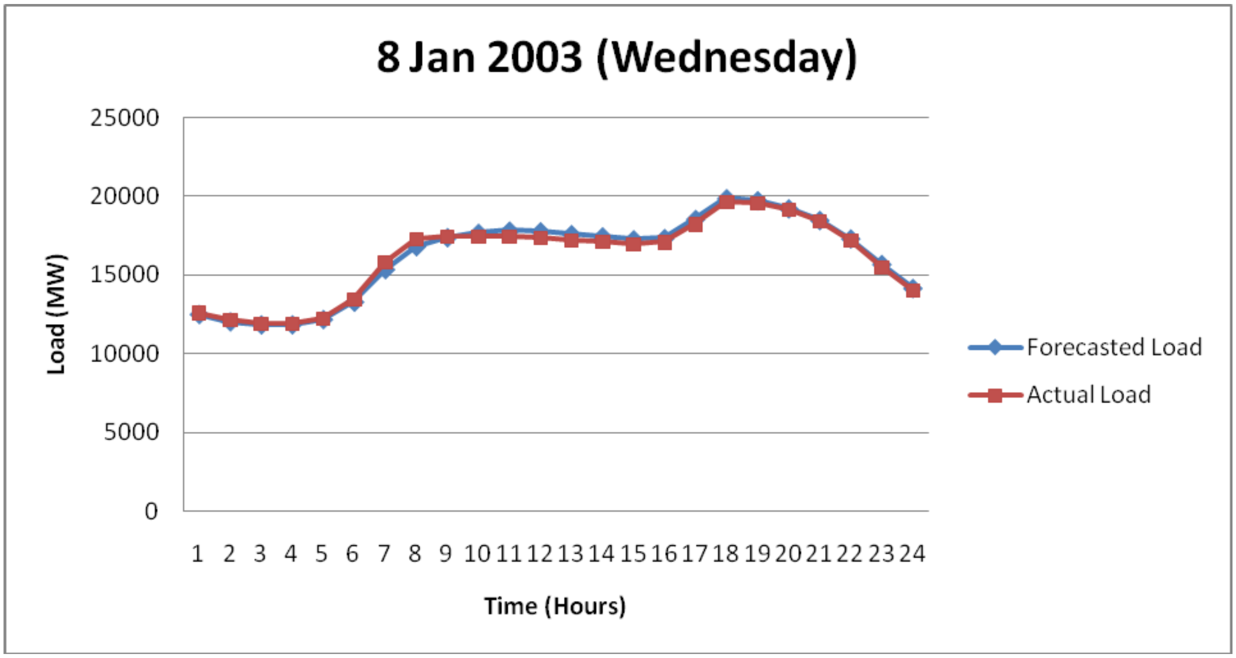

Fig. 22 Forecasted Load and Actual Load curves for 8th January 2003 (Wednesday)

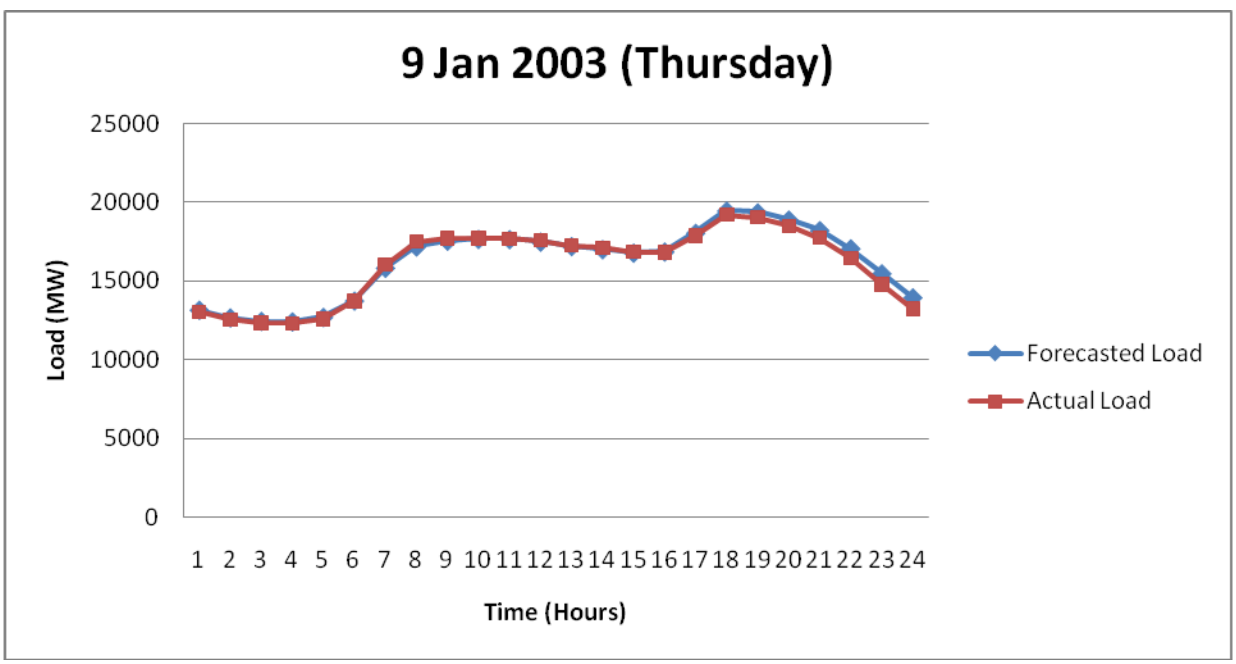

Fig. 23 Forecasted Load and Actual Load curves for 9th January 2003 (Thursday)

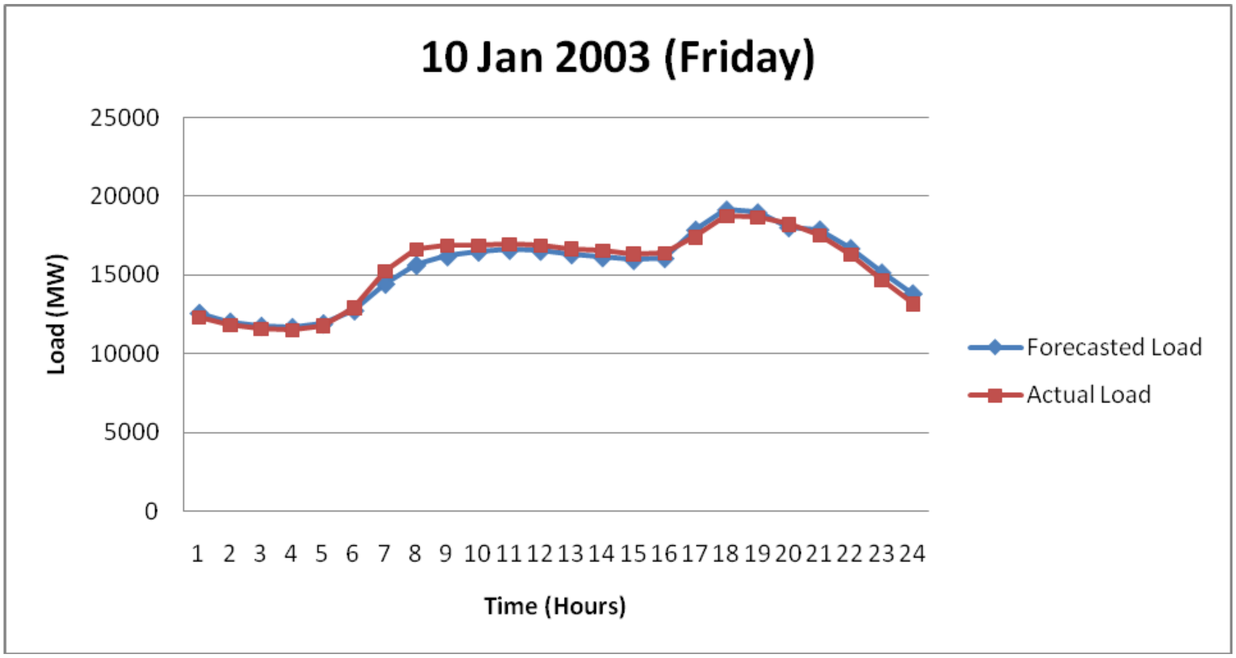

Fig. 24 Forecasted Load and Actual Load curves for 10th January 2003 (Friday)

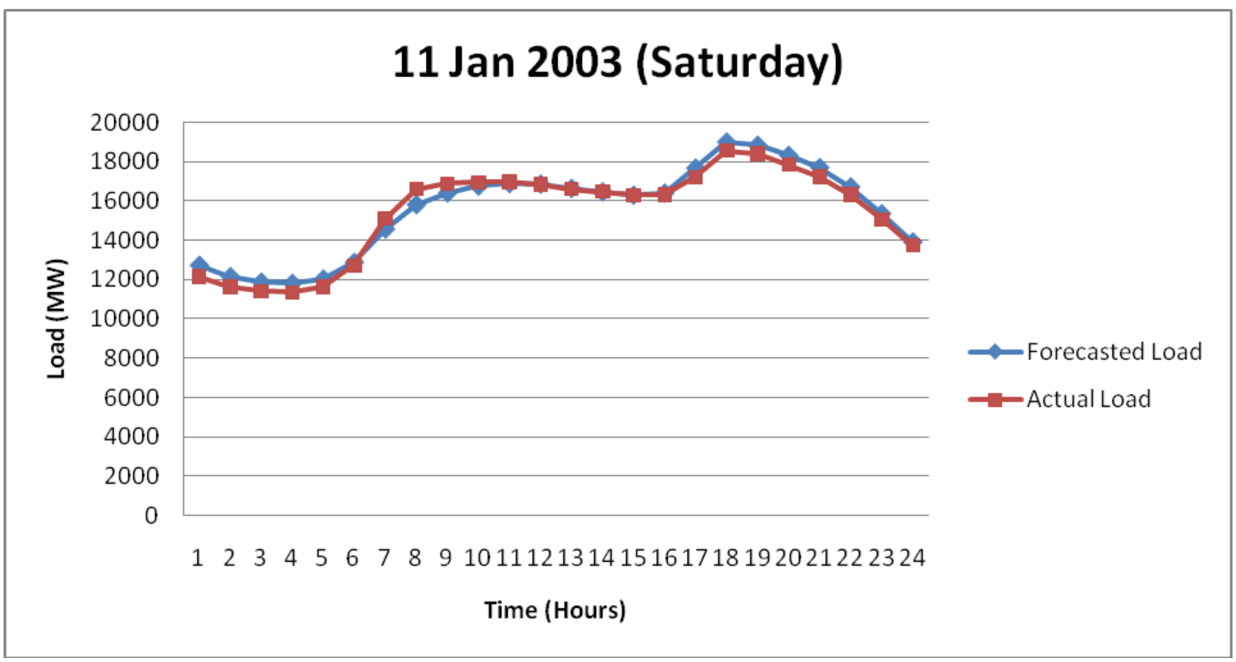

Fig. 25 Forecasted Load and Actual Load curves for 11th January 2003 (Saturday)

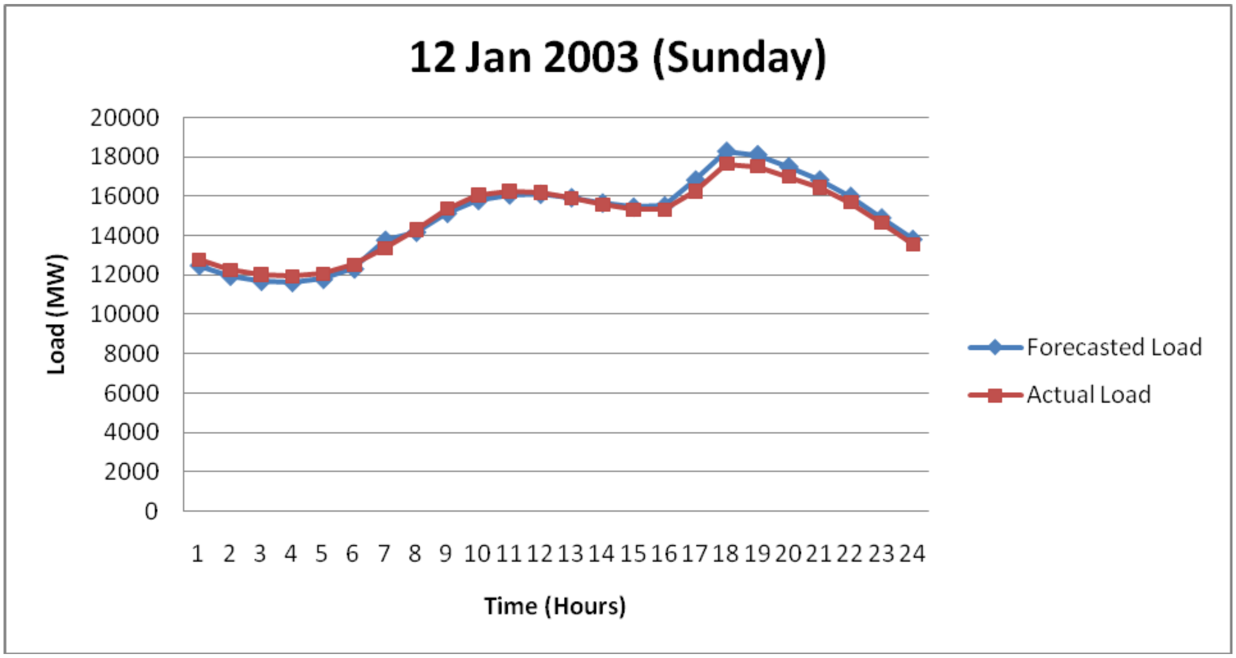

Fig. 26 Forecasted Load and Actual Load curves for 12th January 2003 (Sunday)

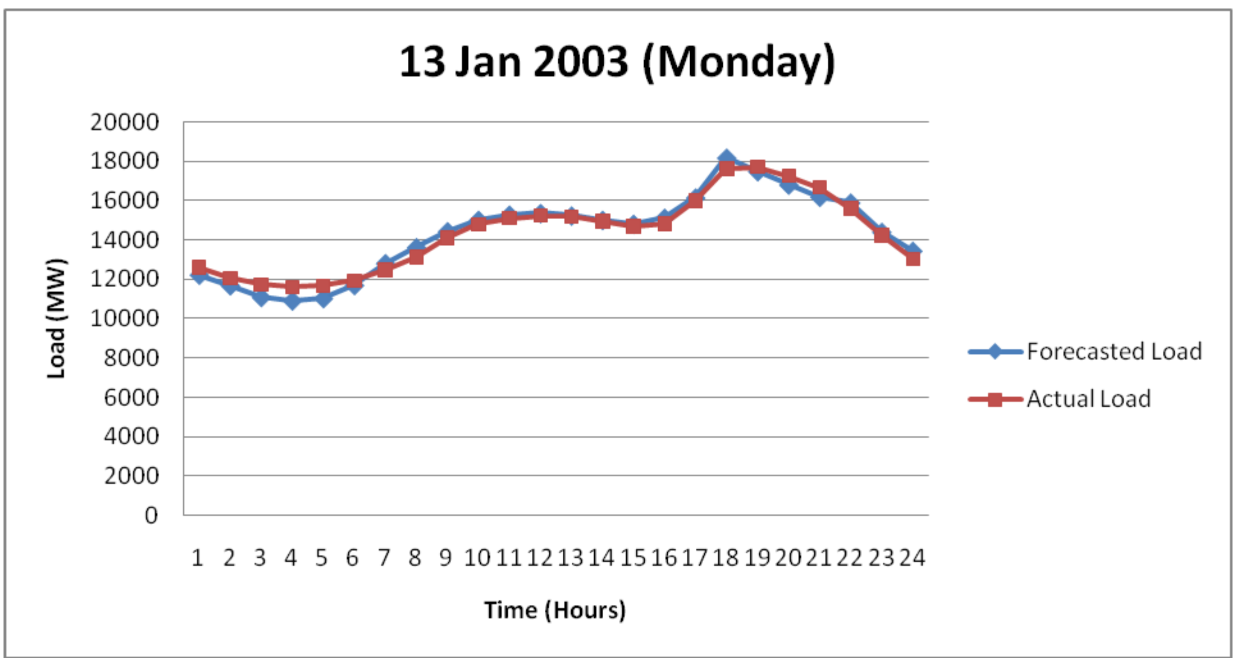

Fig. 27 Forecasted Load and Actual Load curves for 13th January 2003 (Monday)

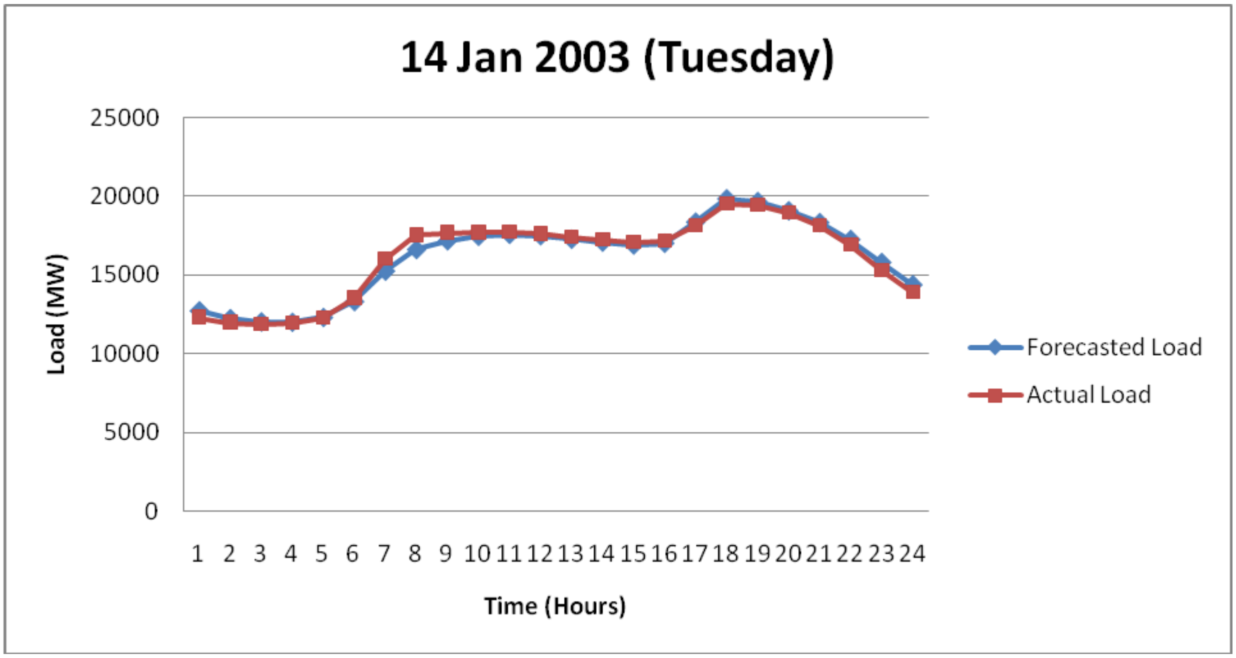

Fig. 28 Forecasted Load and Actual Load curves for 14th January 2003 (Tuesday)

The graphical representations of fuzzy membership parameters using particle swarm optimization are shown in the Fig 29-31.

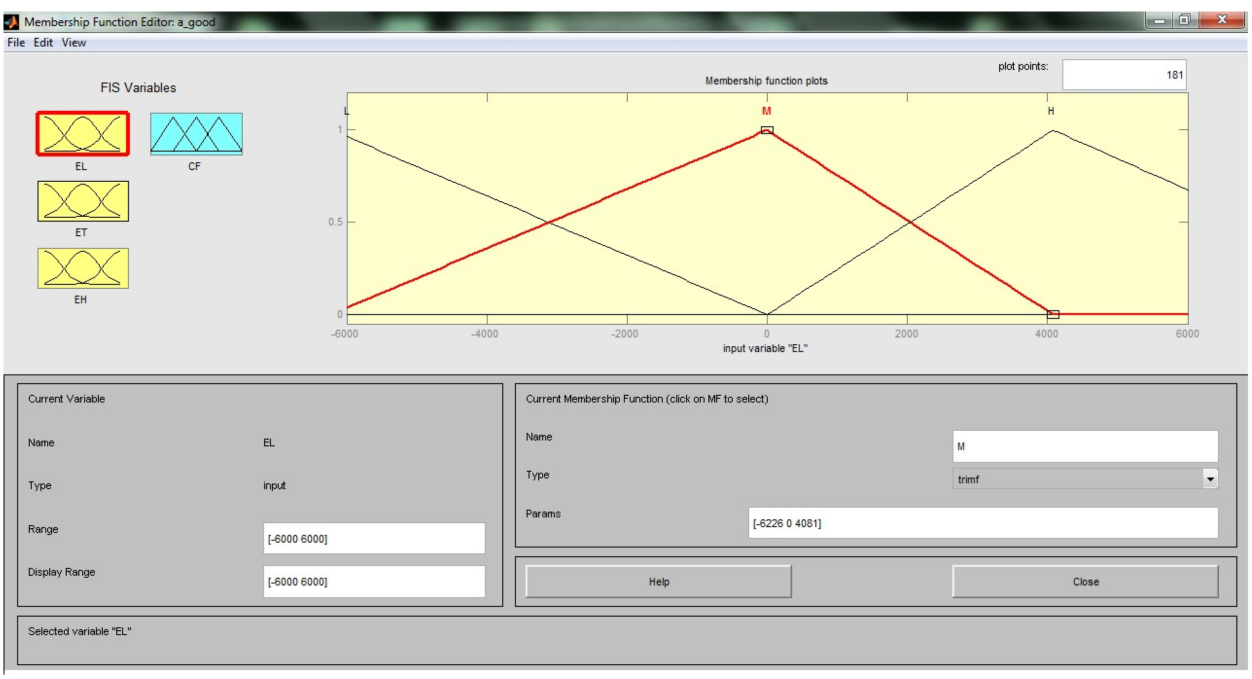

Fig. 29 Fuzzy membership parameters (a1, a2) using PSO

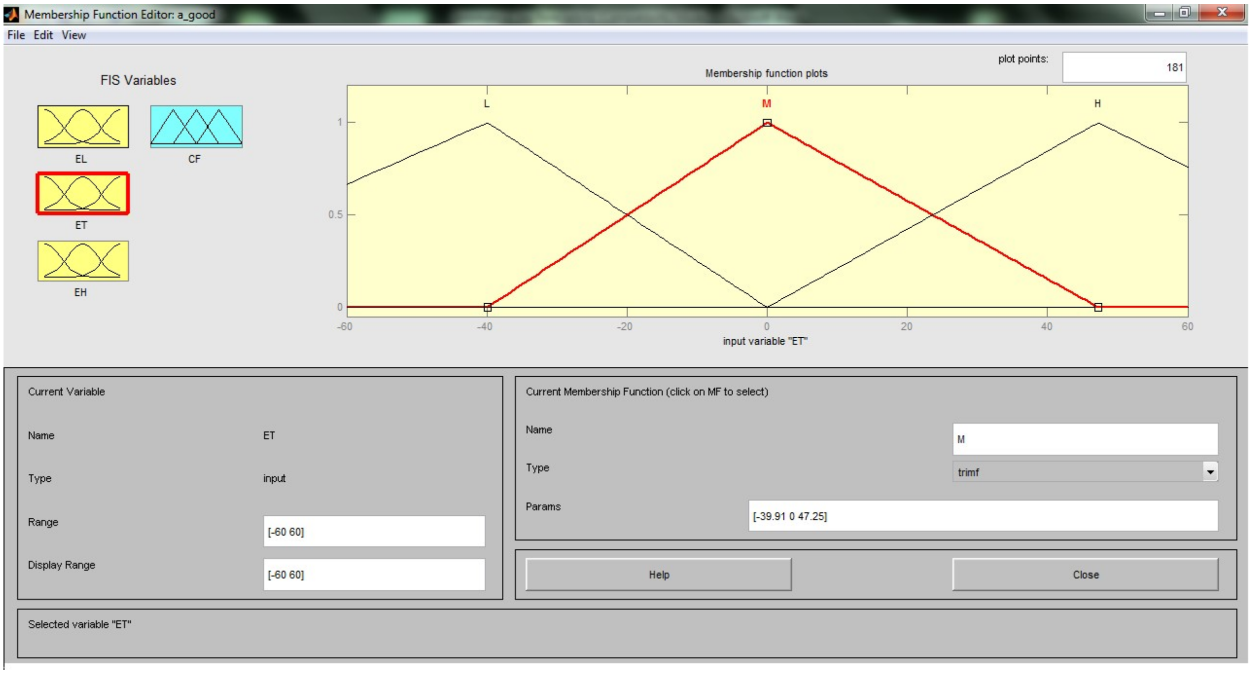

Fig. 30 Fuzzy membership parameters (a3, a4) using PSO

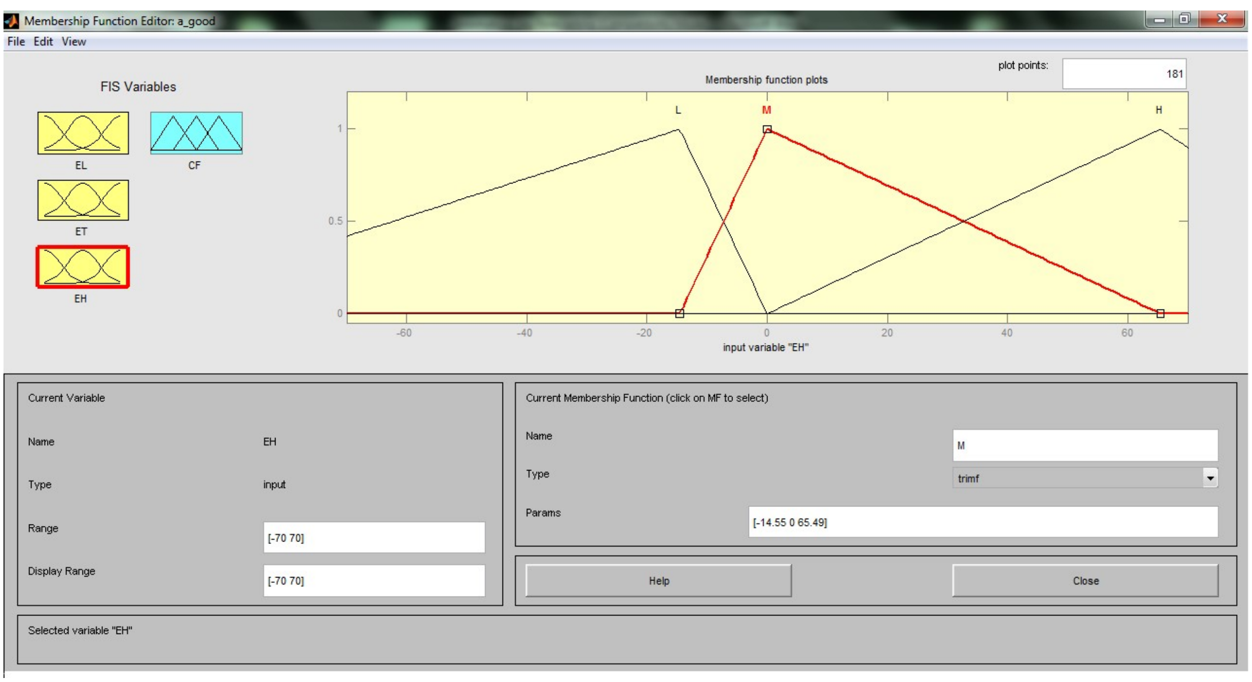

Fig. 31 Fuzzy membership parameters (a5, a6) using PSO

TABLE 15
DAILY FORECAST RESULTS BY USING PSO

Day	MAPE (%) Without optimization	MAPE (%) With PSO
8th Jan 2003 (Wednesday)	3.083	1.299
9th Jan 2003 (Thursday)	4.049	1.360
10th Jan 2003 (Friday)	2.583	2.505
11th Jan 2003 (Saturday)	4.825	2.275
12th Jan 2003 (Sunday)	2.455	1.959
13th Jan 2003 (Monday)	3.390	2.414
14th Jan 2003 (Tuesday)	2.887	1.856

TABLE 16
MEMBERSHIP PARAMETER VALUES BY USING PSO

Membership Parameters	Without Optimization	With PSO
(a1,a2)	(-5000,5000)	(-6226,4081)
(a3,a4)	(-50,50)	(-39.91,47.25)
(a5,a6)	(-55,55)	(-14.55,65.49)

4.4 Impact of Error in Weather parameters on STLF using PSO

Variations in MAPE (%) of STLF using PSO with and without weather forecast errors are shown in the Table 17.

TABLE 17

COMPARATIVE MAPE (%) OF DAILY FORECAST RESULTS WITH AND WITHOUT WEATHER FORECAST ERROR USING PSO

Day	PSO		
	Without Weather Forecast Error	With Weather Forecast Error	
		T+1%, H+3%	T-1%, H-3%
8th Jan 2003 (Wednesday)	1.299	1.647	2.501
9th Jan 2003 (Thursday)	1.360	1.843	1.568
10th Jan 2003 (Friday)	2.505	2.803	2.422
11th Jan 2003 (Saturday)	2.275	2.548	2.679
12th Jan 2003 (Sunday)	1.959	2.328	2.188
13th Jan 2003 (Monday)	2.414	2.465	2.805
14th Jan 2003 (Tuesday)	1.856	1.957	1.837

Where

(T+1%) is Temperature with 1% noise (addition), (H+3%) is Humidity with 3% noise (addition), (T-1%) is Temperature with 1% noise (subtraction), (H-3%) is Humidity with 3% noise (subtraction) and percentage error in temperature applied on Kelvin scale.

4.5 Summary and Observations

Results for particle swarm optimization based fuzzy inference system for STLF are presented for different days and these results included the weekdays and weekends also. MAPE results are compared with and without optimization technique. PSO based forecasting shows better results and MAPE has been less than 3% for all seven representative days. The graphical representations of forecasted and actual load curves show that PSO based forecasted load curve followed a similar pattern to the actual load curve. Variations in MAPE (%) of STLF with PSO with and without weather forecast errors are also presented.

Chapter 5
New Particle Swarm Optimization (NPSO) based Fuzzy Inference System for Short Term Load Forecasting

5.1 Introduction

Learning is a dynamic process and in personal experience an individual not only learns from best but also learns from mistakes. The main idea of New Particle Swarm Optimization (NPSO) [86, 87] is based on the social behavioral concept. The basic theme of NPSO is that each particle tries to leave its previous worst position and the previous worst position of its group. In which, a group of particles with randomly chosen velocities and positions knowing their worst values so far (*pworst*) and the position put into the n-dimensional search space.

In this algorithm, each particle velocity is updated based on its own and other particle's flying experience. Let in an n-dimensional space, the i[th] particle is $x^i = (x^{i1}, x^{i2} \ldots x^{in})$. The previous worst position of the i[th] particle is $pworst_i = (pworst_{i1,}\ pworst_{i2}, \ldots, \ldots, pworst_{in})$ The worst particle index among all the particles is represented as $gworst_i$. The velocity of i[th] particle is $v_i = (v_{i1}, v_{i2}, \ldots, v_{in})$. Using the Eq. 5 and Eq. 6, the velocity and position of each particle can be updated.

$$v_i^{k+1} = v_i^k - c1 * rand() * (pworst_i^k - present_i^k) + c2 * rand() * (gworst_i^k - present_i^k) \qquad (5)$$

$$present_i^{k+1} = present_i^k + v_i^{k+1} \qquad (6)$$

Where, v_i^k is the i[th] particle velocity in k[th] iteration, $c1$, $c2$ are learning factors. Usually $c1 = c2 = 1$, $rand(\ )$ is a random number between (0, 1), $pworst_i^k$ and $gworst_i^k$ are defined as stated before, $present_i^k$ is the i[th] particle position in k[th] iteration.

The evolution procedure of NPSO Algorithms is as follows:

The first step of NPSO is to produce the initial population of chromosomes. The corresponding evaluations of populations are called the "fitness function". The bigger is the fitness value and the better is the performance. The number of the generations and the fitness value determine whether the evolution procedure is stopped or not and iterations may be done up to a maximum number (as chosen initially) of iterations. In this method, the *pworst* of each particle and *gworst* of the population (the worst movement of all particles) are calculated. The updated particle velocity, position, *pworst* and *gworst* give a new best position which is very far from the existing worst position. The process may be repeated for the maximum number of iterations.

5.2 NPSO Implementation for FIS

The methodology followed in this case is a similar line as that of the PSO-FIS implementation given in Section 5.1 and the velocity and particle position updating equations are given by Eq. 5 and Eq. 6, which takes into account of the concept of NPSO. The NPSO function accepts the training data of the previous month to the test forecast month (Dec 2002 as the test forecast month in this case is Jan 2003) and the purpose is to reduce the forecast MAPE of the 30 days of the previous month (Dec 2002) of the test forecast month (Jan 2003). Optimizer function is run for 50 iterations or until MAPE comes as less than 3% (here MAPE is considered as a fitness function). After each of the iterations, the optimizer tunes the latest particle position and velocity using the fitness equations, which are based on the *pworst* and *gworst* of the previous iteration if the fitness function value is better than the previous one. The final parameters obtained from NPSO are input parameter limits of FIS and used to forecast the loads of day for the test forecast month (Jan 2003).

5.3 Results and Discussion

In this section, new particle swarm optimization based fuzzy inference system for STLF using Mahalanobis distance norm for few different days of the testing month (Jan 2003) results are presented. Hourly forecasted load results are shown in the Tables 18-21. The comparison of MAPE for forecasting results with and without optimization techniques is shown in the Table 22. It can be seen that the proposed technique is giving the good quality results with MAPE less than 3%. The variation of fuzzy membership parameter limits of with and without optimization technique is shown in the Table 23.

TABLE 18
Hourly results of 8th Jan 2003 and 9th Jan 2003 using NPSO

	8th Jan 2003		**9th Jan 2003**	
Hour	**Actual Load (MW)**	**Forecasted Load (MW)**	**Actual Load (MW)**	**Forecasted Load (MW)**
1	12606	12744	13033	13046
2	12146	12269	12569	12559
3	11932	12070	12350	12336
4	11927	12077	12328	12298
5	12252	12418	12605	12577
6	13446	13547	13727	13610
7	15835	15652	16038	15671
8	17297	17143	17527	17016
9	17470	17726	17730	17385
10	17465	17512	17722	17502
11	17464	17501	17701	17496
12	17389	17684	17592	17339
13	17197	17502	17275	17056
14	17120	17322	17124	16859
15	16975	17272	16864	16637
16	17083	17411	16844	16708
17	18223	18612	17892	17883
18	19640	19991	19213	19288
19	19582	19706	19049	19173
20	19147	19403	18519	18719
21	18450	18121	17760	18051
22	17226	17512	16469	16899
23	15495	15621	14777	15325
24	14007	14168	13255	13814
MAPE (%):**1.259**			MAPE (%):**1.330**	

TABLE 19
Hourly results of 10th Jan 2003 and 11th Jan 2003 using NPSO

	10th Jan 2003		11th Jan 2003	
Hour	**Actual Load (MW)**	**Forecasted Load (MW)**	**Actual Load (MW)**	**Forecasted Load (MW)**
1	12271	12470	12177	12600
2	11803	11916	11652	12033
3	11552	11646	11425	11756
4	11490	11570	11372	11692
5	11750	11792	11638	11911
6	12903	12629	12735	12736
7	15239	14289	15113	14392
8	16654	15474	16619	15608
9	16866	16040	16892	16193
10	16890	16345	16956	16555
11	16958	16453	16985	16686
12	16864	16406	16858	16663
13	16669	16180	16606	16451
14	16541	15993	16478	16278
15	16344	15813	16301	16109
16	16405	15936	16324	16214
17	17428	17241	17216	17475
18	18756	18612	18551	18780
19	18677	18435	18391	18621
20	18235	17900	17864	18113
21	17527	17253	17235	17502
22	16334	16329	16334	16536
23	14657	15024	15068	15181
24	13170	13709	13749	13761
MAPE (%):**2.467**			MAPE (%):**2.004**	

TABLE 20
Hourly results of 12th Jan 2003 and 13th Jan 2003 using NPSO

	12th Jan 2003		**13th Jan 2003**	
Hour	**Actual Load (MW)**	**Forecasted Load (MW)**	**Actual Load (MW)**	**Forecasted Load (MW)**
1	12793	12569	12610	12225
2	12280	12027	12070	11703
3	12033	11764	11759	11328
4	11955	11698	11633	11229
5	12076	11864	11680	11339
6	12512	12388	11955	11682
7	13376	13343	12495	12371
8	14295	14257	13132	13156
9	15377	15218	14115	13944
10	16058	15881	14805	14506
11	16249	16166	15113	14764
12	16177	16198	15249	14836
13	15911	16025	15200	14716
14	15584	15754	14950	14499
15	15331	15543	14715	14304
16	15322	15608	14819	14409
17	16246	16932	15992	15592
18	17636	18393	17625	17172
19	17527	18220	17702	17217
20	16995	17607	17273	17062
21	16443	16934	16671	16410
22	15703	16103	15607	15267
23	14652	14999	14259	13952
24	13563	13897	13061	12687
MAPE (%): **1.905**			MAPE (%):**2.392**	

TABLE 21
Hourly results of 14th Jan 2003 using NPSO

	14th Jan 2003	
Hour	**Actual Load (MW)**	**Forecasted Load (MW)**
1	12300	12679
2	11971	12177
3	11870	12265
4	11911	12241
5	12278	12551
6	13540	13577
7	16047	15744
8	17543	17131
9	17700	17491
10	17719	17781
11	17769	17904
12	17640	17817
13	17434	17584
14	17270	17397
15	17091	17219
16	17189	17327
17	18167	18687
18	19541	19987
19	19449	20012
20	18969	19416
21	18169	18658
22	16950	17270
23	15303	15687
24	13881	14256
MAPE (%):**1.844**		

The graphical representations of the forecasted load and actual load curves by using NPSO are shown in the Fig 32-38.

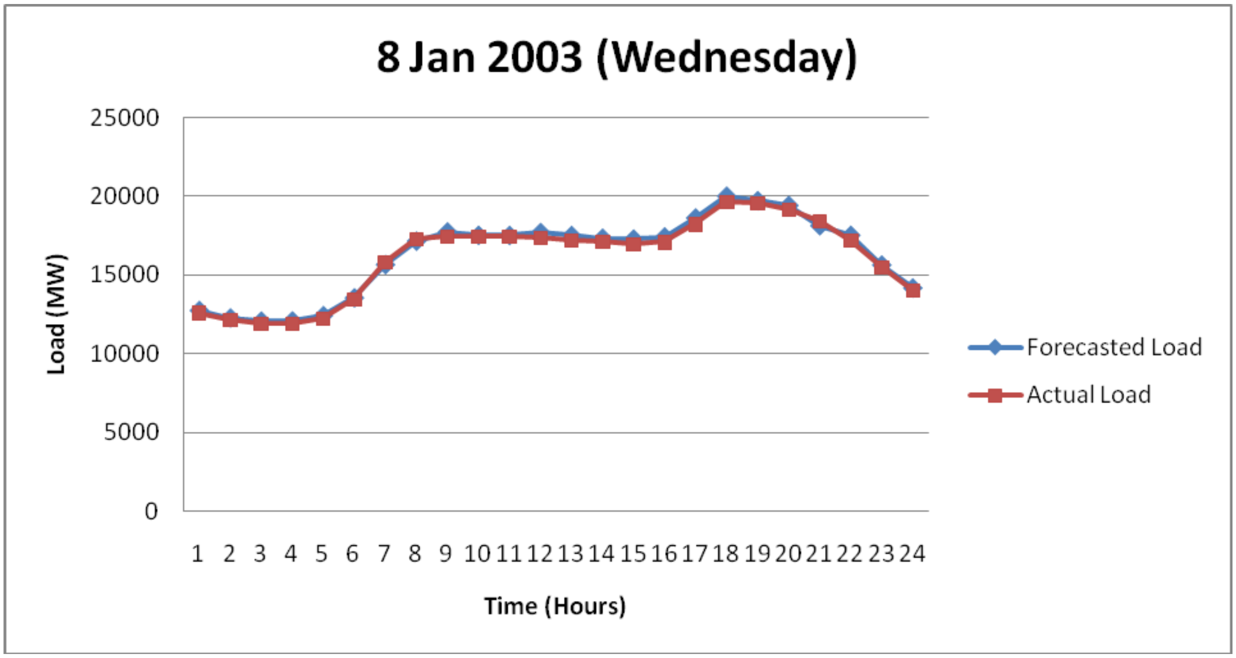

Fig. 32 Forecasted Load and Actual Load curves for 8th January 2003 (Wednesday)

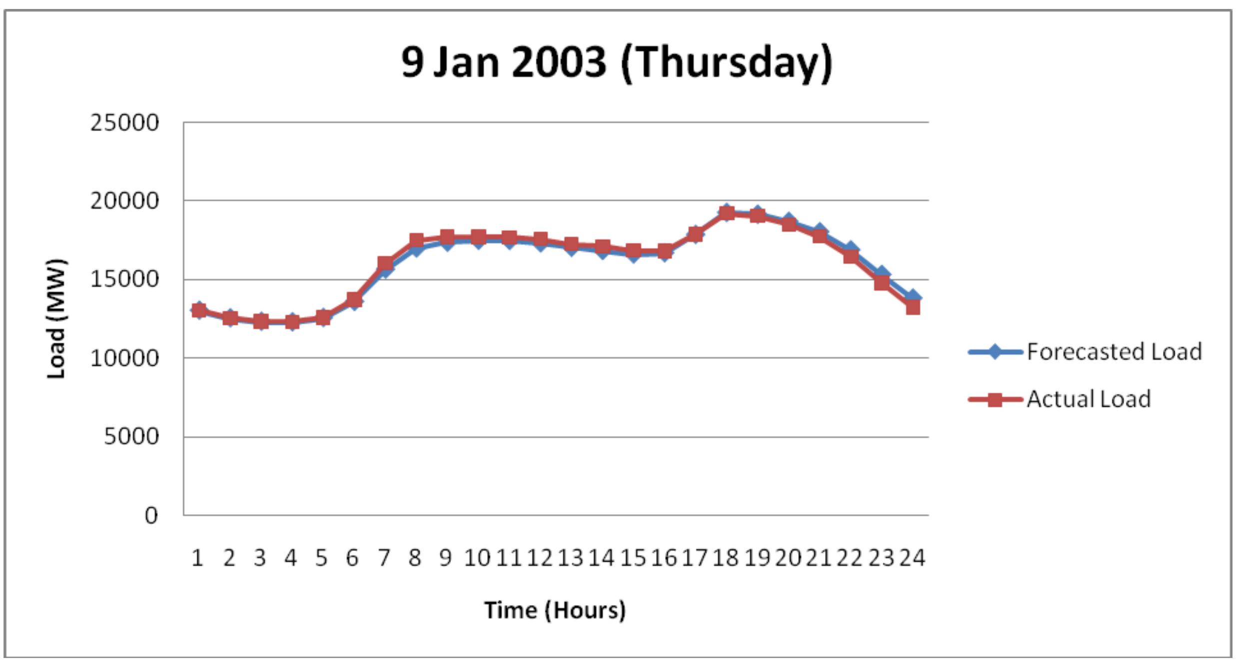

Fig. 33 Forecasted Load and Actual Load curves for 9th January 2003 (Thursday)

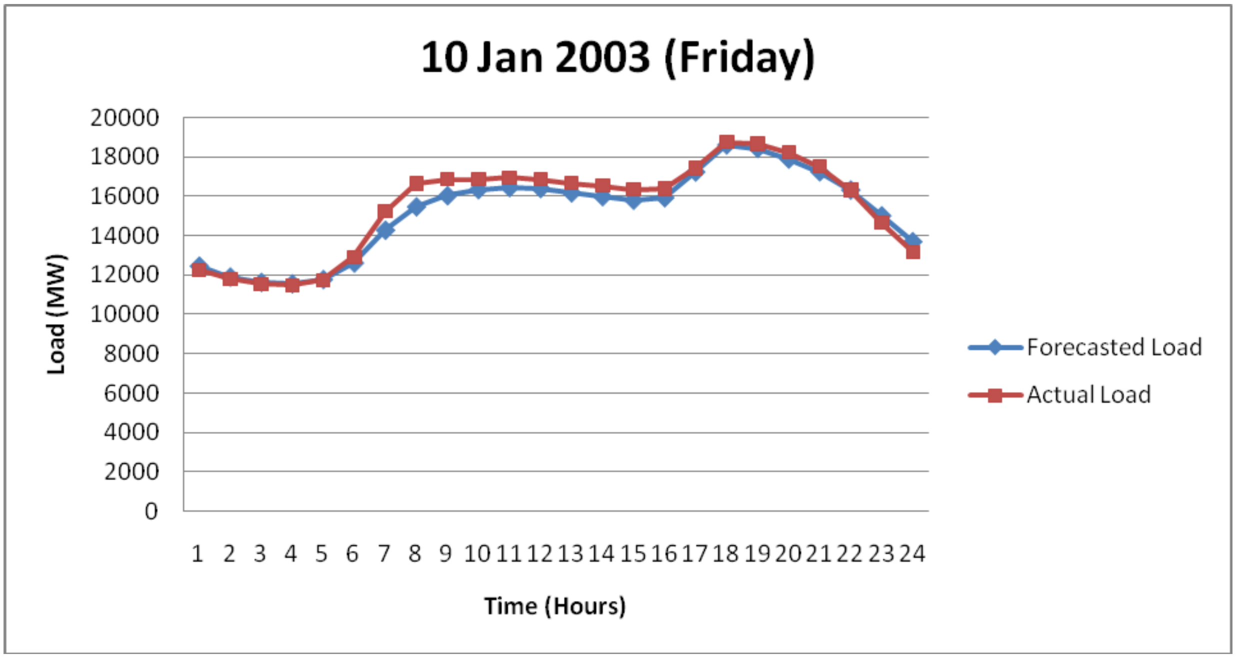

Fig. 34 Forecasted Load and Actual Load curves for 10th January 2003 (Friday)

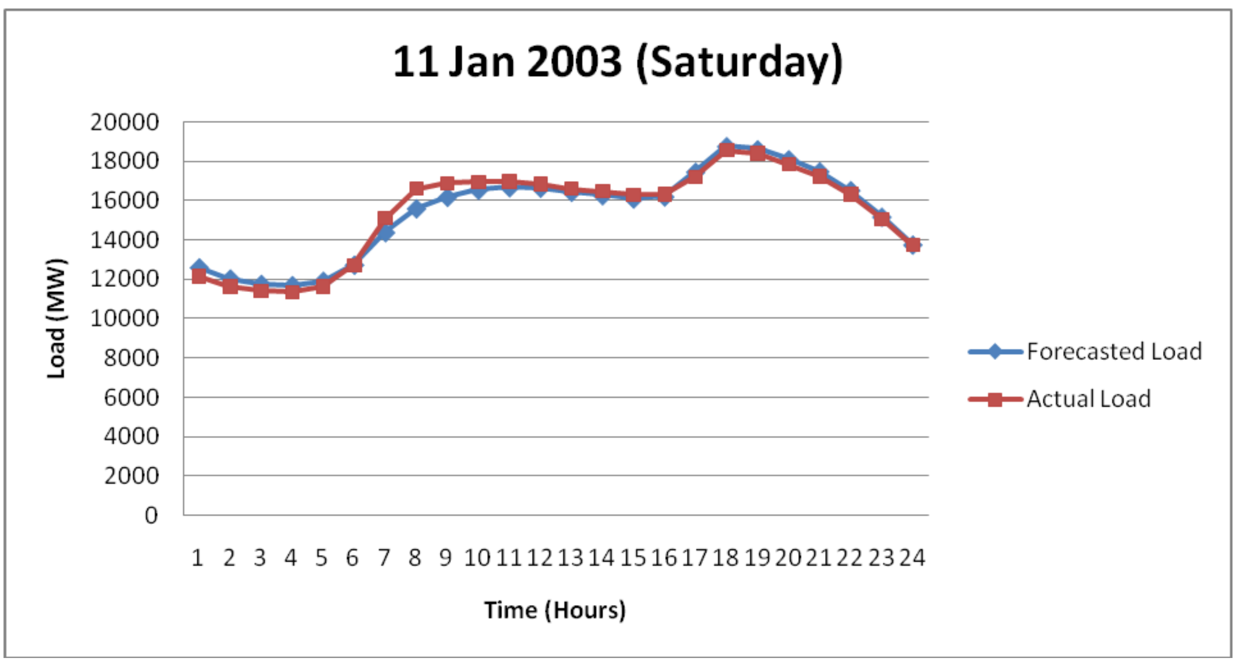

Fig. 35 Forecasted Load and Actual Load curves for 11th January 2003 (Saturday)

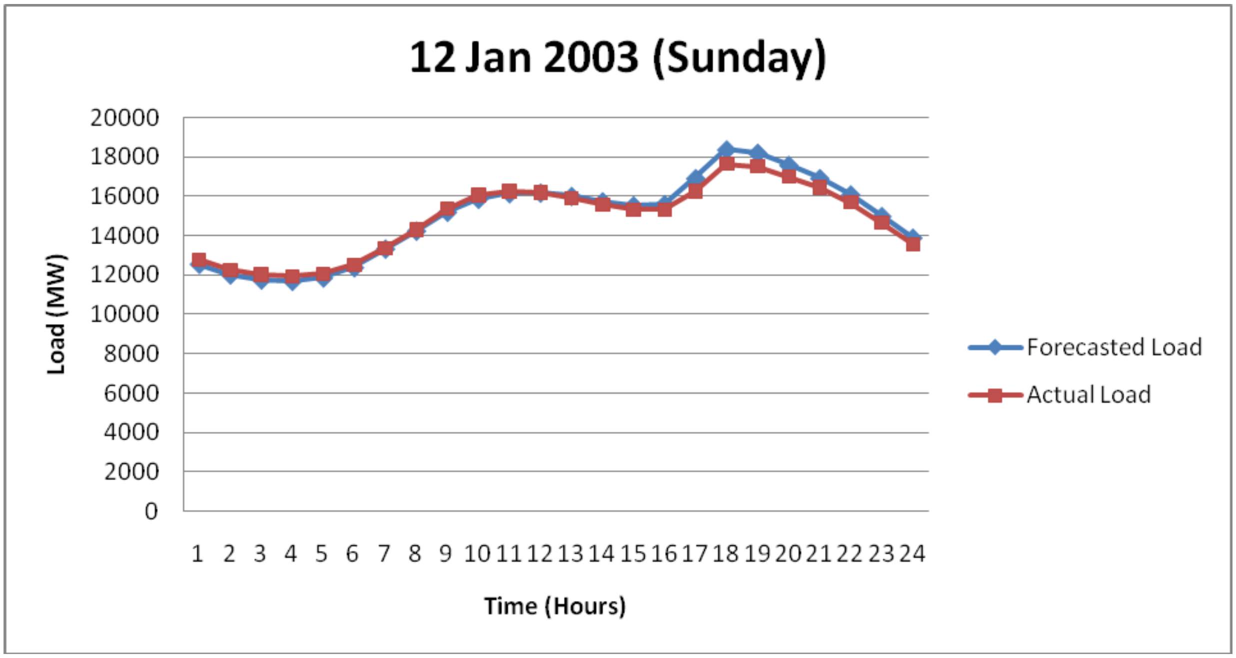

Fig. 36 Forecasted Load and Actual Load curves for 12th January 2003 (Sunday)

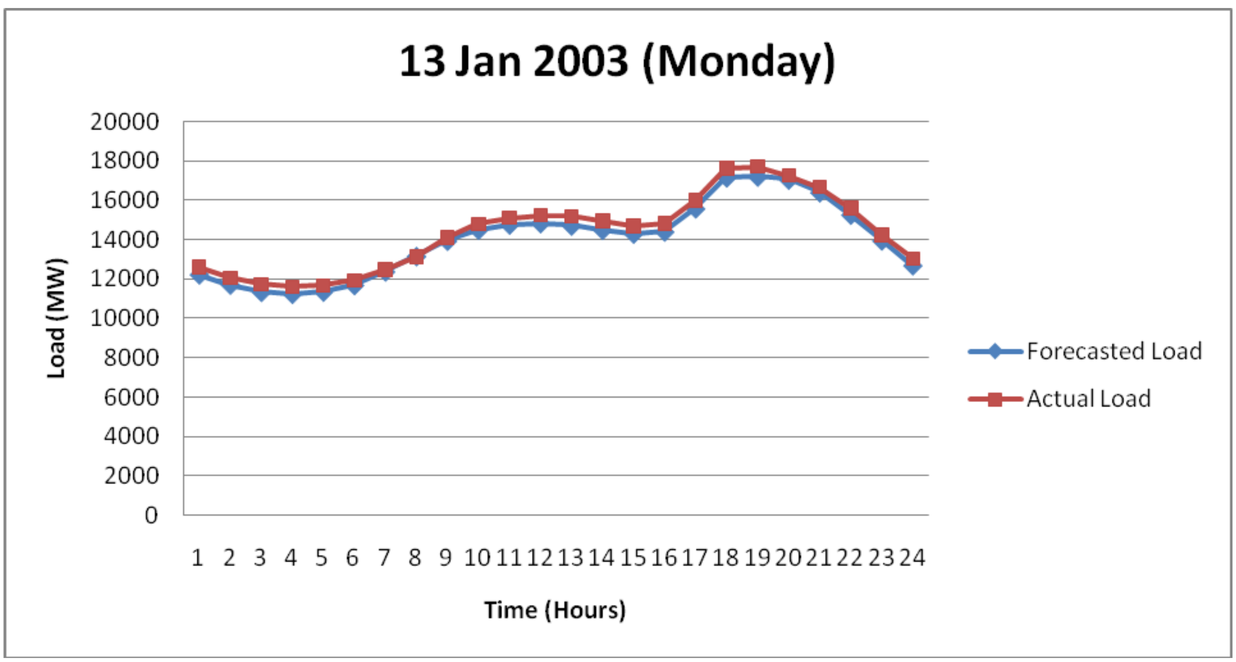

Fig. 37 Forecasted Load and Actual Load curves for 13th January 2003 (Monday)

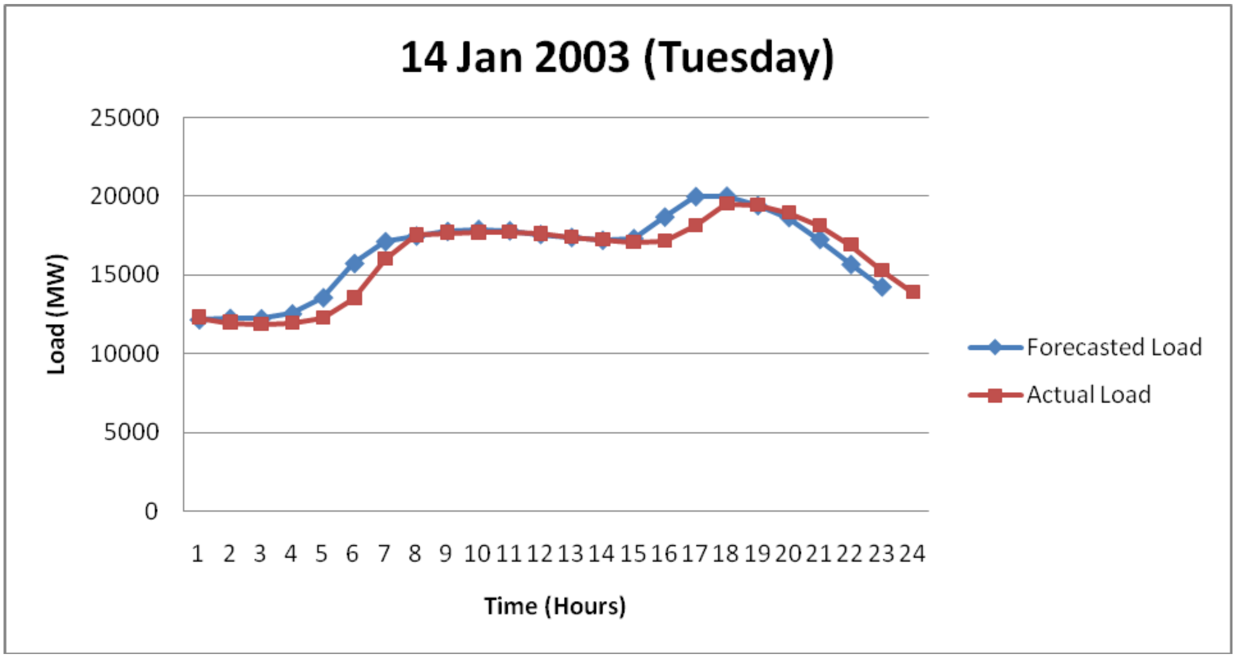

Fig. 38 Forecasted Load and Actual Load curves for 14th January 2003 (Tuesday)

The graphical representations of fuzzy membership parameters using new particle swarm optimization are shown in the Fig 39-41.

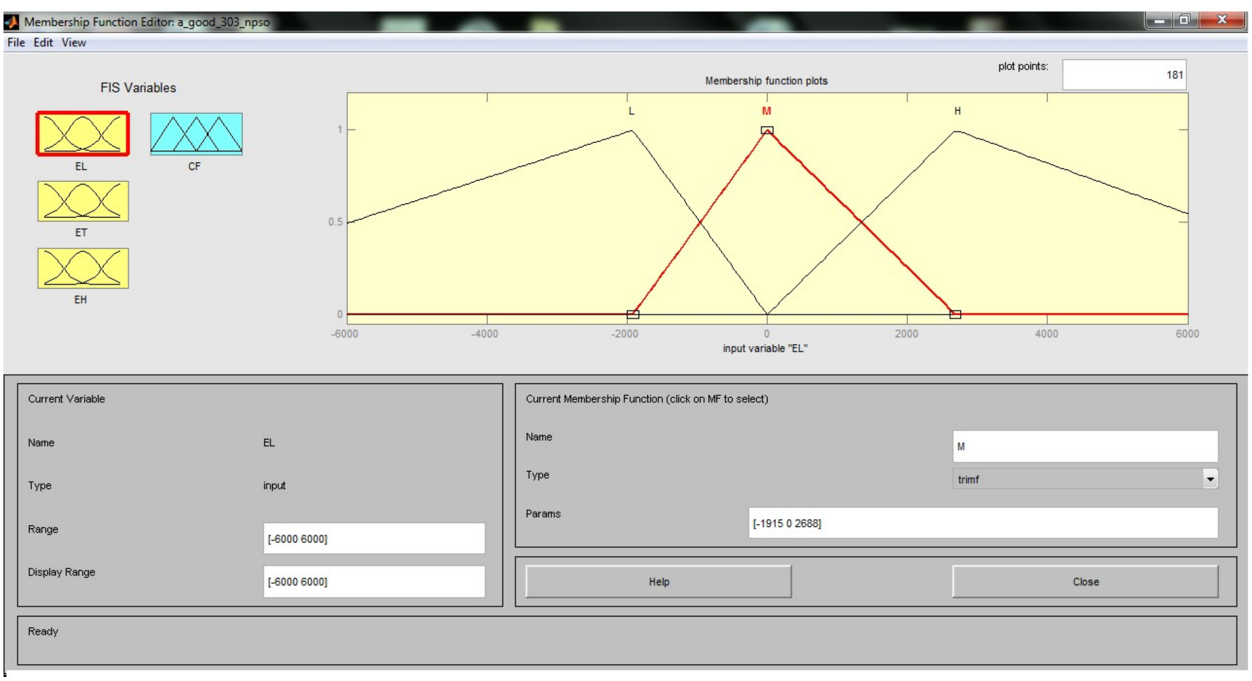

Fig. 39 Fuzzy membership parameters (a1, a2) using NPSO

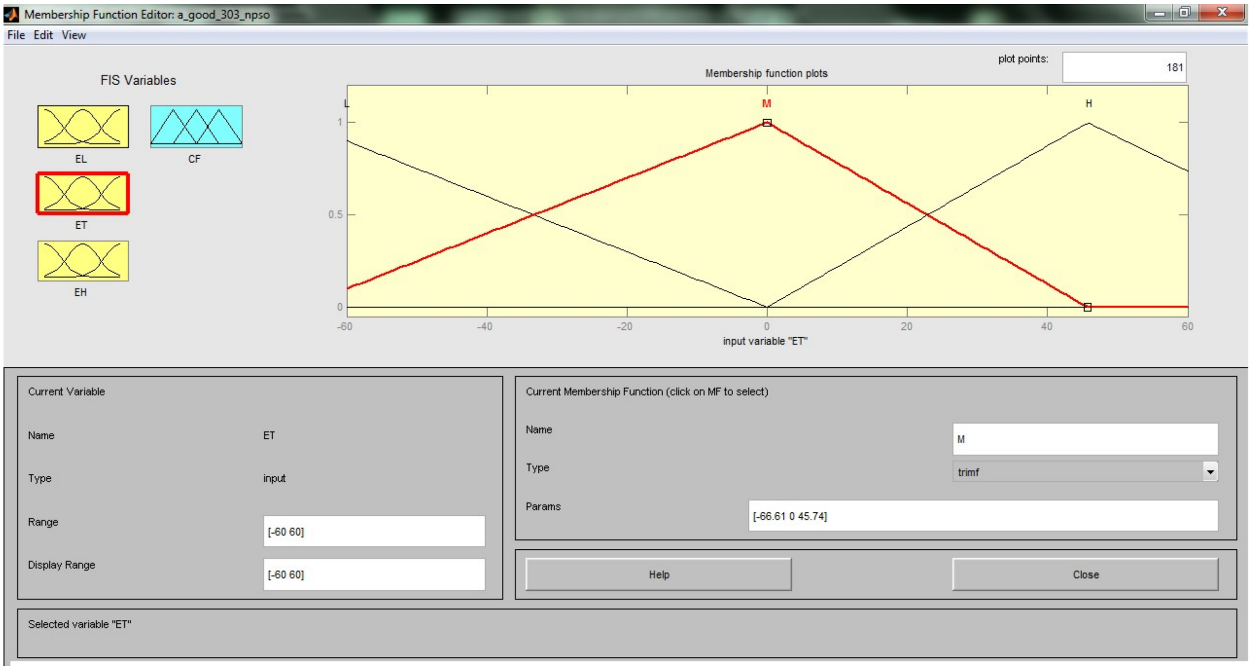

Fig. 40 Fuzzy membership parameters (a3, a4) using NPSO

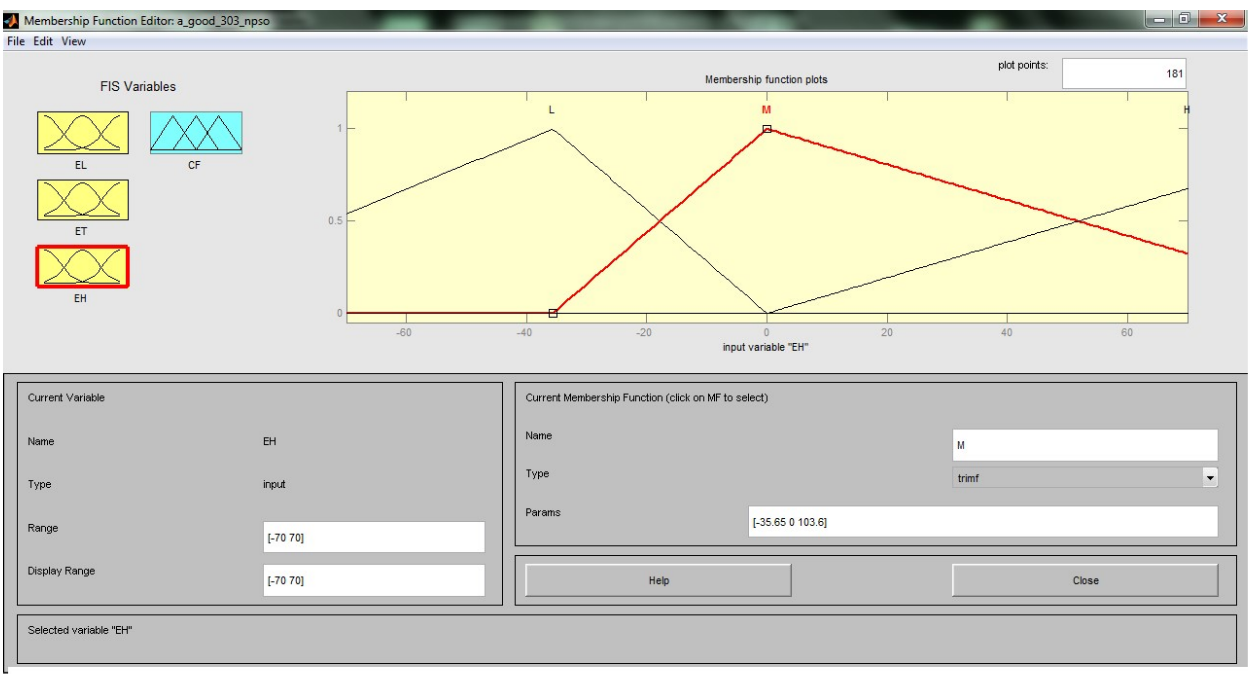

Fig. 41 Fuzzy membership parameters (a5, a6) using NPSO

TABLE 22

DAILY FORECAST RESULTS BY USING NPSO

Day	MAPE (%) Without optimization	MAPE (%) With NPSO
8th Jan 2003 (Wednesday)	3.083	1.259
9th Jan 2003 (Thursday)	4.049	1.330
10th Jan 2003 (Friday)	2.583	2.467
11th Jan 2003 (Saturday)	4.825	2.004
12th Jan 2003 (Sunday)	2.455	1.905
13th Jan 2003 (Monday)	3.390	2.392
14th Jan 2003 (Tuesday)	2.887	1.844

TABLE 23
MEMBERSHIP PARAMETER VALUES BY USING NPSO

Membership Parameters	Without Optimization	With NPSO
(a1,a2)	(-5000,5000)	(-1915,2688)
(a3,a4)	(-50,50)	(-66.61,45.74)
(a5,a6)	(-55,55)	(-35.65,103.6)

5.4 Impact of Error in Weather parameters on STLF using NPSO

Variations in MAPE (%) of STLF using NPSO with and without weather forecast errors are shown in the Table 24.

TABLE 24

COMPARATIVE MAPE (%) OF DAILY FORECAST RESULTS WITH AND WITHOUT WEATHER FORECAST ERROR USING NPSO

Day	NPSO		
	Without Weather Forecast Error	With Weather Forecast Error	
		T+ 1%, H+3%	T-1%, H-3%
8th Jan 2003 (Wednesday)	1.259	1.614	1.583
9th Jan 2003 (Thursday)	1.330	1.304	1.533
10th Jan 2003 (Friday)	2.467	2.534	2.993
11th Jan 2003 (Saturday)	2.004	1.973	1.901
12th Jan 2003 (Sunday)	1.905	1.928	1.962
13th Jan 2003 (Monday)	2.392	2.404	2.640
14th Jan 2003 (Tuesday)	1.844	1.999	2.401

Where

(T+1%) is Temperature with 1% noise (addition), (H+3%) is Humidity with 3% noise (addition), (T-1%) is Temperature with 1% noise (subtraction), (H-3%) is Humidity with 3% noise (subtraction) and percentage error in temperature applied on Kelvin scale.

5.5 Summary and Observations

Results for the new particle swarm optimization based fuzzy inference system for STLF are presented for different days and these results are included for weekdays and weekends also. MAPE results are compared with and without optimization techniques. NPSO based forecasting shows better results and MAPE has been less than 3% for all seven representative days. The graphical representations of forecasted and actual load curves show that NPSO based forecasted load curve followed a similar pattern to the actual load curve. The possibilities of input weather parameters error are considered and their impact has been analyzed and results have been presented.

Chapter 6
Evolutionary Particle Swarm Optimization (EPSO) based Fuzzy Inference System for Short Term Load Forecasting

6.1 Introduction

Evolutionary Particle Swarm Optimization (EPSO) algorithms are derived from evolutionary concepts that bring the movement rule from PSO and self- adapting properties for its parameters [88]. By using this hybrid method, an algorithm is built that has qualities of both approaches i.e PSO and evolutionary algorithms. Hybrid algorithms are commonly used in soft-computing – it is often that the hybrid techniques will combine the good traits of both methods and therefore build a more powerful method. The EPSO technique has the ability to deal with dynamic and complex problems and is a new variant in the meta-heuristic set of tools. It has the advantage of dealing with the abrupt change in the meteorological variables such as temperature, humidity, includes the effect of the day type and has the ability to deal with the nonlinear parts of the load curves.

The thought behind EPSO [89-90] is to have a PSO scheme with an explicit selection process and self-adapting properties. EPSO is composed of *object parameters* (X-variables) and *strategic parameters* (w-weights). A particle is a set of object and strategic parameters [X, w]. The generalized scheme of EPSO (The way each particle is handled) is: Replication ('r' times replicated), Mutation (mutated its weights 'w'), Reproduction (each mutated particle generates an offspring),

Evaluation (offspring fitness evaluated) and Selection (best particle survived to form a next- generation).

The *particle movement* rule is that given a particle, $present_i^k$, a new particle $present_i^{k+1}$ results from the Eq. 7 and Eq. 8.

$$v_i^{k+1} = w_{i0} * v_i^k + w_{i1} * (pbest_i^k - present_i^k) + w_{i2} * (gbest_i^k - present_i^k) \tag{7}$$

$$present_i^{k+1} = present_i^k + v_i^{k+1} \tag{8}$$

Where

v_i^k is the i^{th} particle velocity in k^{th} iteration

$pbest_i^k$ and $gbest_i^k$ are defined as stated before.

$present_i^k$ is the i^{th} particle position in k^{th} iteration

The EPSO is similar to typical PSO – the movement rule retains its terms of inertia, cooperation and memory. Here the weights are taken as object parameters and these are undergoing the mutation process as given by Eq. 9 that is not done with the PSO.

$$w_{ip}^* = w_{ip} + \mu N(0,1) \quad (P=0, 1, 2) \tag{9}$$

N (0, 1) is a random variable with Gaussian distribution of 0 mean and variance 1.

The global best $gbest_i^k$ is randomly disturbed as per the Eq. 10.

$$gbest_i^{k*} = gbest_i^k + \mu' N(0,1) \tag{10}$$

The μ and μ' are learning parameters; these are either fixed or treated as strategic and subject to mutation-fixed in this case.

The logic behind EPSO having this modification from PSO is the following:

a) In case, optimum hasn't been found yet than it is sensible to search that is focused in other region.

b) In case, current global best is the already global optimum than it is irrelevant.

EPSO scheme gets advantage from two "pushes" in the correct direction: one is particle movement rule and the other one is the Darwinist process of selection; therefore, it may have the convergence of properties when compared to evolutionary solutions or PSO only.

6.2 EPSO Implementation for FIS

The FIS has been optimized for six parameters (minima and maxima of each of the input fuzzy variable E_L, E_T, E_H) considering 49 particles as in the case of PSO-FIS. The initial limits for these parameters of the FIS are obtained by using historical data. These parameter values are fed into the FIS to get the forecast errors of the previous month (Dec 2002) to test the forecast month (Jan 2003) in the present case.

The evolutionary particle swarm tuner function takes the training data from the data of the previous months, with the objective to reduce the MAPE fitness function of the forecast of the days of the previous month (Dec 2002) to test forecast month (Jan 2003). After each of the iterations, the EPSO tuner function modifies the latest particle position (which in the present case are the input parameter limits) using the optimization equations based on the global best b_g of the previous iteration if the evaluation function value is better than the previous one. The evolutionary tuner function is run up to 50 iterations and by then the MAPE of the previous month (Dec 2002) attains a fixed value which is less than 3%. The parameters obtained after the EPSO optimization of the FIS are the final fuzzy input parameter limits for the FIS inputs ΔE_L, ΔE_T, ΔE_H and these are used to forecast the load of the days for the test forecast month (Jan 2003 in the present case).

6.3 Results and Discussion

In this section, results of STLF using evolutionary particle swarm optimization based fuzzy inference system, for few different days of the testing month (Jan 2003) are presented. Hourly forecasted load results are shown in the Tables 25-28. The comparison of MAPE for forecasting results with and without optimization technique is shown in the Table 29. It can be seen from Table 29 that the MAPE of STLF by EPSO has been less than 3% for the results of all representative seven days and these have been even less than 2% in most cases therefore, the EPSO based proposed technique is quite good for STLF. The variation of fuzzy membership parameter limits of with and without optimization technique is shown in the Table 30.

TABLE 25
Hourly results of 8th Jan 2003 and 9th Jan 2003 using EPSO

	8th Jan 2003		9th Jan 2003	
Hour	**Actual Load (MW)**	**Forecasted Load (MW)**	**Actual Load (MW)**	**Forecasted Load (MW)**
1	12606	12484	13033	13081
2	12146	12019	12569	12594
3	11932	11823	12350	12371
4	11927	11830	12328	12335
5	12252	12164	12605	12617
6	13446	13269	13727	13660
7	15835	15331	16038	15739
8	17297	16791	17527	17090
9	17470	17361	17730	17454
10	17465	17635	17722	17565
11	17464	17777	17701	17556
12	17389	17733	17592	17398
13	17197	17554	17275	17115
14	17120	17409	17124	16918
15	16975	17225	16864	16696
16	17083	17302	16844	16769
17	18223	18515	17892	17950
18	19640	19830	19213	19360
19	19582	19702	19049	19246
20	19147	19187	18519	18792
21	18450	18447	17760	18123
22	17226	17280	16469	16964
23	15495	15656	14777	15381
24	14007	14135	13255	13862
MAPE (%):**1.227**			MAPE (%):**1.291**	

TABLE 26
Hourly results of 10th Jan 2003 and 11th Jan 2003 using EPSO

	10th Jan 2003		**11th Jan 2003**	
Hour	**Actual Load (MW)**	**Forecasted Load (MW)**	**Actual Load (MW)**	**Forecasted Load (MW)**
1	12271	12430	12177	12565
2	11803	11877	11652	11999
3	11552	11609	11425	11722
4	11490	11533	11372	11659
5	11750	11757	11638	11879
6	12903	12601	12735	12707
7	15239	14275	15113	14371
8	16654	15465	16619	15591
9	16866	16022	16892	16170
10	16890	16318	16956	16527
11	16958	16423	16985	16655
12	16864	16372	16858	16628
13	16669	16144	16606	16414
14	16541	15959	16478	16242
15	16344	15780	16301	16074
16	16405	15902	16324	16178
17	17428	17200	17216	17436
18	18756	18566	18551	18738
19	18677	18391	18391	18577
20	18235	17858	17864	18070
21	17527	17213	17235	17460
22	16334	16288	16334	16496
23	14657	14981	15068	15146
24	13170	13463	13749	13730
MAPE (%):**2.447**			MAPE (%):**1.960**	

TABLE 27
Hourly results of 12th Jan 2003 and 13th Jan 2003 using EPSO

	12th Jan 2003		**13th Jan 2003**	
Hour	**Actual Load (MW)**	**Forecasted Load (MW)**	**Actual Load (MW)**	**Forecasted Load (MW)**
1	12793	12444	12610	12062
2	12280	11908	12070	11529
3	12033	11648	11759	11250
4	11955	11583	11633	11150
5	12076	11748	11680	11265
6	12512	12269	11955	11724
7	13376	13218	12495	12644
8	14295	14126	13132	13451
9	15377	15077	14115	14248
10	16058	15732	14805	14815
11	16249	16014	15113	15078
12	16177	16044	15249	15151
13	15911	15871	15200	15029
14	15584	15603	14950	14810
15	15331	15393	14715	14613
16	15322	15457	14819	14721
17	16246	16766	15992	15928
18	17636	18213	17625	17335
19	17527	18040	17702	17255
20	16995	17431	17273	16779
21	16443	16764	16671	16165
22	15703	15941	15607	15284
23	14652	14849	14259	14094
24	13563	13760	13061	12957
MAPE (%):**1.884**			MAPE (%):**1.925**	

TABLE 28
Hourly results of 14th Jan 2003 using EPSO

	14th Jan 2003	
Hour	**Actual Load (MW)**	**Forecasted Load (MW)**
1	12300	12682
2	11971	12191
3	11870	11984
4	11911	11960
5	12278	12263
6	13540	13265
7	16047	15183
8	17543	16537
9	17700	17087
10	17719	17372
11	17769	17493
12	17640	17408
13	17434	17182
14	17270	16999
15	17091	16825
16	17189	16930
17	18167	18259
18	19541	19724
19	19449	19555
20	18969	18972
21	18169	18231
22	16950	17168
23	15303	15719
24	13881	14320
MAPE (%):**1.810**		

The graphical representations of the forecasted load and actual load curves by using EPSO are shown in the Fig 42-48.

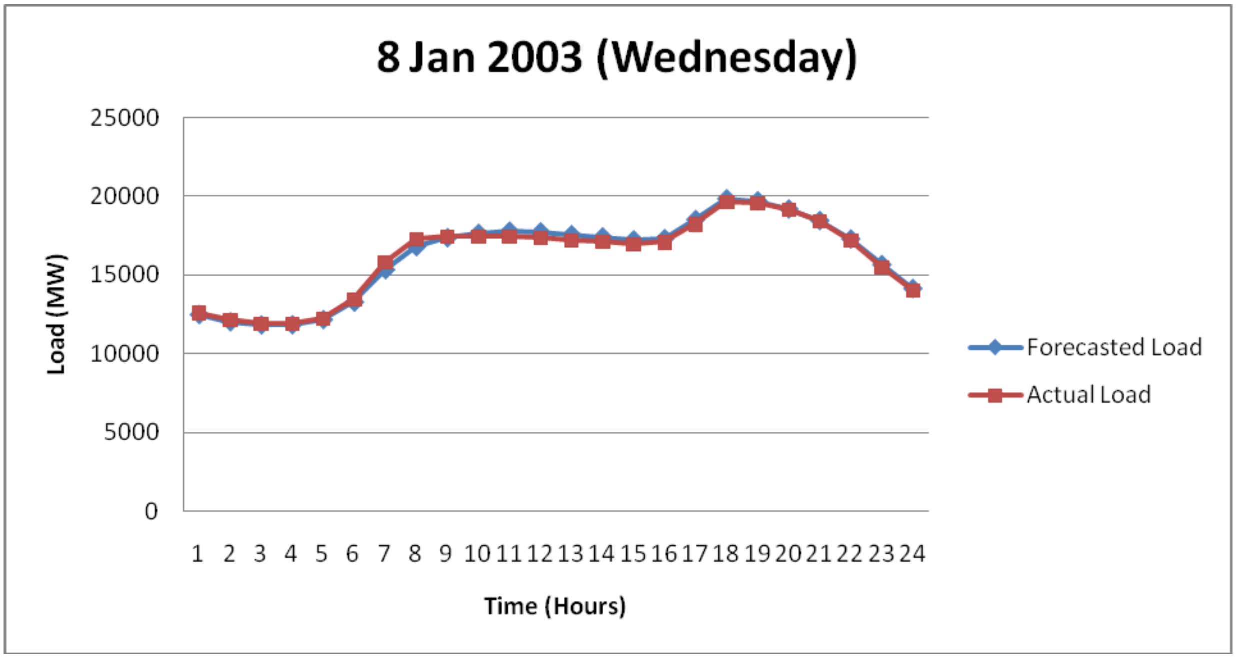

Fig. 42 Forecasted Load and Actual Load curves for 8th January 2003 (Wednesday)

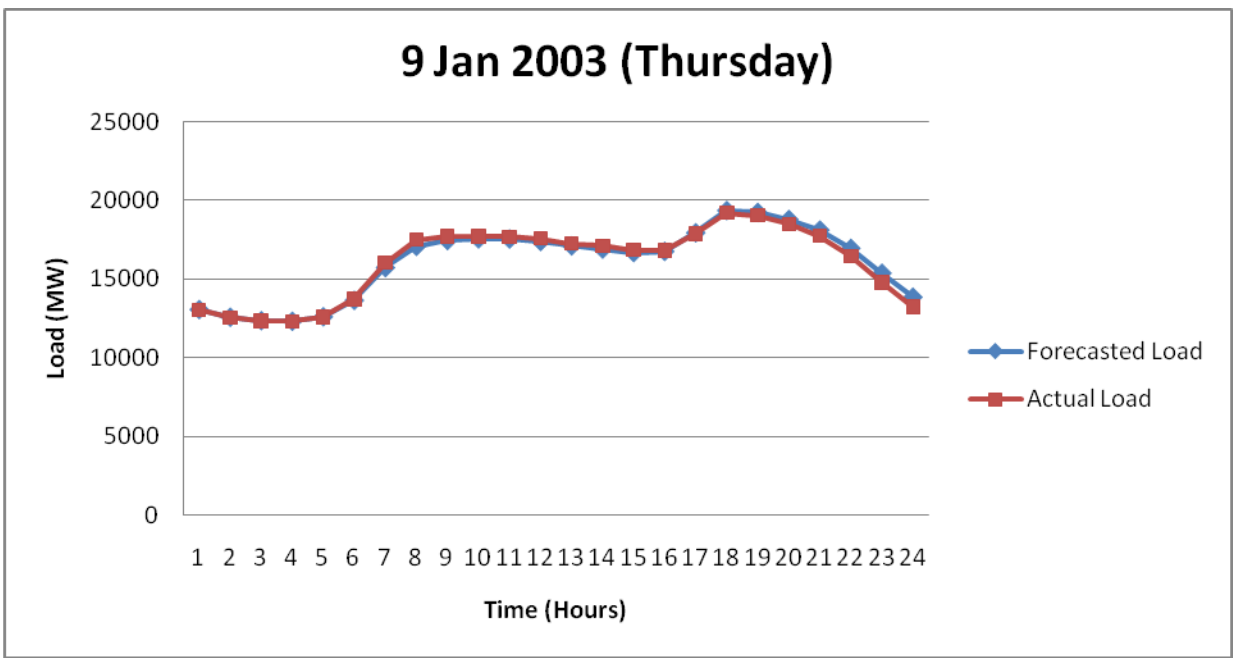

Fig. 43 Forecasted Load and Actual Load curves for 9th January 2003 (Thursday)

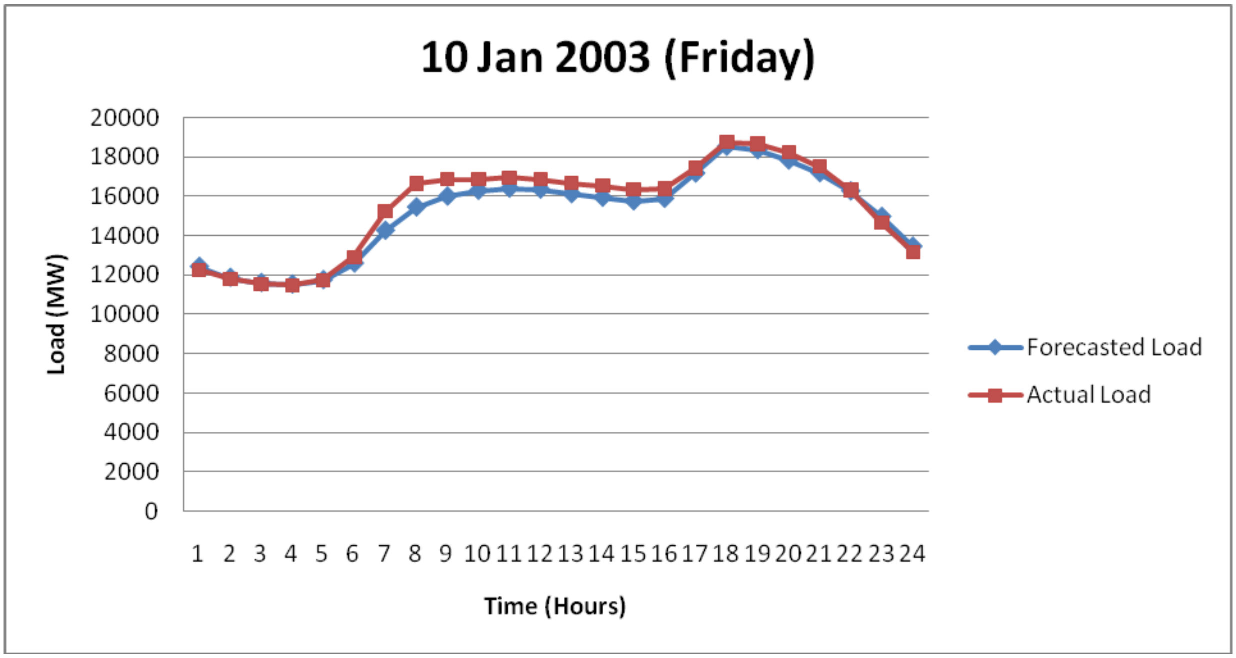

Fig. 44 Forecasted Load and Actual Load curves for 10th January 2003 (Friday)

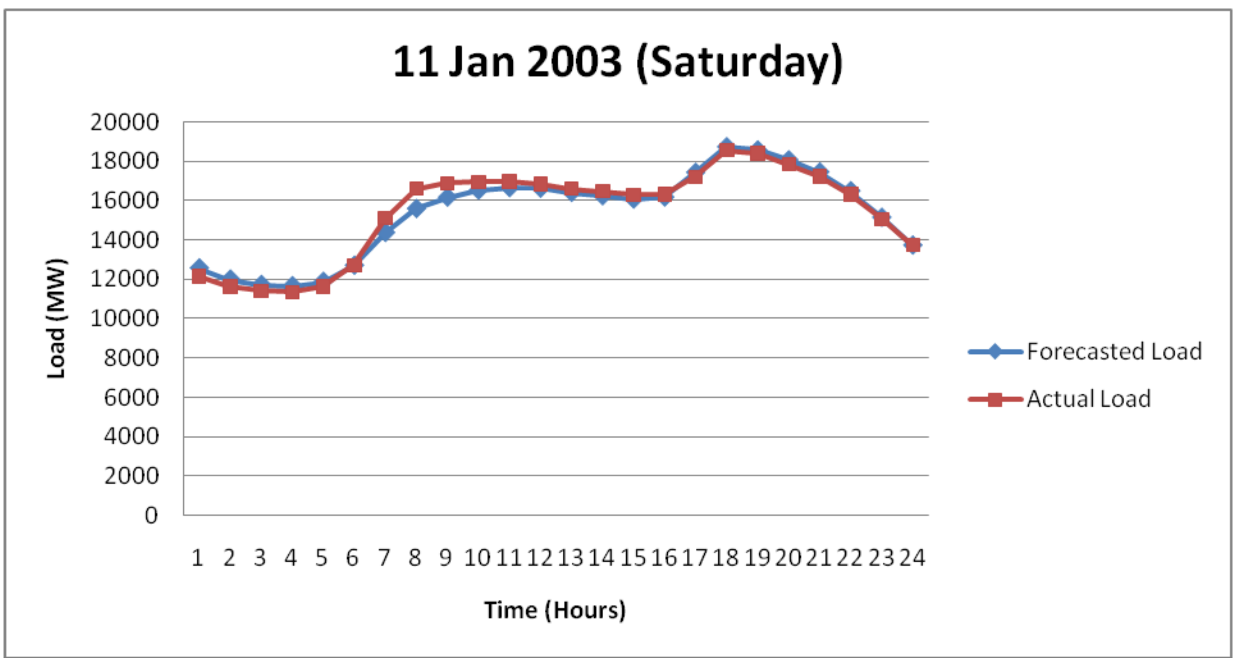

Fig. 45 Forecasted Load and Actual Load curves for 11th January 2003 (Saturday)

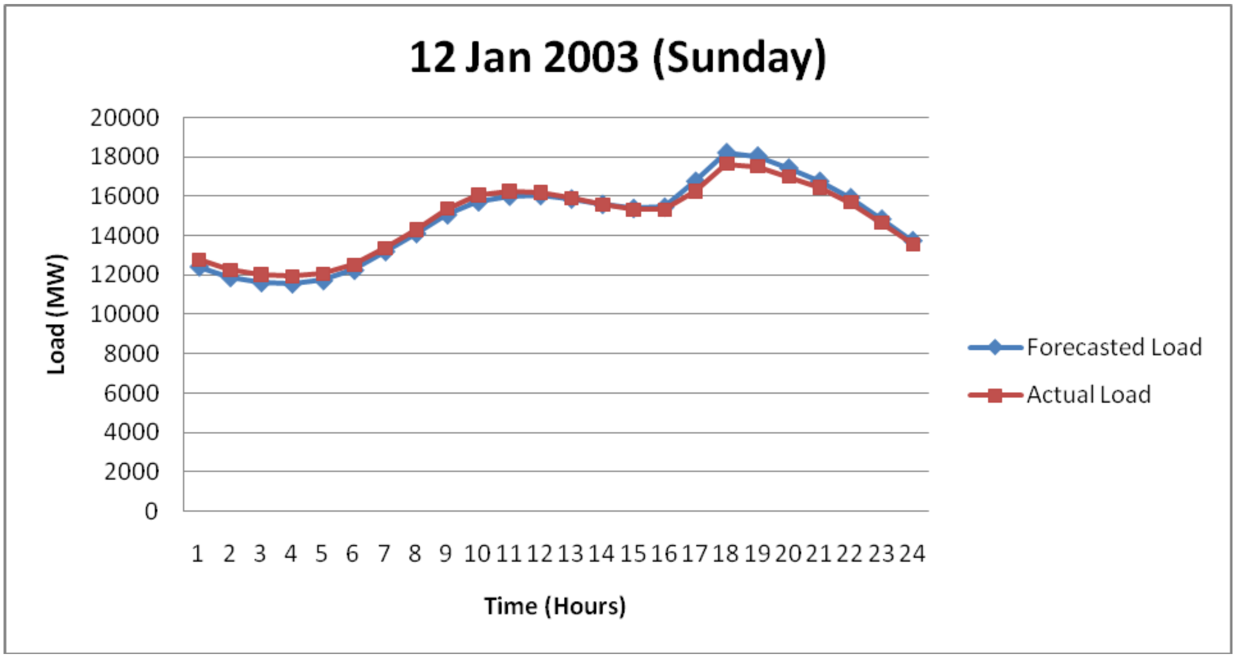

Fig. 46 Forecasted Load and Actual Load curves for 12th January 2003 (Sunday)

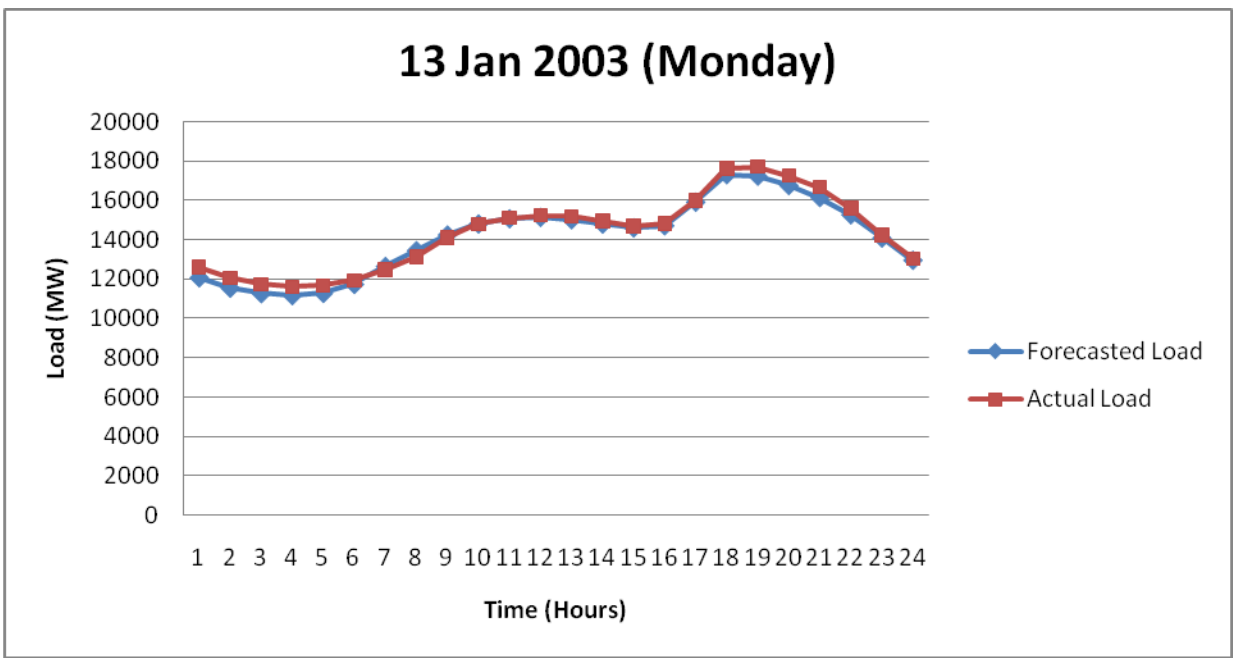

Fig. 47 Forecasted Load and Actual Load curves for 13th January 2003 (Monday)

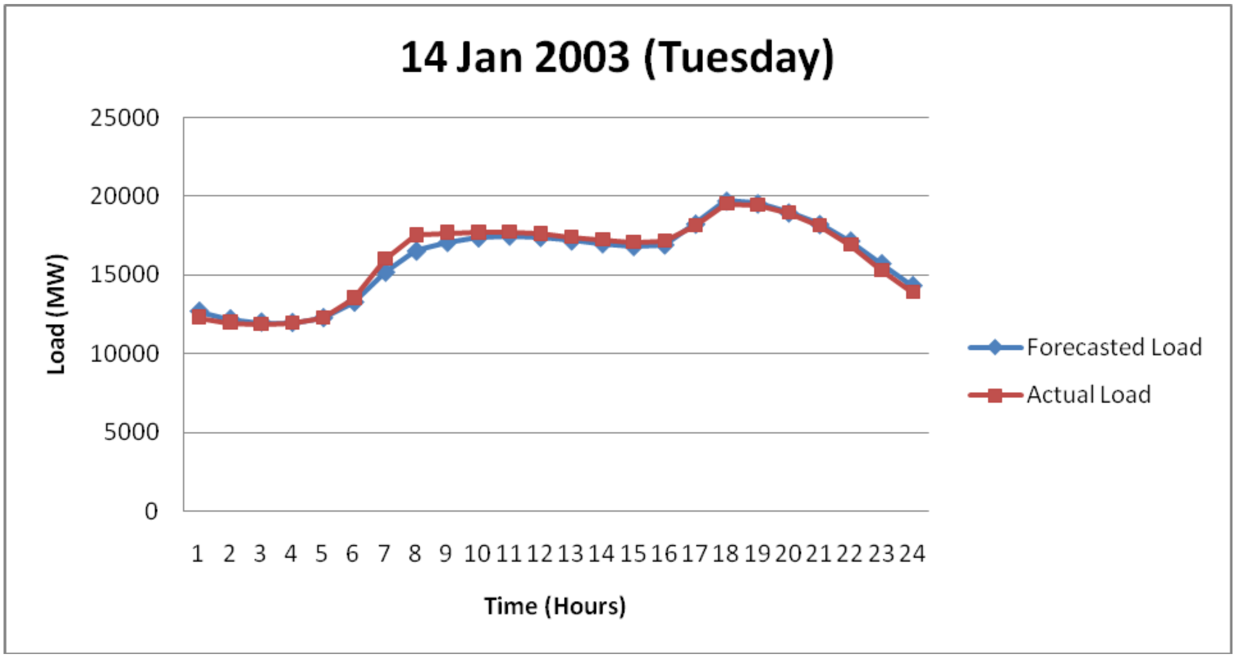

Fig. 48 Forecasted Load and Actual Load curves for 14th January 2003 (Tuesday)

The graphical representations of fuzzy membership parameters using evolutionary particle swarm optimization are shown in the Fig 49-51.

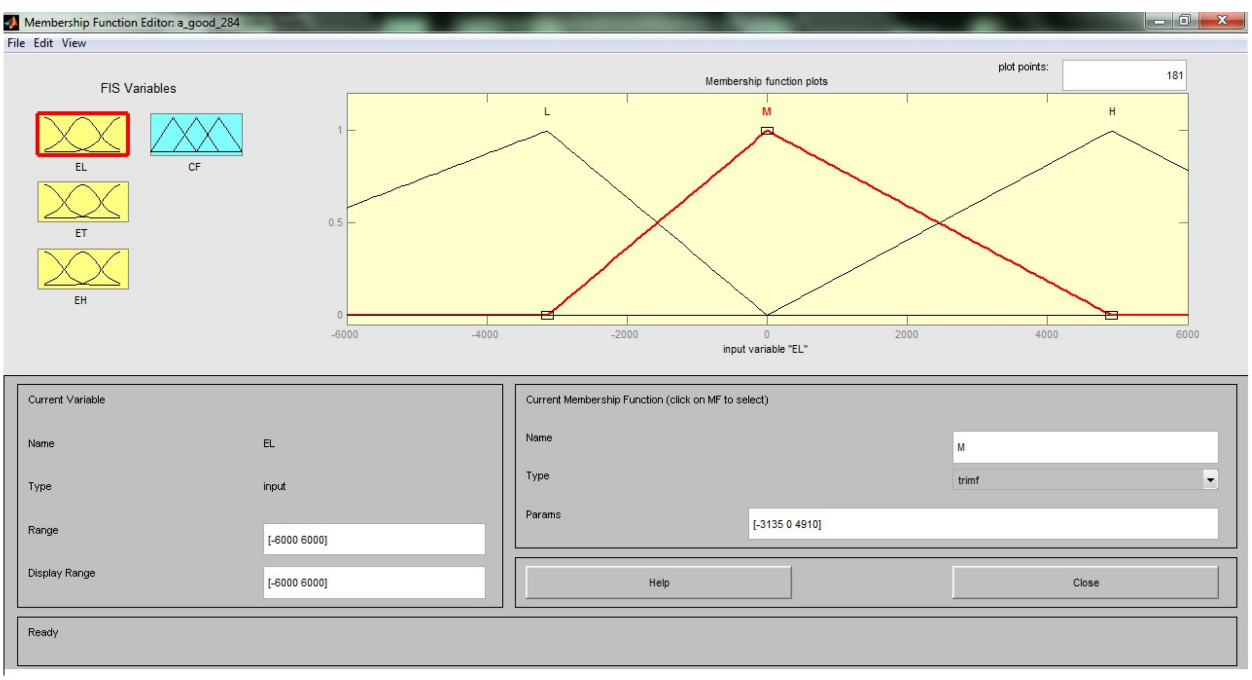

Fig. 49 Fuzzy membership parameters (a1, a2) using EPSO

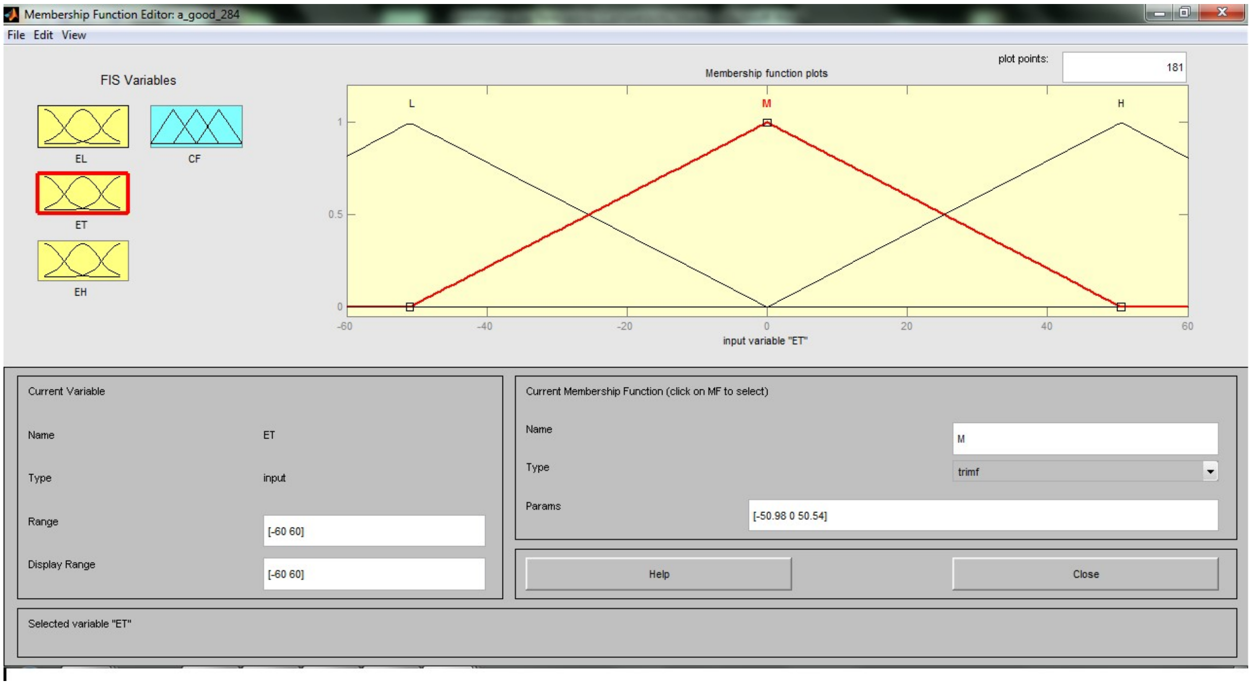

Fig. 50 Fuzzy membership parameters (a3, a4) using EPSO

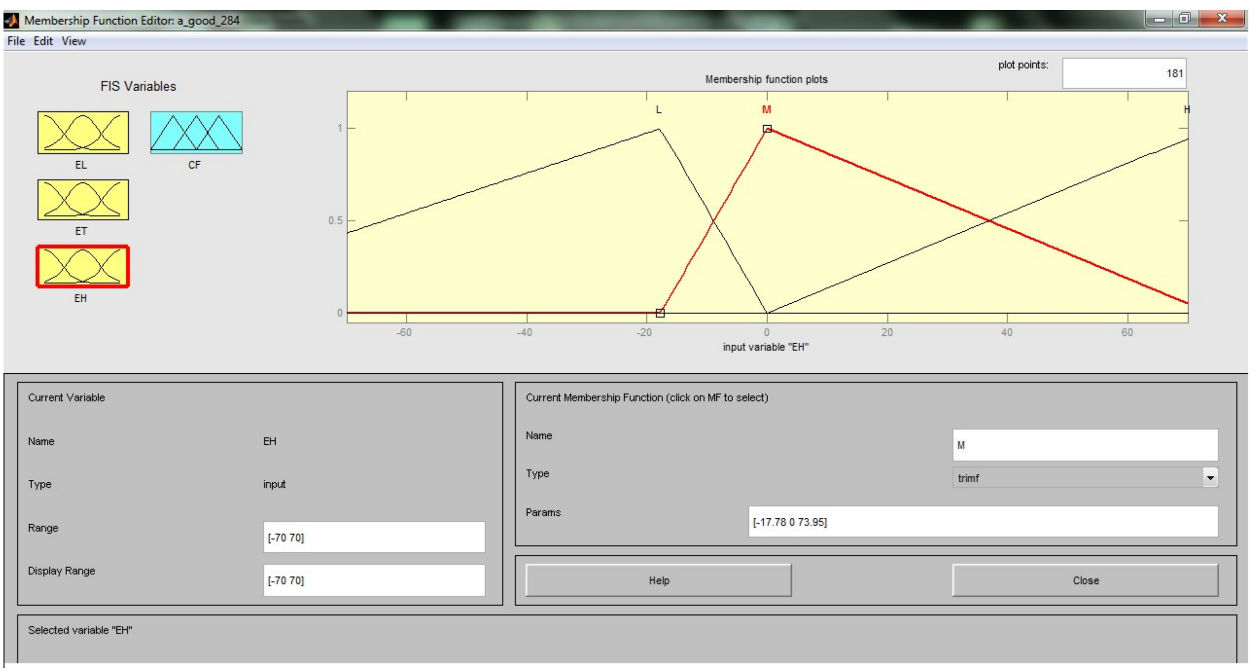

Fig. 51 Fuzzy membership parameters (a5, a6) using EPSO

TABLE 29

DAILY FORECAST RESULTS BY USING EPSO

Day	MAPE (%) Without optimization	MAPE (%) With EPSO
8th Jan 2003 (Wednesday)	3.083	1.227
9th Jan 2003 (Thursday)	4.049	1.297
10th Jan 2003 (Friday)	2.583	2.447
11th Jan 2003 (Saturday)	4.825	1.960
12th Jan 2003 (Sunday)	2.455	1.884
13th Jan 2003 (Monday)	3.390	1.925
14th Jan 2003 (Tuesday)	2.887	1.810

TABLE 30
MEMBERSHIP PARAMETER VALUES BY USING EPSO

Membership Parameters	Without Optimization	With EPSO
(a1,a2)	(-5000,5000)	(-3135,4910)
(a3,a4)	(-50,50)	(-50.98,50.54)
(a5,a6)	(-55,55)	(-17.78,73.95)

6.4 Impact of Error in Weather Parameters on STLF using EPSO

Variations in MAPE (%) of STLF using EPSO techniques with and without weather forecast errors are shown in the Table 31.

TABLE 31

COMPARATIVE MAPE (%) OF DAILY FORECAST RESULTS WITH AND WITHOUT WEATHER FORECAST ERROR USING EPSO

Day	EPSO		
	Without Weather Forecast Error	With Weather Forecast Error	
		T+1%, H+3%	T-1%, H-3%
8th Jan 2003 (Wednesday)	1.227	1.271	1.256
9th Jan 2003 (Thursday)	1.297	1.300	1.423
10th Jan 2003 (Friday)	2.447	2.633	2.511
11th Jan 2003 (Saturday)	1.960	1.954	1.966
12th Jan 2003 (Sunday)	1.884	2.188	2.730
13th Jan 2003 (Monday)	1.925	1.956	2.136
14th Jan 2003 (Tuesday)	1.810	2.089	1.806

Where, (T+1%) is Temperature with 1% noise (addition), (H+3%) is Humidity with 3% noise (addition), (T-1%) is Temperature with 1% noise (subtraction), (H-3%) is Humidity with 3% noise (subtraction) and percentage error in temperature applied on Kelvin scale.

6.5 Comparison of STLF results with different techniques

This section presents the comparison of STLF by the proposed techniques of Heuristic, PSO, NPSO and EPSO using the Mahalanobis distance norm for few different days of a month (Jan 2003). In the Table 32, MAPE of STLF results without optimization are compared with optimization by using the proposed techniques of Mahalanobis distance norm based similar days using heuristic approach, PSO, NPSO and EPSO. As can be seen from Table 32 and 34, MAPE of STLF by EPSO has been less than 3% for all representative seven days and these have been even less than 2% in most cases and MAPE is least for the each forecasted day in all four techniques and computation burden is also lesser than PSO and NPSO so it is a better candidate for STLF. The variation of fuzzy membership parameter limits of all proposed techniques with and without optimization are shown in the Table 33.

TABLE 32
COMPARATIVE MAPE (%) OF DAILY FORECAST RESULTS BY USING HEURISTIC, PSO, NPSO AND EPSO

Day	Without optimization	Heuristic	PSO	NPSO	EPSO
8th Jan 2003 (Wednesday)	3.083	2.155	1.299	1.259	1.227
9th Jan 2003 (Thursday)	4.049	4.023	1.360	1.330	1.297
10th Jan 2003 (Friday)	2.583	2.577	2.505	2.467	2.447
11th Jan 2003 (Saturday)	4.825	3.231	2.275	2.004	1.960
12th Jan 2003 (Sunday)	2.455	1.972	1.959	1.905	1.884
13th Jan 2003 (Monday)	3.390	1.960	2.414	2.392	1.925
14th Jan 2003 (Tuesday)	2.887	2.420	1.856	1.844	1.810

TABLE 33
COMPARATIVE MEMBERSHIP PARAMETER VALUES BY USING HEURISTIC, PSO, NPSO AND EPSO

Membership Parameters	Without Optimization	Heuristic	PSO	NPSO	EPSO
(a1,a2)	(-5000,5000)	(-2500,1500)	(-6226,4081)	(-1915,2688)	(-3135,4910)
(a3,a4)	(-50,50)	(-25,25)	(-39.91,47.25)	(-66.61,45.74)	(-50.98,50.54)
(a5,a6)	(-55,55)	(-25,25)	(-14.55,65.49)	(-35.65,103.6)	(-17.78,73.95)

MATLAB programming tool is used for the simulation of STLF results with various techniques presented in this thesis. The simulation has been done on the Intel processor of 2.53 GHz Windows 7 NT 32 Bit operating system. The computational burden associated with the simulation efforts for STLF using different optimization techniques is given in Table 34

TABLE 34

Computational burden associated with HA, PSO, NPSO and EPSO.

Description	HA	PSO	NPSO	EPSO
No of Parameters used	6	6	6	6
No of Particles used	Not Applicable	49	49	49
Parameter's updated	Step by step increment/ decrement	As per PSO technique	As per NPSO technique	As per EPSO technique
No of Iterations done for optimum solution	Less	Very large	Very large	large
Time consumed for optimum solution	Few minutes	Few hours	Few hours	Less than PSO & NPSO

6.6 Summary and Observations

Results for evolutionary particle swarm optimization based fuzzy inference system for STLF are presented for different days and these include weekdays and weekends also. MAPE results are compared with and without optimization techniques. EPSO based forecasting shows the better results and MAPE has been less than 3% for all the seven representative days. The graphical representations of forecasted and actual load curves show that EPSO based forecasted load curve followed a similar pattern to the actual load curve.

Proposed optimization techniques based fuzzy inference system with Mahalanobis distance norm for STLF results are presented and compared for different days that included weekdays and weekends. EPSO based forecasting shows better results for all different days when compared with the results by other optimization techniques as well as without optimization. Assessment of impact of error possibilities of weather parameters on STLF have been done and result in Table 31 showed that the proposed EPSO technique based fuzzy inference system with Mahalanobis distance norm for similar day based STLF is quite robust and the error in input weather parameters does not impact much the quality of STLF results.

A comparison of computation burden of optimization by four different techniques has been given in table 34. Though the time taken in HA technique is less but optimization of FIS is done only one time before the STLF for the days of the month and it will not affect the forecasting time duration once the FIS is tuned. As can be seen from Table 29, MAPE of STLF by EPSO has been less than 3% for all representative seven days and these have been even less than 2% in most cases and MAPE is least for the each forecasted day in all four techniques and computation burden is also lesser than PSO and NPSO so it is a better candidate for STLF.

Chapter 7

Anomalous Day Load Forecasting

7.1 Introduction

It is a challenge to forecast the load of anomalous days like holidays, religious days and special days as the load profile of anomalous days is different when compared to normal days. Anomalous day load depends upon the type of the day, geographical conditions, special events, religious occasions and socio-economic conditions of the area. Hence, load forecasting for anomalous days is a challenging task. Also, only a small number of historical data profiles will be available when compared to the availability of normal day's load profiles.

The load profile is dissimilar for different types of anomalous days. Also, for a given anomalous day, the load profile may vary from one year to next, based on the occurrence of the day of the week and time of the year. Hence, anomalous days forecasting is an important field to do research.

A new approach for forecasting the anomalous day's load is presented in this thesis work. Four different case studies using four different methodologies for the anomalous days load prediction are presented in the following sections. In this chapter, real-time load data of ISO New England is considered the anomalous days dates of the year 2000 to the year 2002 are given in the Tables 35-37 for the representative anomalous days of the year 2003 that are considered as testing data as shown in the Table 38. One can see that there are shifts in the dates of few anomalous days that brings further complexity in the forecasting of the loads for anomalous days.

TABLE 35
Dates of Anomalous Days of the Year 2000

S.No	Date (DD-MM-YYYY)	Name of Anomalous Day
1	01-01-2000	New Year’s Day
2	21-02-2000	President’s Day
3	17-04-2000	Tax Day
4	29-05-2000	Memorial Day
5	18-06-2000	Father’s Day
6	04-09-2000	Labor Day
7	23-11-2000	Thanksgiving Day
8	25-12-2000	Christmas Day

TABLE 36
Dates of Anomalous Days of the Year 2001

S.No	Date (DD-MM-YYYY)	Name of Anomalous Day
1	01-01-2001	New Year’s Day
2	29-02-2001	President’s Day
3	16-04-2001	Tax Day
4	28-05-2001	Memorial Day
5	17-06-2001	Father’s Day
6	03-09-2001	Labor day
7	22-11-2001	Thanksgiving Day
8	25-12-2001	Christmas Day

TABLE 37
Dates of Anomalous Days of the Year 2002

S.No	Date (DD-MM-YYYY)	Name of Anomalous Day
1	01-01-2002	New Year's Day
2	18-02-2002	President's Day
3	15-04-2002	Tax Day
4	27-05-2002	Memorial Day
5	16-06-2002	Father's Day
6	02-09-2002	Labor day
7	28-11-2002	Thanksgiving Day
8	25-12-2002	Christmas Day

TABLE 38
Dates of Anomalous Days of the Year 2003

S.No	Date (DD-MM-YYYY)	Name of Anomalous Day
1	01-01-2003	New Year's Day
2	17-02-2003	President's Day
3	15-04-2003	Tax Day
4	26-05-2003	Memorial Day
5	15-06-2003	Father's Day
6	01-09-2003	Labor day
7	27-11-2003	Thanksgiving Day
8	25-12-2003	Christmas Day

7.2 Case Study I: Forecasting using Previous Anomalous Days

7.2.1 Implementation

In this case study, anomalous days of the years 2000 to 2002 is considered as the training data and anomalous days of the year 2003 is considered as the testing data.

Five similar days are found from previous data based on 24 hours of Temperature, 24 hours of Humidity and Day type of a given testing anomalous day. Mahalanobis distance norm is applied for the selection of similar days. For example, similar days of testing anomalous day 01-01-2003 (**New Year's Day)** are found from the input data of anomalous days of the years 2000 to 2002.

Similarly, five similar days are found from previous data based on 24 hours of Load, 24 hours of Temperature, 24 hours of Humidity and Day type of a given previous anomalous day of testing anomalous day. (e.g, the previous anomalous day is **31-12-2002, New Year's Eve** for the testing anomalous day of **01-01-2003: New Year's Day**).

Next, calculate the correction factors with the difference of Load, Temperature, and Humidity for five similar days of the previous anomalous day of the testing anomalous day.

Fuzzify the values of correction factors by sending it to FIS developed in the chapter 6 and get the de-fuzzify values. These are fuzzy correction factors which are applied on forecasted similar days. Take the average of forecasted similar days of testing anomalous day to get the forecasted load value. Similarly, calculate for all the anomalous days of the year 2003

7.2.2 Results

In this section, the MAPE for hourly actual load and forecasted load results of considered anomalous days are provided in the Tables 39-42.

TABLE 39
Hourly results of New Year's Day and President's Day using Case Study I

	New Year's Day		**President's Day**	
Hour	**Actual Load (MW)**	**Forecasted Load (MW)**	**Actual Load (MW)**	**Forecasted Load (MW)**
1	11860	11269	11860	11269
2	11129	10712	11129	10712
3	10587	10385	10587	10385
4	10312	10257	10312	10257
5	10264	10387	10264	10387
6	10503	11037	10503	11037
7	10968	12378	10968	12378
8	11264	13514	11264	13514
9	11926	14284	11926	14284
10	12796	14797	12796	14797
11	13511	15104	13511	15104
12	13994	15159	13994	15159
13	14162	14989	14162	14989
14	14133	14773	14133	14773
15	14108	14511	14108	14511
16	14413	14415	14413	14415
17	15826	14883	15826	14883
18	16790	15567	16790	15567
19	16700	15894	16700	15894
20	16375	15836	16375	15836
21	15749	15469	15749	15469
22	14752	14580	14752	14580
23	13411	13191	13411	13191
24	12211	11879	12211	11879
MAPE (%):**6.154**			MAPE (%):**7.934**	

TABLE 40
Hourly results of Tax Day and Memorial Day using Case Study I

	Tax Day		Memorial Day	
Hour	**Actual Load (MW)**	**Forecasted Load (MW)**	**Actual Load (MW)**	**Forecasted Load (MW)**
1	11034	11968	9852	10647
2	10521	11479	9331	10197
3	10270	11217	9067	9980
4	10188	11148	8934	9915
5	10436	11299	8973	10053
6	11500	11820	9168	10582
7	13378	12736	9636	11456
8	14880	13700	10502	12504
9	15342	14638	11690	13427
10	15539	15327	12850	13957
11	15703	15680	13608	14113
12	15777	15752	14044	14042
13	15676	15519	14118	13757
14	15673	15155	13909	13314
15	15555	14824	13701	12933
16	15428	14757	13682	12848
17	15366	15475	13946	13351
18	15151	16483	14330	14016
19	15040	16562	14340	14443
20	15563	16337	14360	14499
21	15939	15992	14410	14278
22	14911	15161	13593	13498
23	13213	13800	12144	12334
24	11685	12555	10829	11224
MAPE (%):**4.927**			MAPE (%):**6.854**	

TABLE 41
Hourly results of Father's Day and Labor Day using Case Study I

	Father's Day		**Labor Day**	
Hour	**Actual Load (MW)**	**Forecasted Load (MW)**	**Actual Load (MW)**	**Forecasted Load (MW)**
1	10952	10898	10554	11190
2	10230	10391	10052	10639
3	9818	10120	9778	10348
4	9580	10024	9648	10250
5	9483	10126	9679	10377
6	9343	10596	9969	10887
7	9829	11362	10384	11903
8	10787	12372	11114	13052
9	12069	13455	12286	14082
10	13112	14170	13437	14795
11	13747	14451	14150	15165
12	14058	14418	14450	15261
13	14092	14154	14460	15089
14	13947	13754	14241	14822
15	13830	13443	14071	14582
16	13783	13417	14016	14557
17	13867	14142	14227	15178
18	13984	14967	14599	15673
19	13952	15203	14819	15386
20	13944	15025	15338	15147
21	14423	14576	15204	15181
22	14460	13828	14109	14575
23	13040	12777	12662	13525
24	11561	11722	11446	12387
MAPE (%):**5.389**			MAPE (%):**6.811**	

TABLE 42
Hourly results of Thanksgiving Day and Christmas Day using Case Study I

	Thanksgiving Day		**Christmas Day**	
Hour	**Actual Load (MW)**	**Forecasted Load (MW)**	**Actual Load (MW)**	**Forecasted Load (MW)**
1	11372	11591	11177	11038
2	10730	10957	10375	10557
3	10393	10596	9922	10303
4	10236	10423	9731	10191
5	10325	10483	9746	10313
6	10741	10906	10056	10893
7	11497	11826	10687	11984
8	12474	12985	11601	13181
9	13630	13987	12634	14123
10	14373	14651	13442	14666
11	14637	14968	13848	14894
12	14520	14991	14006	14868
13	13941	14808	13925	14606
14	13032	14479	13561	14223
15	12285	14184	13168	13867
16	12134	14084	13052	13736
17	12860	14529	13883	14154
18	13358	14972	14652	14789
19	13373	15007	14739	14821
20	13300	14880	14723	14747
21	13153	14813	14648	14630
22	12694	14263	14213	13816
23	11811	13137	13313	12645
24	10895	11905	12176	11514
MAPE (%):**7.141**			MAPE (%):**5.139**	

The graphical representations of the forecasted load and actual load curves for the anomalous days are shown in the Fig 52-59.

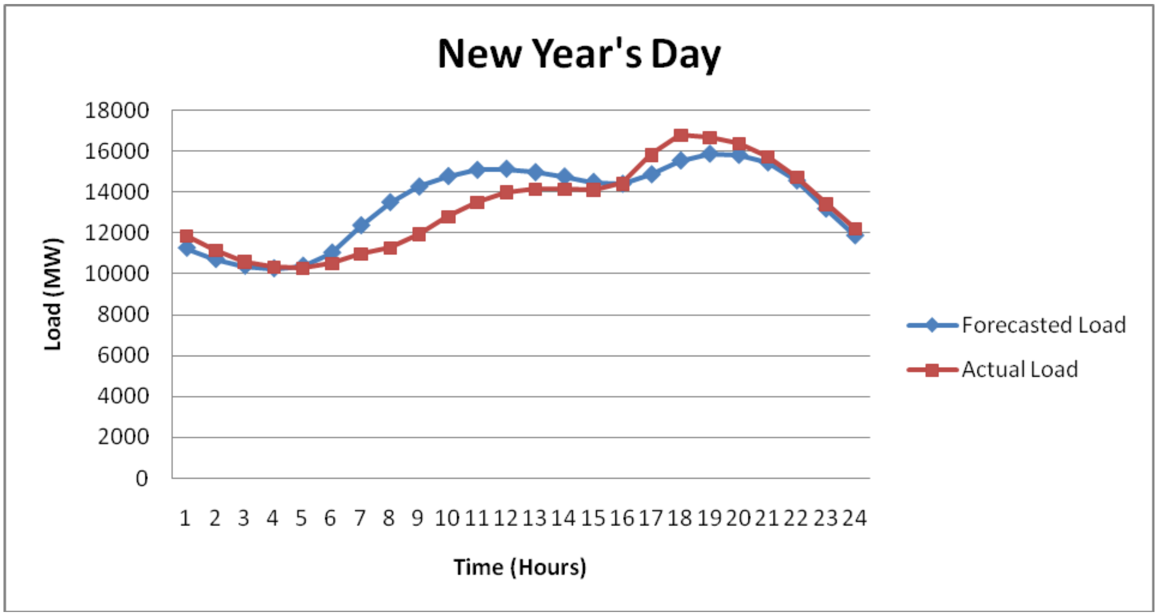

Fig. 52 Forecasted Load and Actual Load curves for New Year’s Day

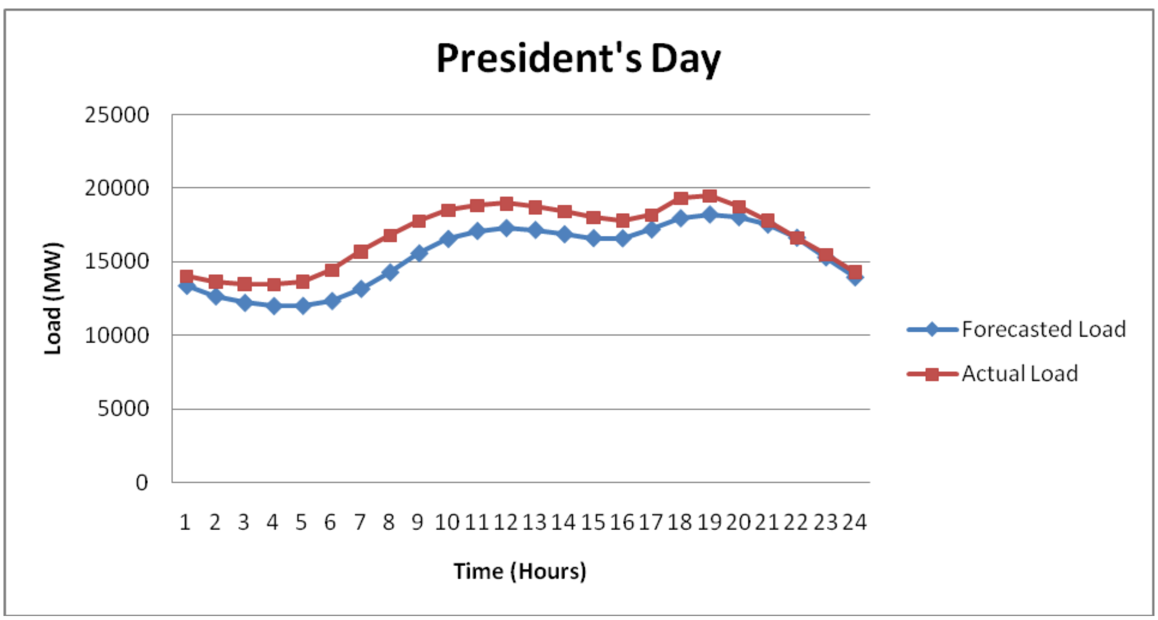

Fig. 53 Forecasted Load and Actual Load curves for President’s Day

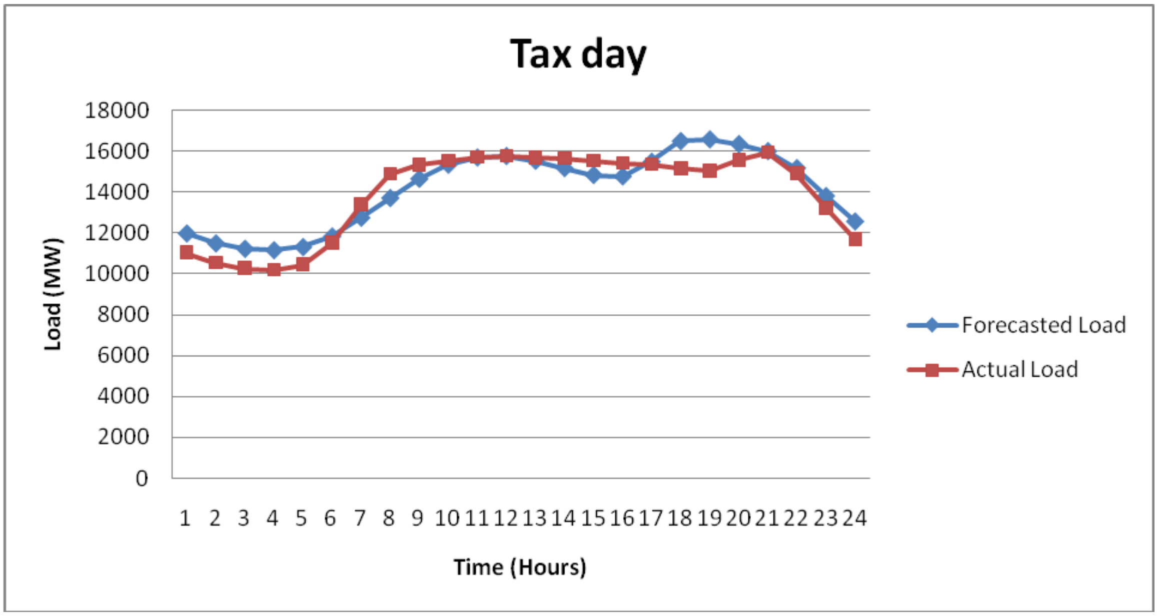

Fig. 54 Forecasted Load and Actual Load curves for Tax Day

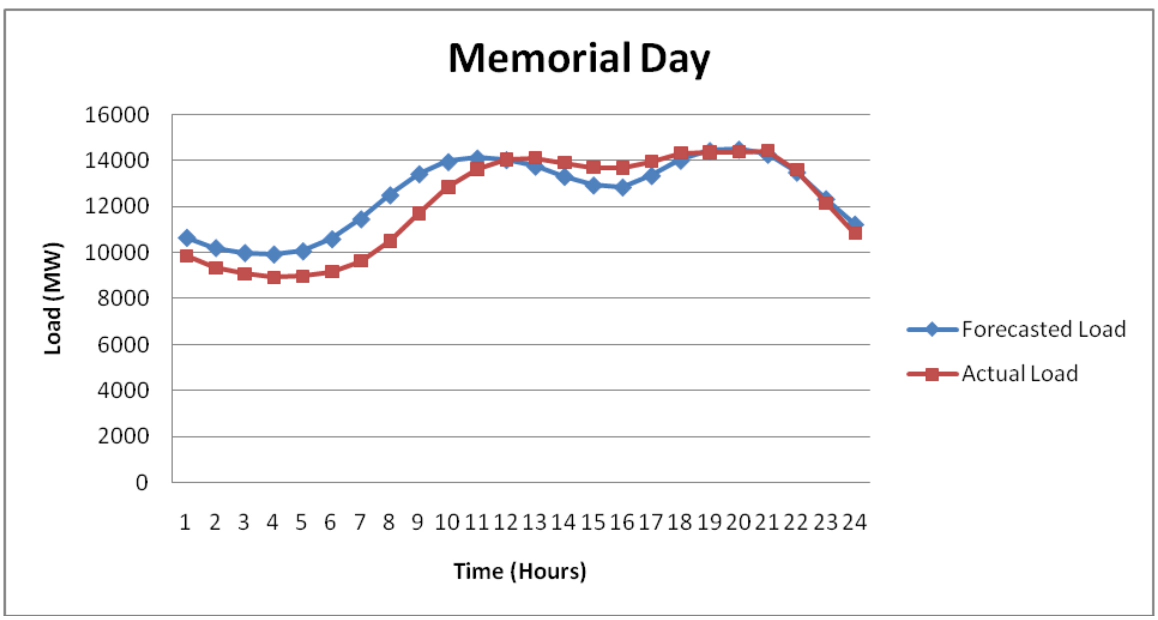

Fig. 55 Forecasted Load and Actual Load curves for Memorial Day

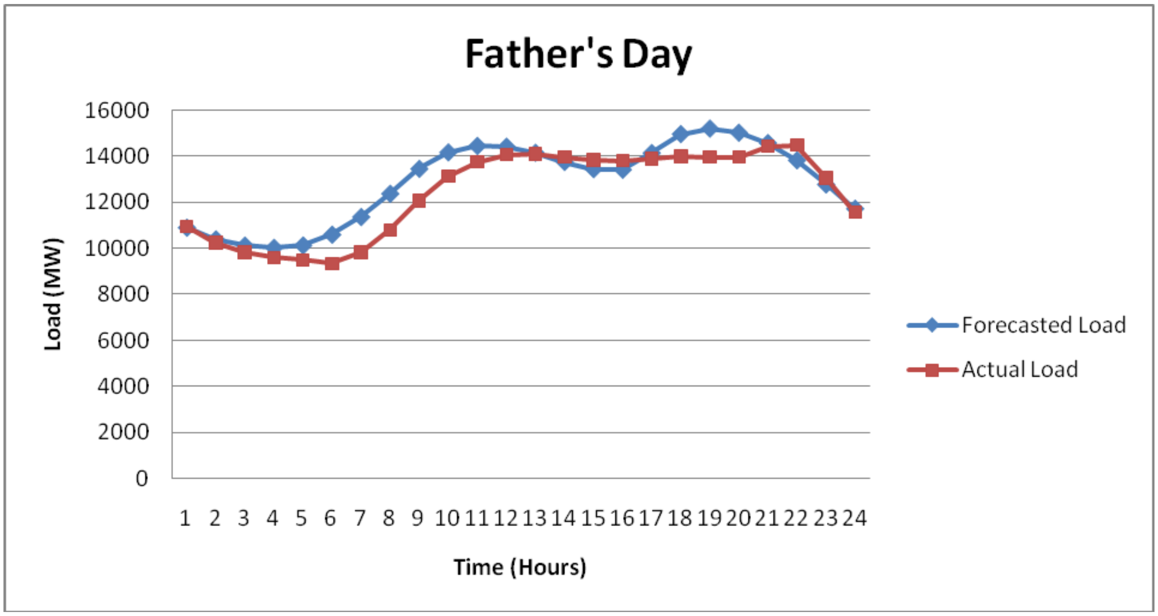

Fig. 56 Forecasted Load and Actual Load curves for Father's Day

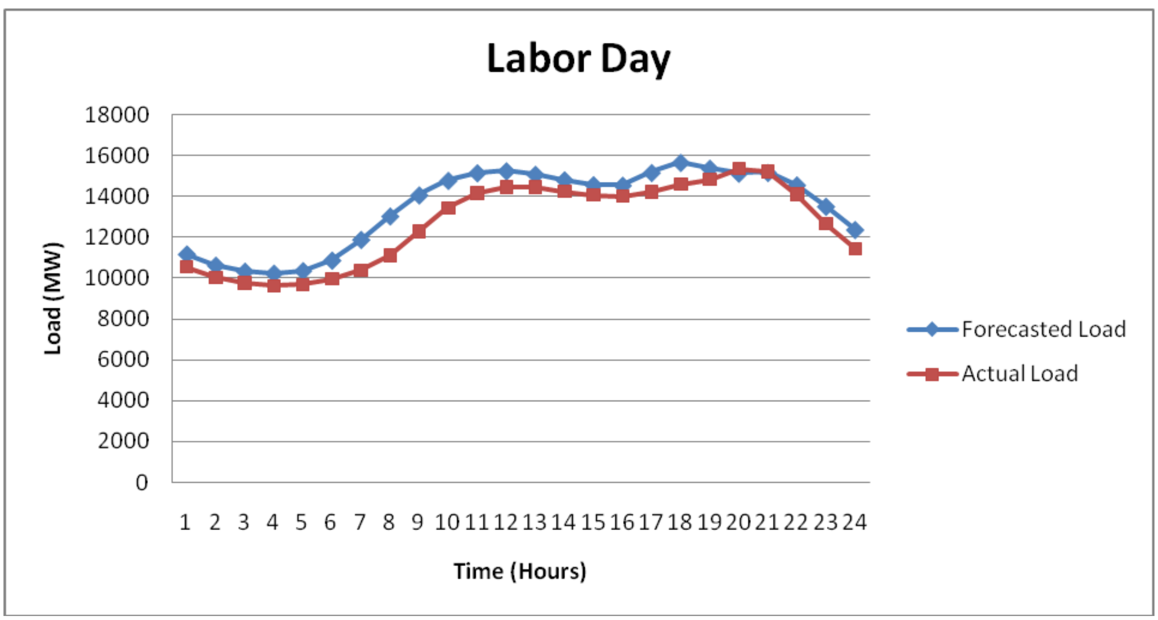

Fig. 57 Forecasted Load and Actual Load curves for Labor Day

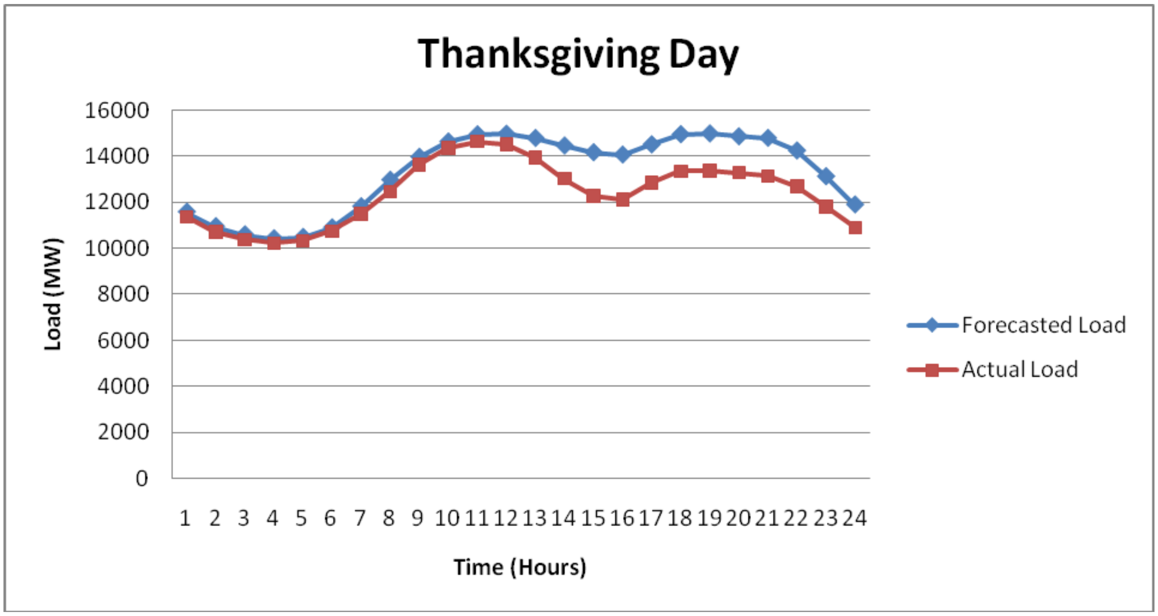

Fig. 58 Forecasted Load and Actual Load curves for Thanks giving Day

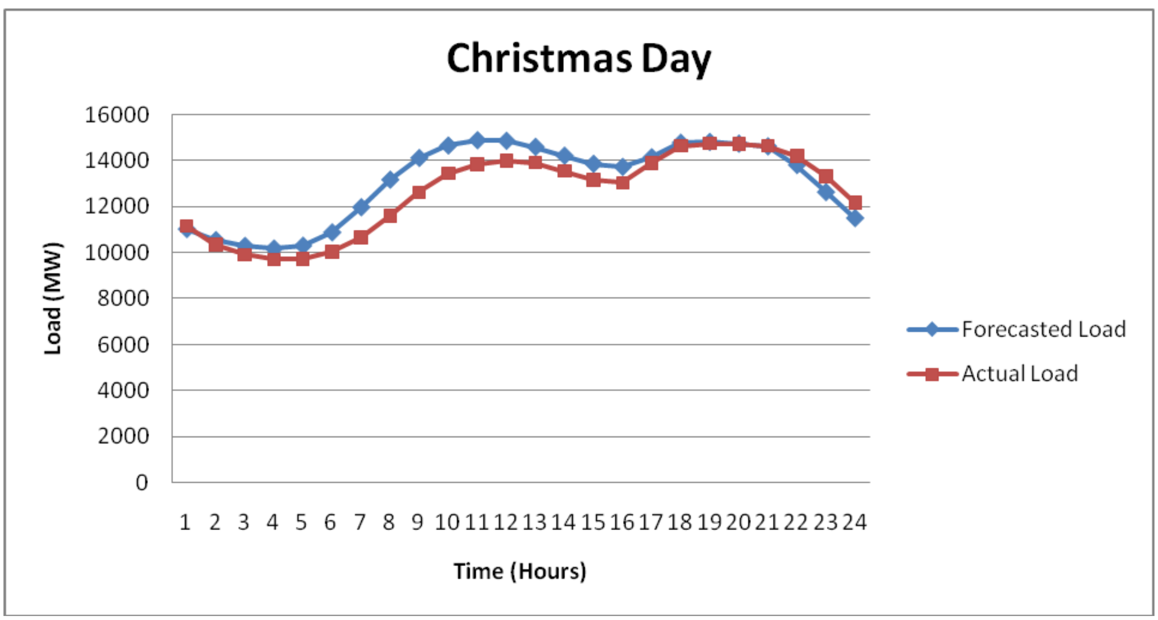

Fig. 59 Forecasted Load and Actual Load curves for Christmas Day

Summary of anomalous days MAPE results are shown in the Table 43.

TABLE 43
Summary of Anomalous Days results using Case Study I

S.No	Name of Anomalous Day	Date	MAPE (%)
1	New Year Day	01-01-2003	6.154
2	President's Day	17-02-2003	7.934
3	Tax Day	15-04-2003	4.927
4	Memorial Day	26-05-2003	6.854
5	Father's Day	15-06-2003	5.389
6	Labor Day	01-09-2003	6.811
7	Thanksgiving Day	27-11-2003	7.141
8	Christmas Day	25-12-2003	5.139

7.3 Case Study II: Forecasting using Previous Anomalous Days and Immediately Previous Weekends before Testing Anomalous Day

7.3.1 Implementation

It is observed that in Case Study 1, the MAPE is high, so further improvement of anomalous day load forecasting is required. An attempt for the same has been in this case study.

In this case, input data is anomalous days of the years 2000 to 2002 and immediately previous weekends before testing anomalous day are also considered and testing data is anomalous days of the year 2003. Load forecasting is done similar to Case Study I as explained in section 7.2.1, where the difference is that while calculating the similar days, data is also taken for the immediately previous weekends before testing anomalous days in addition to the dates of Case Study 1.

For example, five similar days are found from previous data based on 24 hours of Temperature, 24 hours of Humidity and Day type of a testing anomalous day (e.g **15-04-2003: Tax Day**). Here previous data means anomalous day's data of the years 2000 to 2002 and previous anomalous days of the year 2003 before the testing anomalous day and immediately previous weekends before the testing anomalous days.

Similarly, five similar days are found from previous data based on 24 hours of Load, 24 hours of Temperature, 24 hours of Humidity and Day type of a given previous anomalous day of testing anomalous day.

Next, calculate the correction factors with the difference of Load, Temperature, and Humidity for five similar days of the previous anomalous day of the testing anomalous day. Fuzzify the values of correction factors by sending it to FIS developed in the previous chapter 6 and get the de-fuzzify values which are fuzzy correction factors that are applied on forecasted similar days. Take the average of forecasted similar days of testing anomalous day (**15-04-2003: Tax Day**) to get the forecasted load value. Similarly, calculate for all the anomalous days of the year 2003.

7.3.2 Results

In this section, MAPE for hourly actual load and forecasted load results of the anomalous days are shown in the Tables 44-47.

TABLE 44
Hourly results of New Year's Day and President's Day using Case Study II

	New Year's Day		President's Day	
Hour	**Actual Load (MW)**	**Forecasted Load (MW)**	**Actual Load (MW)**	**Forecasted Load (MW)**
1	11860	11350	14007	13468
2	11129	10825	13633	12769
3	10587	10562	13465	12386
4	10312	10482	13442	12217
5	10264	10639	13644	12308
6	10503	11235	14398	12847
7	10968	11863	15686	13963
8	11264	13175	16762	15315
9	11926	12445	17786	16608
10	12796	15221	18500	17528
11	13511	15610	18857	18065
12	13994	15653	18956	18279
13	14162	15451	18723	18235
14	14133	15152	18404	18080
15	14108	14835	18039	17911
16	14413	14686	17797	17901
17	15826	15128	18186	18491
18	16790	15884	19348	18877
19	16700	16419	19474	18738
20	16375	16361	18745	18331
21	15749	15843	17795	17971
22	14752	14847	16625	17267
23	13411	13532	15487	16098
24	12211	12339	14291	14775
MAPE (%):**5.562**			MAPE (%):**4.795**	

TABLE 45
Hourly results of Tax Day and Memorial Day using Case Study II

	Tax Day		Memorial Day	
Hour	**Actual Load (MW)**	**Forecasted Load (MW)**	**Actual Load (MW)**	**Forecasted Load (MW)**
1	11034	11618	9852	10298
2	10521	11136	9331	9776
3	10270	10910	9067	9497
4	10188	10834	8934	9372
5	10436	10982	8973	9407
6	11500	11587	9168	9633
7	13378	12817	9636	10155
8	14880	14090	10502	11112
9	15342	15027	11690	12161
10	15539	15625	12850	12822
11	15703	15946	13608	13068
12	15777	16026	14044	13085
13	15676	15861	14118	12885
14	15673	15646	13909	12575
15	15555	15415	13701	12306
16	15428	15367	13682	12258
17	15366	15681	13946	12536
18	15151	16479	14330	12845
19	15040	17051	14340	12895
20	15563	16796	14360	13095
21	15939	16331	14410	13599
22	14911	15511	13593	13041
23	13213	14204	12144	11916
24	11685	12904	10829	10761
MAPE (%):**4.338**			MAPE (%):**6.065**	

TABLE 46
Hourly results of Father’s Day and Labor Day using Case Study II

	Father’s Day		**Labor Day**	
Hour	**Actual Load (MW)**	**Forecasted Load (MW)**	**Actual Load (MW)**	**Forecasted Load (MW)**
1	10952	10499	10554	10915
2	10230	9975	10052	10424
3	9818	9677	9778	10194
4	9580	9583	9648	10159
5	9483	9714	9679	10390
6	9343	10222	9969	11194
7	9829	11205	10384	12631
8	10787	12129	11114	13727
9	12069	12913	12286	14384
10	13112	13459	13437	14806
11	13747	13767	14150	15031
12	14058	13846	14450	15071
13	14092	13680	14460	14920
14	13947	13379	14241	14695
15	13830	13083	14071	14459
16	13783	13044	14016	14400
17	13867	13715	14227	14979
18	13984	14749	14599	15793
19	13952	15038	14819	15757
20	13944	14782	15338	15439
21	14423	14444	15204	15072
22	14460	13701	14109	14258
23	13040	12409	12662	12995
24	11561	11155	11446	11698
MAPE (%):**4.564**			MAPE (%):**6.597**	

TABLE 47
Hourly results of Thanks giving Day and Christmas Day using Case Study II

	Thanksgiving Day		Christmas Day	
Hour	**Actual Load (MW)**	**Forecasted Load (MW)**	**Actual Load (MW)**	**Forecasted Load (MW)**
1	11372	11271	11177	10924
2	10730	10651	10375	10445
3	10393	10284	9922	10191
4	10236	10091	9731	10078
5	10325	10085	9746	10197
6	10741	10204	10056	10766
7	11497	10633	10687	11834
8	12474	11356	11601	13016
9	13630	12396	12634	13956
10	14373	13261	13442	14499
11	14637	13777	13848	14725
12	14520	14023	14006	14697
13	13941	13996	13925	14433
14	13032	13762	13561	14046
15	12285	13544	13168	13688
16	12134	13506	13052	13557
17	12860	13955	13883	13973
18	13358	14634	14652	14596
19	13373	14615	14739	14625
20	13300	14540	14723	14559
21	13153	14568	14648	14452
22	12694	13932	14213	13652
23	11811	12685	13313	12499
24	10895	11443	12176	11382
MAPE (%):**6.298**			MAPE (%):**4.555**	

The graphical representation of the forecasted load and actual load curves are shown in the Fig 60-67.

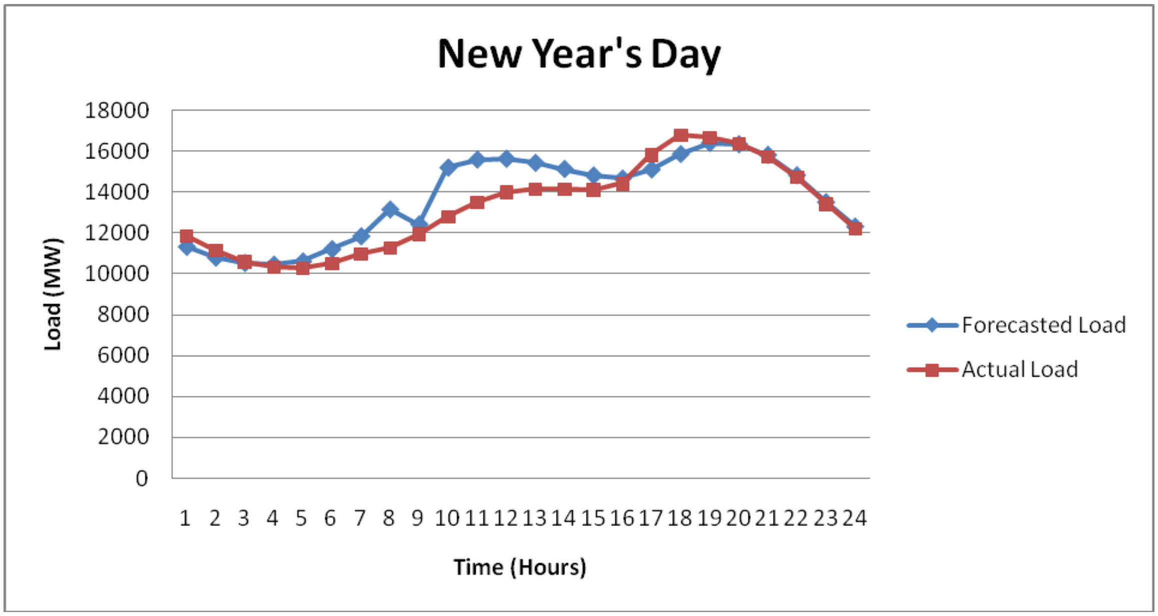

Fig. 60 Forecasted Load and Actual Load curves for New Year's Day

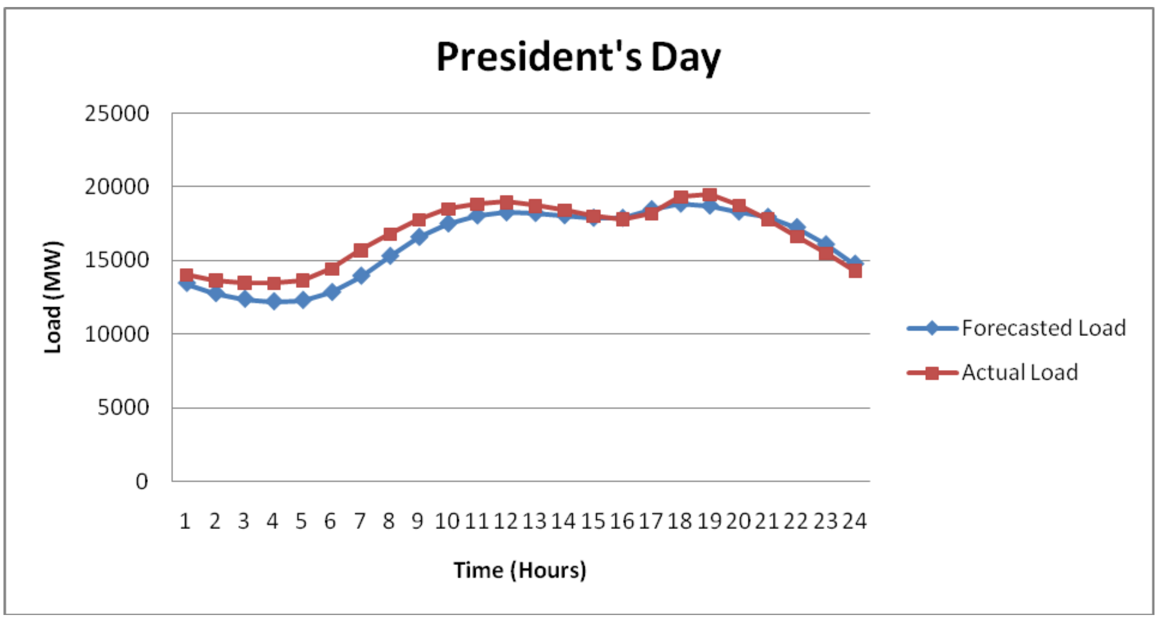

Fig. 61 Forecasted Load and Actual Load curves for President's Day

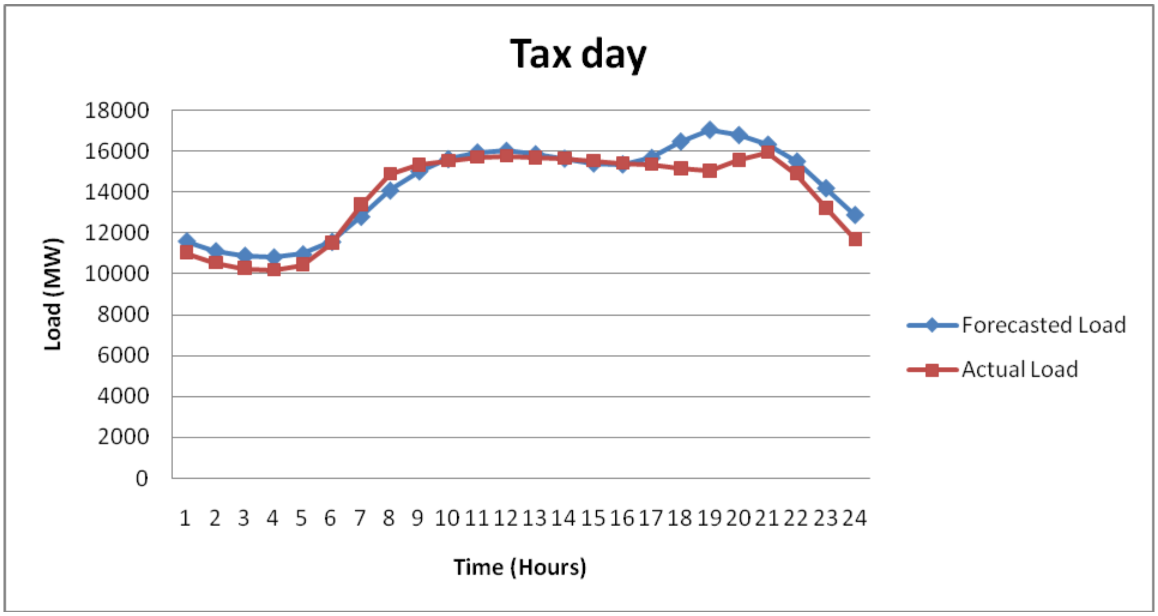

Fig. 62 Forecasted Load and Actual Load curves for Tax Day

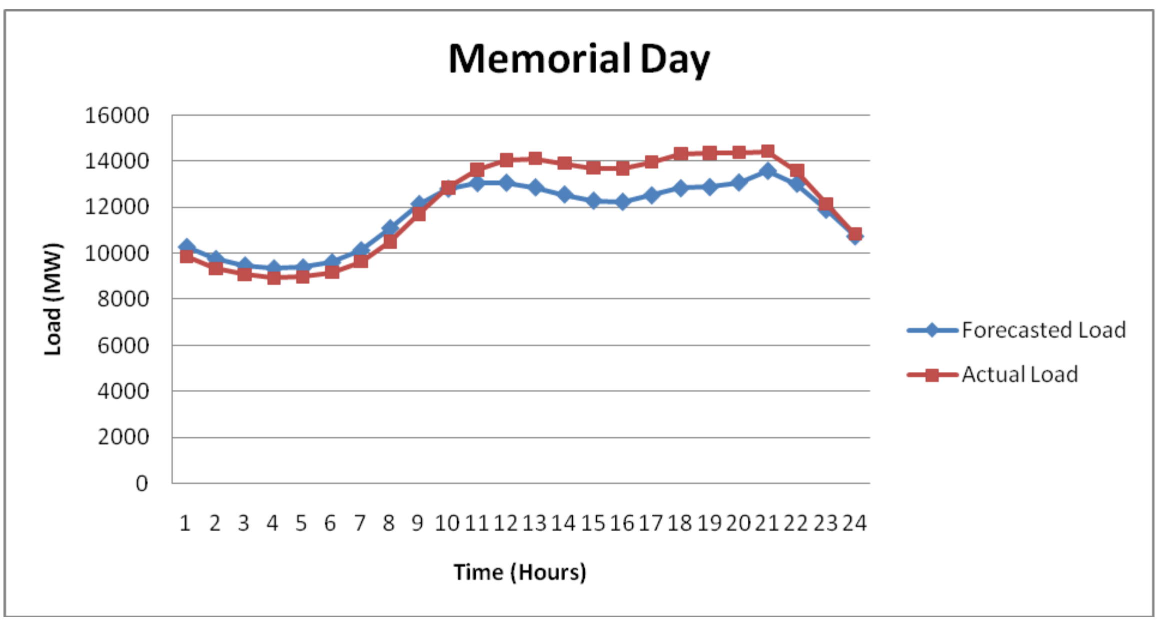

Fig. 63 Forecasted Load and Actual load curves for Memorial Day

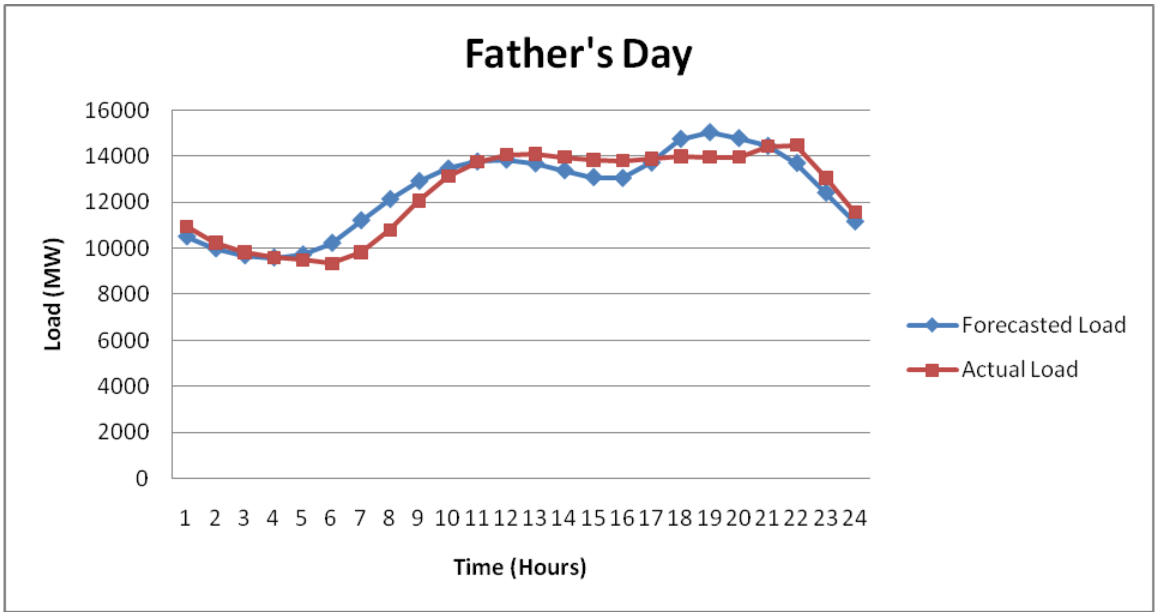

Fig. 64 Forecasted Load and Actual Load curves for Father's Day

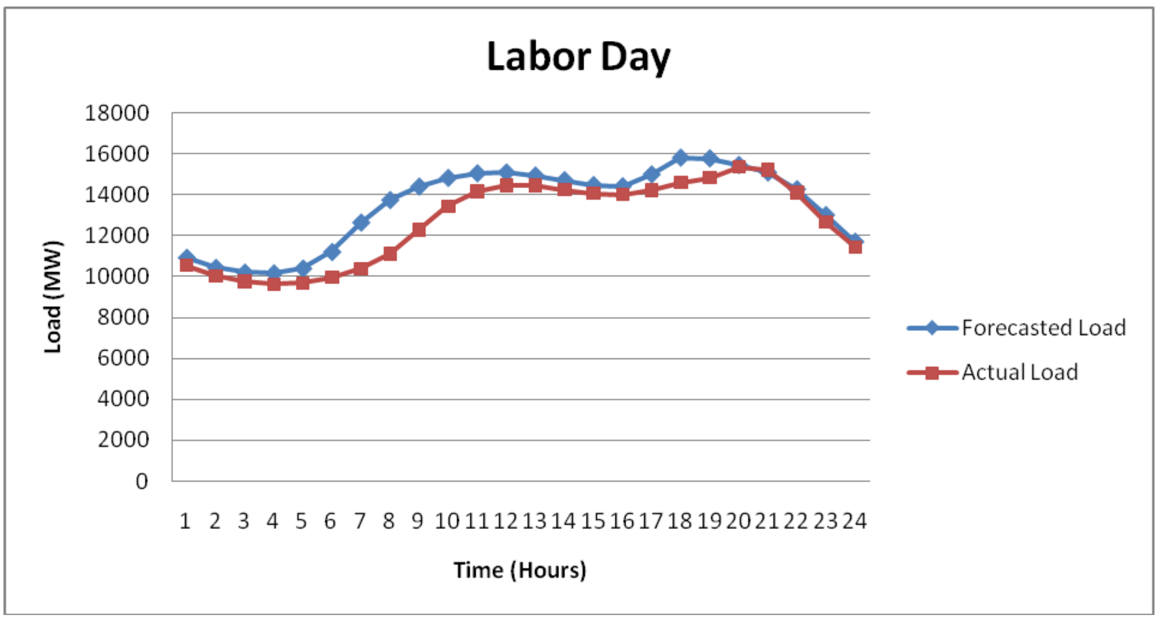

Fig. 65 Forecasted Load and Actual Load curves for Labor Day

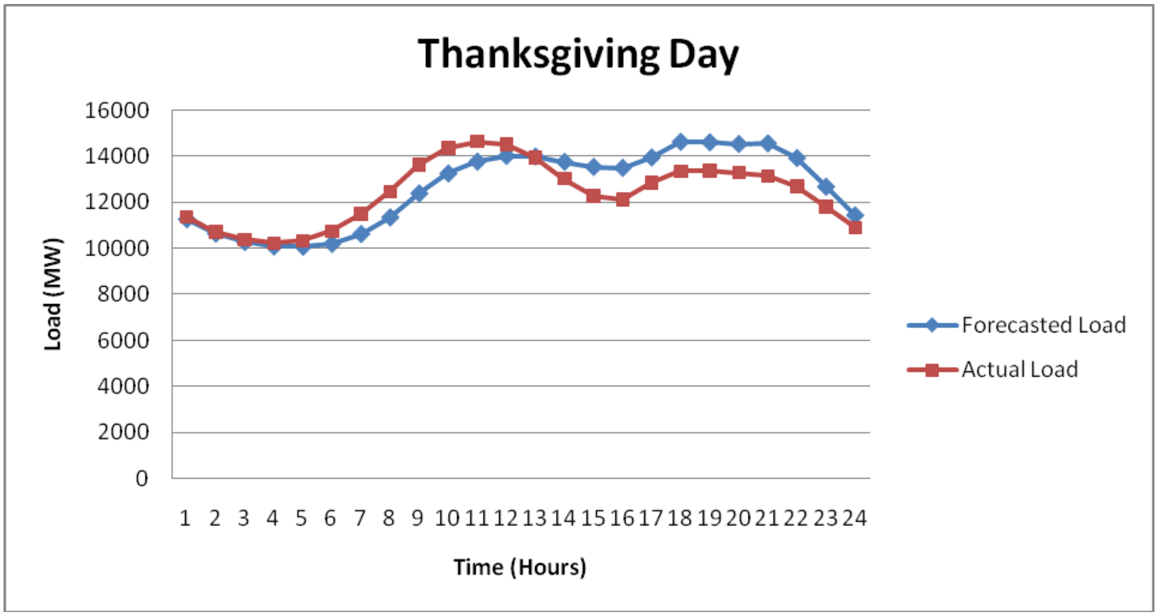

Fig. 66 Forecasted Load and Actual Load curves for Thanks giving Day

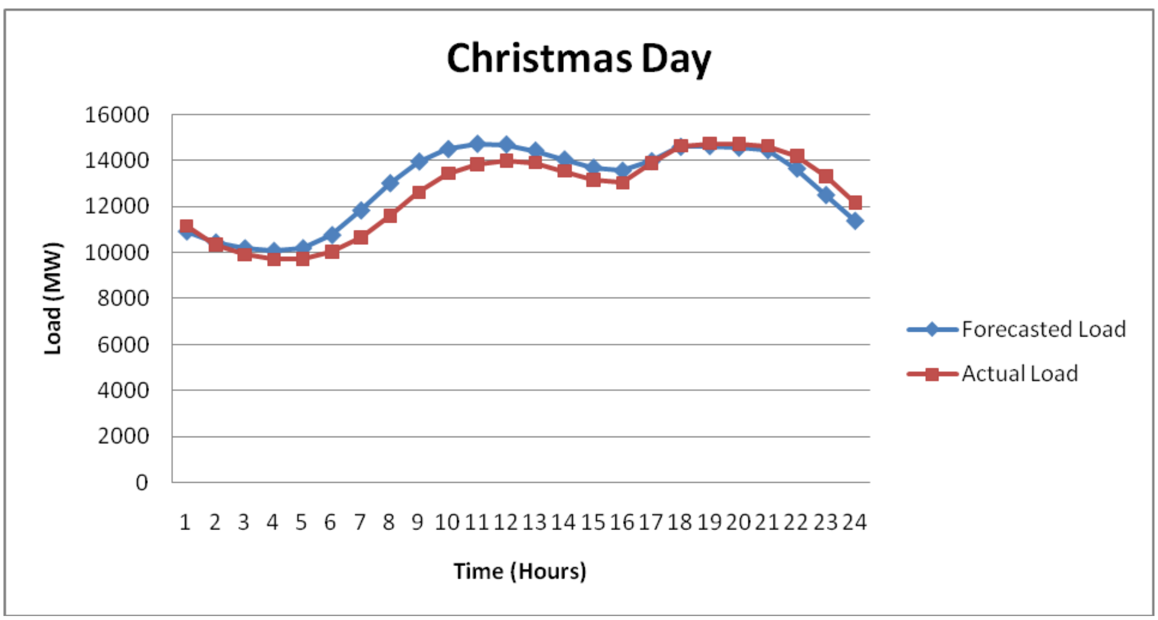

Fig. 67 Forecasted Load and Actual Load curves for Christmas Day

Summary of the anomalous days MAPE results are shown in the Table 48.

TABLE 48
Summary of Anomalous Days results using Case Study II

S.No	Name of Anomalous Day	Date	MAPE (%)
1	New Year Day	01-01-2003	5.562
2	President's Day	17-02-2003	4.795
3	Tax Day	15-04-2003	4.338
4	Memorial Day	26-05-2003	6.065
5	Father's Day	15-06-2003	4.564
6	Labor Day	01-09-2003	6.597
7	Thanksgiving Day	27-11-2003	6.298
8	Christmas Day	25-12-2003	4.555

7.4 Case Study III: Forecasting using Previous Anomalous Days and Weekends before Anomalous Days

7.4.1 Implementation

It is observed that in Case Study II, MAPE is reduced compared to Case Study I but further improvement of anomalous day load forecasting is required. So further attempt is made for another case study. In this case, input data taken are anomalous days of the years 2000 to 2002 and also considered weekends before anomalous days and testing data is anomalous days of the year 2003. Load forecasting is done for the testing data.

For example, five similar days are found from the previous data based on 24 hours of Temperature, 24 hours of Humidity, and Day type of the testing anomalous day (e.g **27-11-2003: Thanksgiving Day**). Here previous data means anomalous days and weekends before anomalous days of the years 2000 to 2002 and previous anomalous days and weekends of the year 2003 before the testing anomalous day.

Similarly, five similar days are found from the previous data based on 24 hours of Load, 24 hours of Temperature, 24 hours of Humidity, and Day type of the given previous anomalous day of the testing anomalous day.

Next, calculate the correction factors with the difference of Load, Temperature, and Humidity for five similar days of the previous anomalous day of the testing anomalous day. Fuzzify the values of correction factors by sending it to FIS developed in the previous chapter 6 and get the de-fuzzify values. These are fuzzy correction factors that are on forecasted similar days. Take the average of load of forecasted similar days of the testing anomalous day **(27-11-2003: Thanksgiving Day)** to get the forecasted load value. Similarly, calculate for all the anomalous days of the year 2003.

7.4.2 Results

In this section, the MAPE for hourly actual load and forecasted load results of selected anomalous days are shown in the Tables 49-52.

TABLE 49
Hourly results of New Year's Day and President's Day using Case Study III

	New Year's Day		**President's Day**	
Hour	**Actual Load (MW)**	**Forecasted Load (MW)**	**Actual Load (MW)**	**Forecasted Load (MW)**
1	11860	11311	14007	15370
2	11129	10757	13633	14787
3	10587	10436	13465	14477
4	10312	10332	13442	14326
5	10264	10488	13644	14352
6	10503	11159	14398	14691
7	10968	12478	15686	15459
8	11264	13409	16762	16291
9	11926	14035	17786	17194
10	12796	14482	18500	17885
11	13511	14738	18857	18232
12	13994	14797	18956	18355
13	14162	14681	18723	18286
14	14133	14527	18404	18063
15	14108	14368	18039	17822
16	14413	14553	17797	17763
17	15826	15873	18186	18199
18	16790	16842	19348	18843
19	16700	16624	19474	19056
20	16375	16127	18745	18939
21	15749	15514	17795	18671
22	14752	14643	16625	17878
23	13411	13446	15487	16658
24	12211	12258	14291	15443
MAPE (%):**4.635**			MAPE (%):**4.018**	

TABLE 50
Hourly results of Tax Day and Memorial Day using Case Study III

	Tax Day		Memorial Day	
Hour	**Actual Load (MW)**	**Forecasted Load (MW)**	**Actual Load (MW)**	**Forecasted Load (MW)**
1	11034	11668	9852	10436
2	10521	11204	9331	9896
3	10270	10987	9067	9623
4	10188	10914	8934	9491
5	10436	11056	8973	9517
6	11500	11635	9168	9739
7	13378	12813	9636	10246
8	14880	14036	10502	11218
9	15342	14937	11690	12336
10	15539	15512	12850	13127
11	15703	15821	13608	13458
12	15777	15897	14044	13488
13	15676	15740	14118	13327
14	15673	15534	13909	13054
15	15555	15313	13701	12830
16	15428	15267	13682	12746
17	15366	15568	13946	12942
18	15151	16328	14330	13406
19	15040	16881	14340	13928
20	15563	16644	14360	13978
21	15939	16200	14410	14116
22	14911	15416	13593	13464
23	13213	14163	12144	12360
24	11685	12915	10829	11286
MAPE (%):**4.274**			MAPE (%):**4.819**	

TABLE 51
Hourly results of Father's Day and Labor Day using Case Study III

	Father's Day		**Labor Day**	
Hour	**Actual Load (MW)**	**Forecasted Load (MW)**	**Actual Load (MW)**	**Forecasted Load (MW)**
1	10952	10662	10554	11410
2	10230	10136	10052	10843
3	9818	9860	9778	10554
4	9580	9742	9648	10440
5	9483	9764	9679	10498
6	9343	9999	9969	10837
7	9829	10477	10384	11473
8	10787	11411	11114	12385
9	12069	12499	12286	13454
10	13112	13234	13437	14117
11	13747	13553	14150	14298
12	14058	13676	14450	14221
13	14092	13554	14460	13989
14	13947	13230	14241	13692
15	13830	12909	14071	13499
16	13783	12817	14016	13581
17	13867	12999	14227	14489
18	13984	13429	14599	15502
19	13952	13787	14819	15728
20	13944	14083	15338	15577
21	14423	14095	15204	15236
22	14460	13242	14109	14482
23	13040	12092	12662	13393
24	11561	10982	11446	12246
MAPE (%):**3.945**			MAPE (%):**5.584**	

TABLE 52
Hourly results of Thanks Giving Day and Christmas Day using Case Study III

	Thanks Giving Day		**Christmas Day**	
Hour	**Actual Load (MW)**	**Forecasted Load (MW)**	**Actual Load (MW)**	**Forecasted Load (MW)**
1	11372	10757	11177	11128
2	10730	10123	10375	10533
3	10393	9763	9922	10205
4	10236	9589	9731	10033
5	10325	9650	9746	10018
6	10741	10073	10056	10087
7	11497	10993	10687	10506
8	12474	12151	11601	11377
9	13630	13154	12634	12541
10	14373	13818	13442	13493
11	14637	14135	13848	14071
12	14520	14157	14006	14431
13	13941	13974	13925	14559
14	13032	13646	13561	14469
15	12285	13350	13168	14327
16	12134	13251	13052	14298
17	12860	13695	13883	14652
18	13358	14138	14652	14998
19	13373	14173	14739	14936
20	13300	14046	14723	14934
21	13153	13979	14648	15169
22	12694	13429	14213	14580
23	11811	12303	13313	13246
24	10895	11071	12176	11896
MAPE (%):**5.044**			MAPE (%):**2.899**	

The graphical representation of the forecasted load and actual load curves are shown in the Fig 68-75.

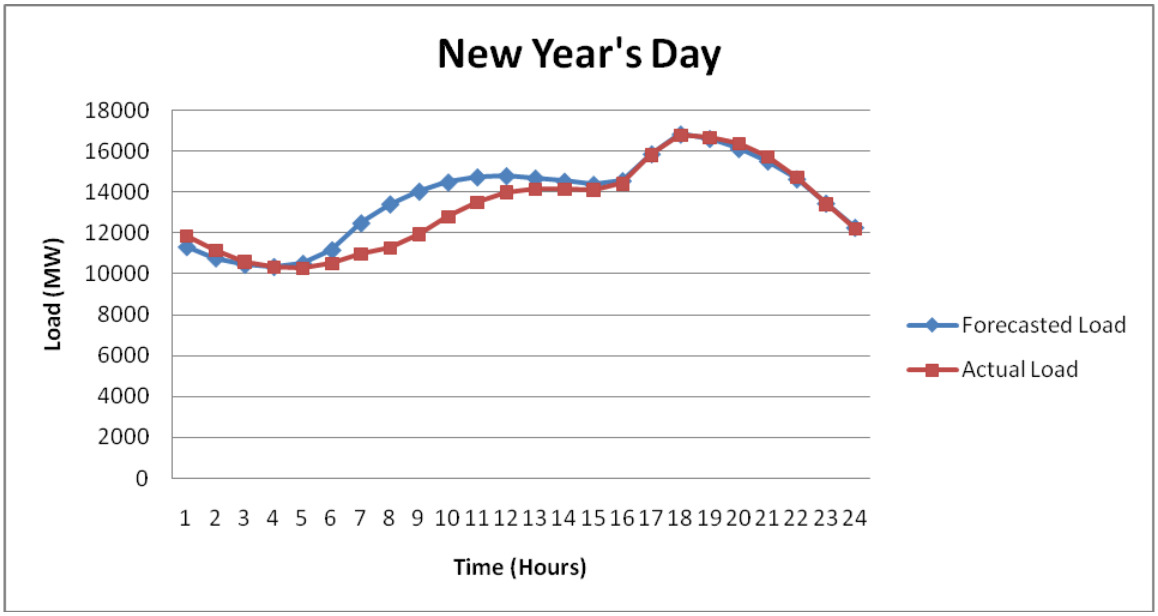

Fig. 68 Forecasted Load and Actual Load curves for New Year's Day

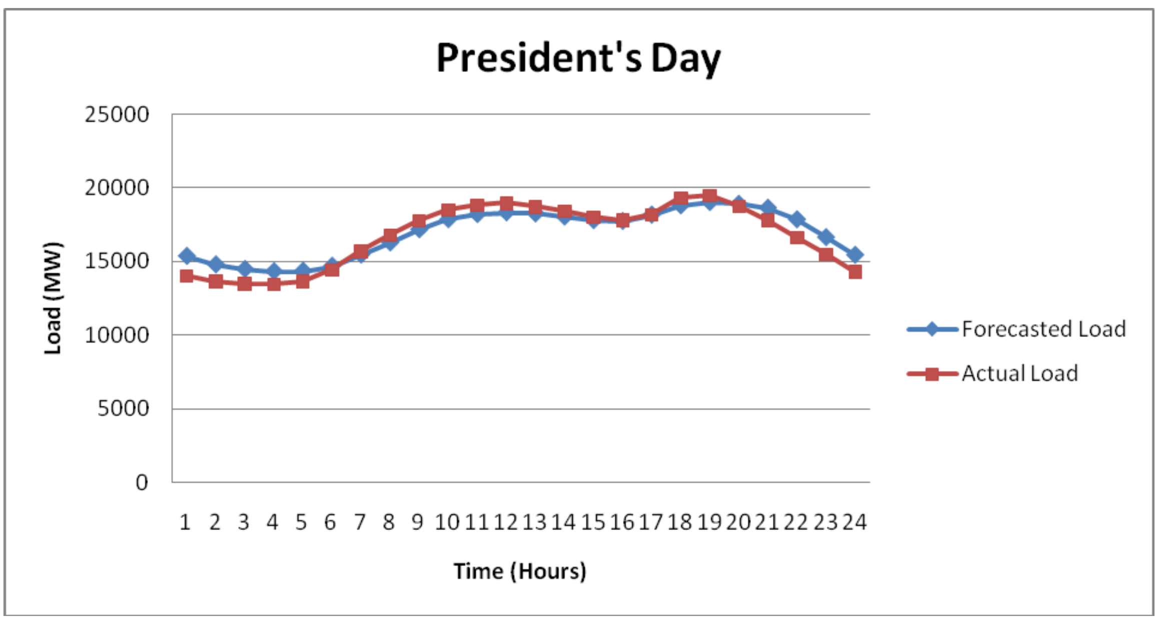

Fig. 69 Forecasted Load and Actual Load curves for President's Day

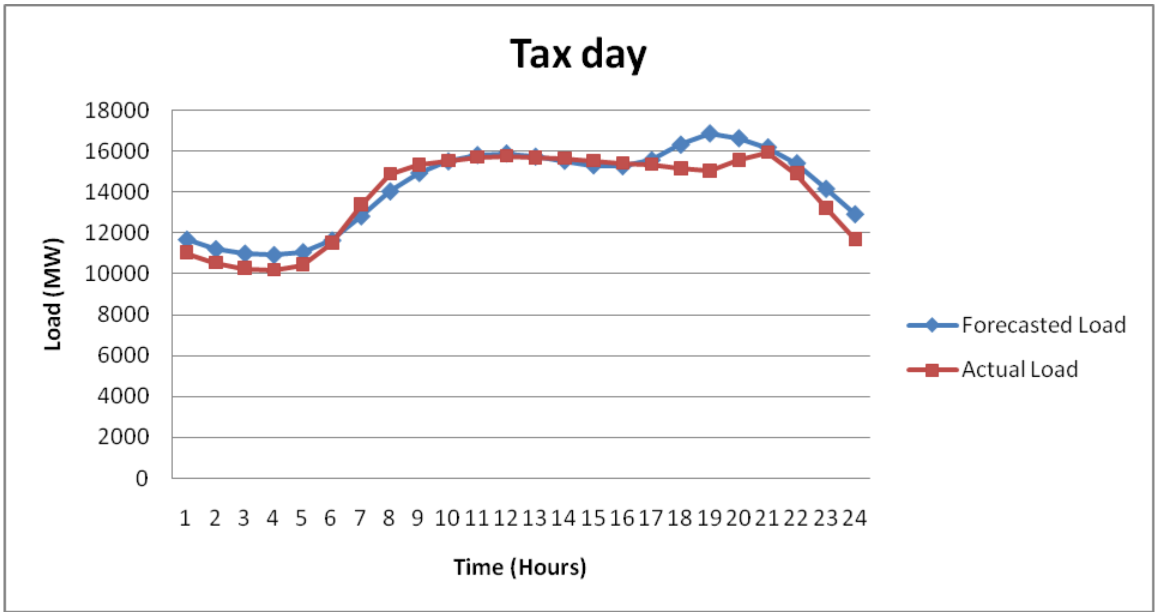

Fig. 70 Forecasted Load and Actual Load curves for Tax Day

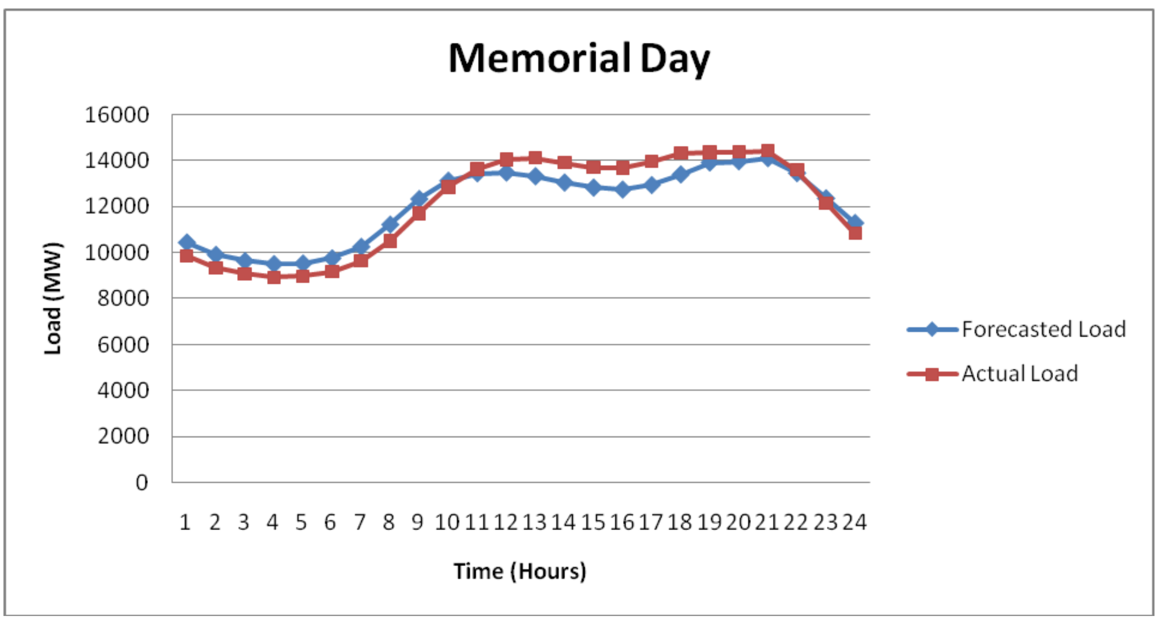

Fig. 71 Forecasted Load and Actual Load curves for Memorial Day

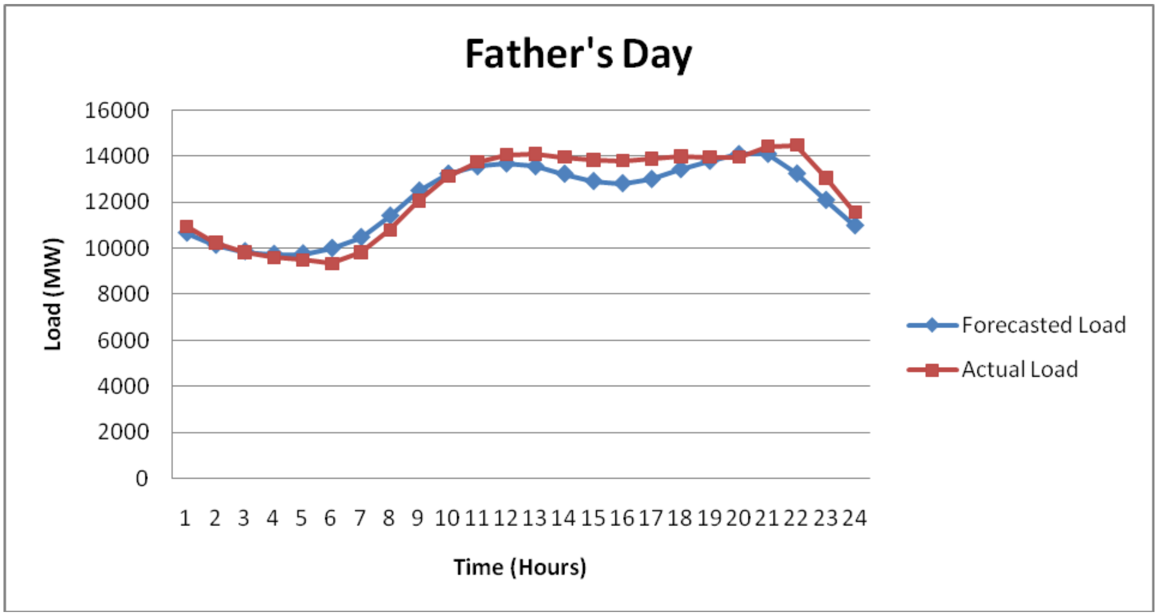

Fig. 72 Forecasted Load and Actual Load curves for Father's Day

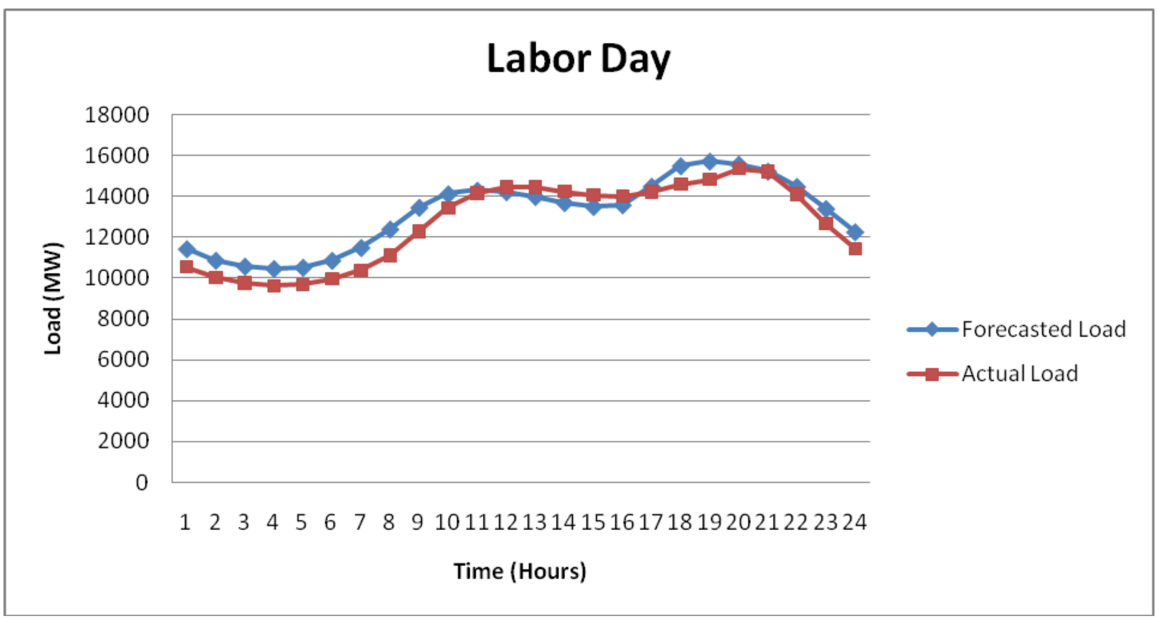

Fig. 73 Forecasted Load and Actual Load curves for Labor Day

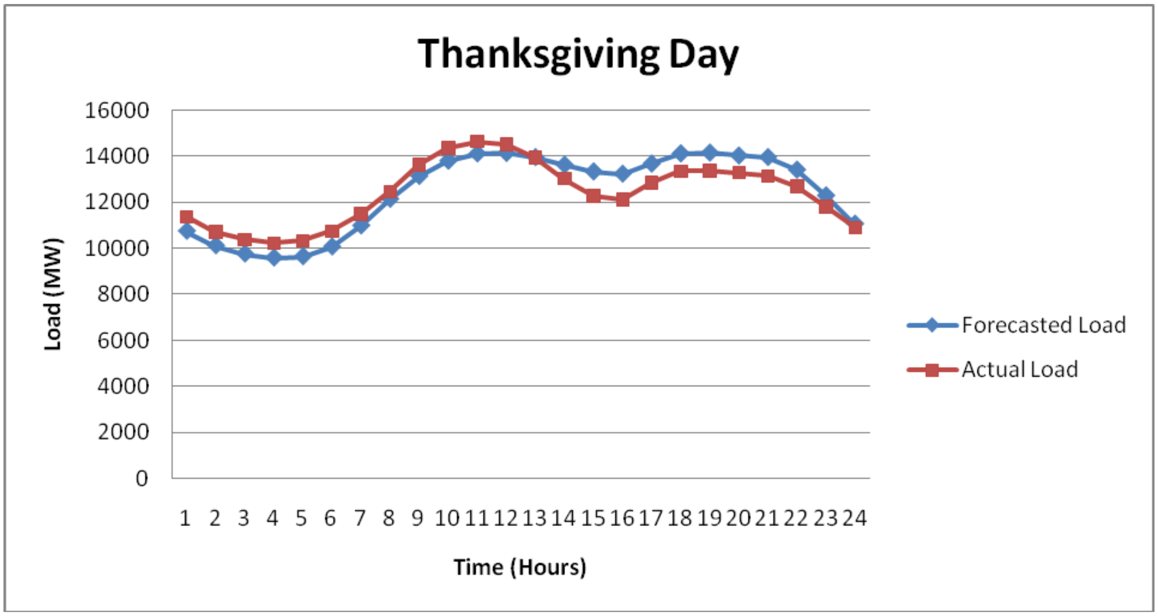

Fig. 74 Forecasted Load and Actual Load curves for Thanks giving Day

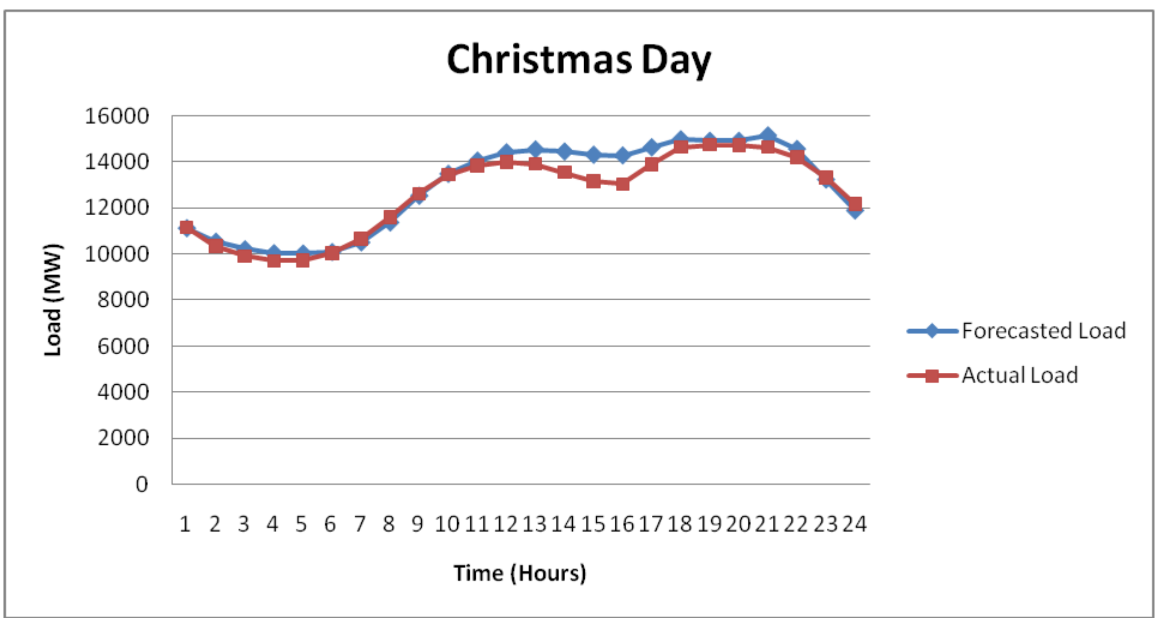

Fig. 75 Forecasted Load and Actual Load curves for Christmas Day

Summary of the anomalous days MAPE results are shown in the Table 53.

TABLE 53
Summary of Anomalous Days results using Case Study III

S.No	Name of Anomalous Day	Date	MAPE (%)
1	New Year Day	01-01-2003	4.635
2	President’s Day	17-02-2003	4.018
3	Tax Day	15-04-2003	4.274
4	Memorial Day	26-05-2003	4.819
5	Father’s Day	15-06-2003	3.945
6	Labor Day	01-09-2003	5.584
7	Thanksgiving Day	27-11-2003	5.044
8	Christmas Day	25-12-2003	2.899

7.5 Case Study IV: Forecasting using Season wise Previous Anomalous Days and Weekends before Anomalous Days

7.5.1 Implementation

It is observed that in Case Study III, MAPE is reduced compared with Case Study I and II and improvement is good in some cases. But it still requires further improvement to have a reasonably good forecasting of load for anomalous days so a further attempt is made where an idea for inclusion of season wise grouping is considered. Testing anomalous days are grouped into four seasons namely winter (December-February), spring (March-May), summer (June - August), and fall (September- November). Similarly, the input data for the years 2000 to 2002 are grouped into four seasons. Here input data is season wise anomalous days and previous weekends of anomalous days. Load forecasting is done similar to the previous case studies

For example, five similar days are found from previous data based on 24 hours of Temperature, 24 hours of Humidity, and Day type of a testing anomalous day (e.g **25-12-2003: Christmas Day**). The testing anomalous day belongs to the winter season group, so previous data means the anomalous days of winter season and weekends before anomalous days of the years 2000 to 2002 and winter season of the previous anomalous days and weekends of the year 2003 before the testing anomalous day.

Similarly, five similar days are found from previous data based on 24 hours of Load, 24 hours of Temperature, 24 hours of Humidity, and Day type of a given previous anomalous day of the testing anomalous day.

Next, calculate the correction factors with the difference of Load, Temperature, and Humidity for five similar days of the previous anomalous day of testing anomalous day. Fuzzify the values of correction factors by sending it to FIS developed in the previous chapter 6 and get the de-fuzzify values. These are fuzzy correction factors that are applied on similar days. Take the average of loads of forecasted similar days of the testing anomalous day **(25-12-2003: Christmas Day)** to get the forecasted load value. Similarly, calculate for all the anomalous days of the year 2003.

7.5.2 Results

In this section, the MAPE for hourly actual load and forecasted load results of selected anomalous days are shown in the Tables 54-57.

TABLE 54
Hourly results of New Year's Day and President's Day using Case Study IV

	New Year's Day		President's Day	
Hour	**Actual Load (MW)**	**Forecasted Load (MW)**	**Actual Load (MW)**	**Forecasted Load (MW)**
1	11860	11576	14007	14288
2	11129	10942	13633	13787
3	10587	10586	13465	13478
4	10312	10414	13442	13382
5	10264	10402	13644	13550
6	10503	10547	14398	14263
7	10968	11003	15686	15577
8	11264	11760	16762	16537
9	11926	12847	17786	17190
10	12796	13707	18500	17647
11	13511	14189	18857	17941
12	13994	14425	18956	17980
13	14162	14462	18723	17801
14	14133	14269	18404	17582
15	14108	14105	18039	17335
16	14413	14134	17797	17306
17	15826	14885	18186	18038
18	16790	15920	19348	19042
19	16700	15961	19474	19361
20	16375	15702	18745	19241
21	15749	15550	17795	18684
22	14752	14939	16625	17700
23	13411	13655	15487	16290
24	12211	12321	14291	15022
MAPE (%):**2.685**			MAPE (%):**2.864**	

TABLE 55
Hourly results of Tax Day and Memorial Day using Case Study IV

	Tax Day		**Memorial Day**	
Hour	**Actual Load (MW)**	**Forecasted Load (MW)**	**Actual Load (MW)**	**Forecasted Load (MW)**
1	11034	11129	9852	10125
2	10521	10666	9331	9464
3	10270	10449	9067	9047
4	10188	10375	8934	8832
5	10436	10517	8973	8817
6	11500	11097	9168	9085
7	13378	12275	9636	9842
8	14880	13498	10502	10854
9	15342	14398	11690	11931
10	15539	14973	12850	12802
11	15703	15282	13608	13337
12	15777	15359	14044	13582
13	15676	15202	14118	13504
14	15673	14996	13909	13248
15	15555	14775	13701	12959
16	15428	14728	13682	12858
17	15366	15029	13946	13133
18	15151	15790	14330	13467
19	15040	16343	14340	13446
20	15563	16105	14360	13481
21	15939	15662	14410	13611
22	14911	14878	13593	13080
23	13213	13624	12144	11908
24	11685	12376	10829	10649
MAPE (%):**3.716**			MAPE (%):**3.295**	

TABLE 56
Hourly results of Father's Day and Labor Day using Case Study IV

	Father's Day		Labor Day	
Hour	**Actual Load (MW)**	**Forecasted Load (MW)**	**Actual Load (MW)**	**Forecasted Load (MW)**
1	10952	10799	10554	10426
2	10230	10267	10052	9935
3	9818	9988	9778	9682
4	9580	9870	9648	9579
5	9483	9892	9679	9632
6	9343	10131	9969	9969
7	9829	10615	10384	10572
8	10787	11557	11114	11392
9	12069	12658	12286	12398
10	13112	13403	13437	13032
11	13747	13728	14150	13265
12	14058	13856	14450	13294
13	14092	13735	14460	13156
14	13947	13410	14241	12926
15	13830	13088	14071	12762
16	13783	12997	14016	12888
17	13867	13184	14227	13924
18	13984	13620	14599	14964
19	13952	13971	14819	14974
20	13944	14262	15338	14614
21	14423	14273	15204	14082
22	14460	13409	14109	13240
23	13040	12244	12662	12217
24	11561	11120	11446	11201
MAPE (%):**3.696**			MAPE (%):**3.843**	

TABLE 57
Hourly results of Thanks giving Day and Christmas Day using Case Study IV

	Thanksgiving Day		Christmas Day	
Hour	**Actual Load (MW)**	**Forecasted Load (MW)**	**Actual Load (MW)**	**Forecasted Load (MW)**
1	11372	11300	11177	10864
2	10730	10681	10375	10284
3	10393	10330	9922	9964
4	10236	10161	9731	9797
5	10325	10220	9746	9783
6	10741	10631	10056	9853
7	11497	11527	10687	10264
8	12474	12655	11601	11110
9	13630	13635	12634	12243
10	14373	14287	13442	13169
11	14637	14600	13848	13731
12	14520	14623	14006	14079
13	13941	14445	13925	14200
14	13032	14125	13561	14109
15	12285	12838	13168	13970
16	12134	13141	13052	13943
17	12860	14177	13883	14300
18	13358	14209	14652	14650
19	13373	14336	14739	14595
20	13300	14307	14723	14594
21	13153	14437	14648	14816
22	12694	13404	14213	14236
23	11811	12811	13313	12936
24	10895	11612	12176	11621
MAPE (%):**3.932**			MAPE (%):**2.265**	

The graphical representation of the forecasted load and actual load curves are shown in the Fig 76-83.

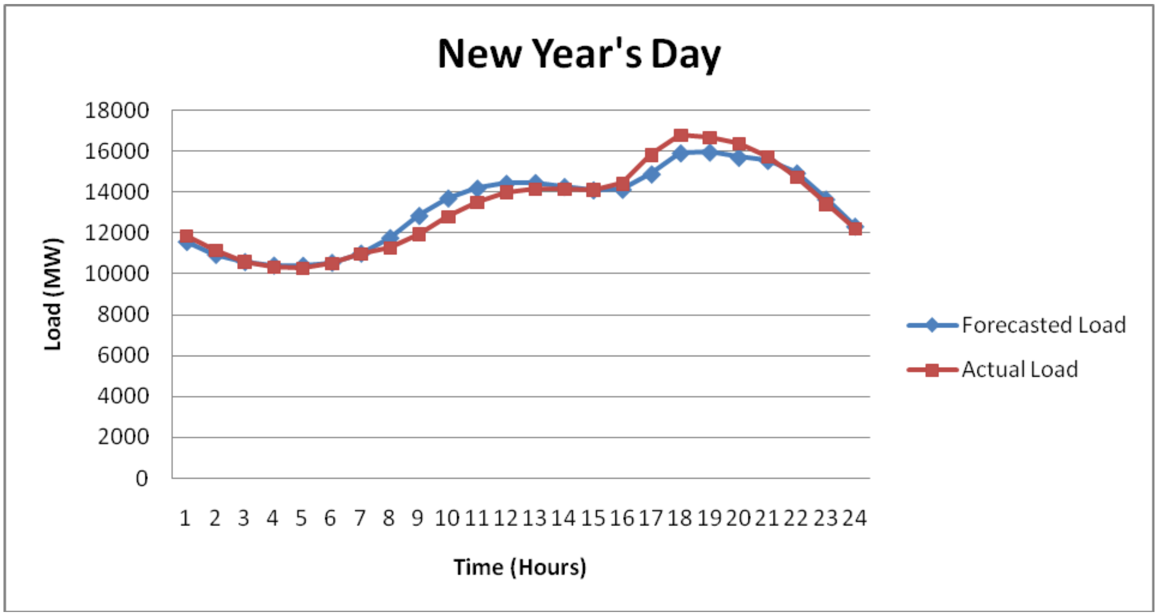

Fig. 76 Forecasted Load and Actual Load curves for New Year's Day

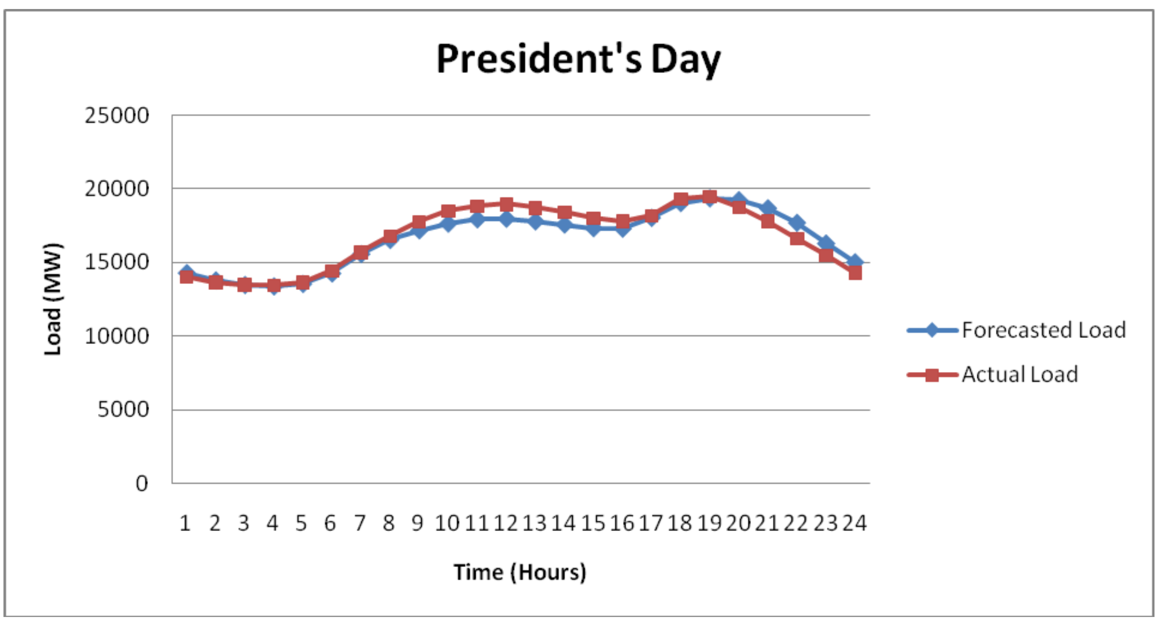

Fig. 77 Forecasted Load and Actual Load curves for President's Day

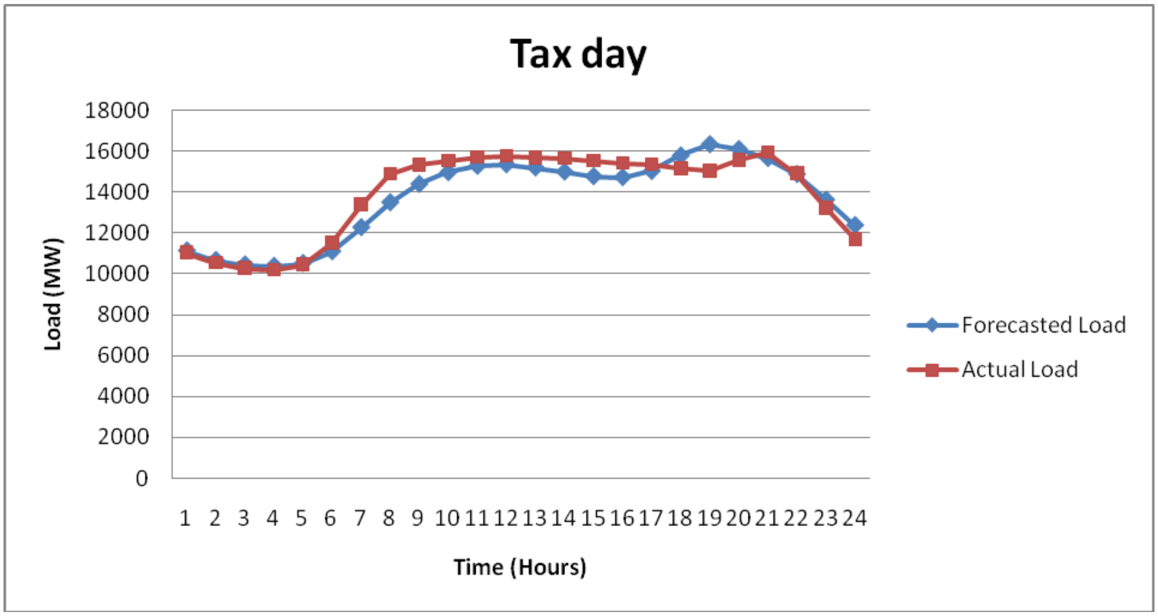

Fig. 78 Forecasted Load and Actual Load curves for Tax Day

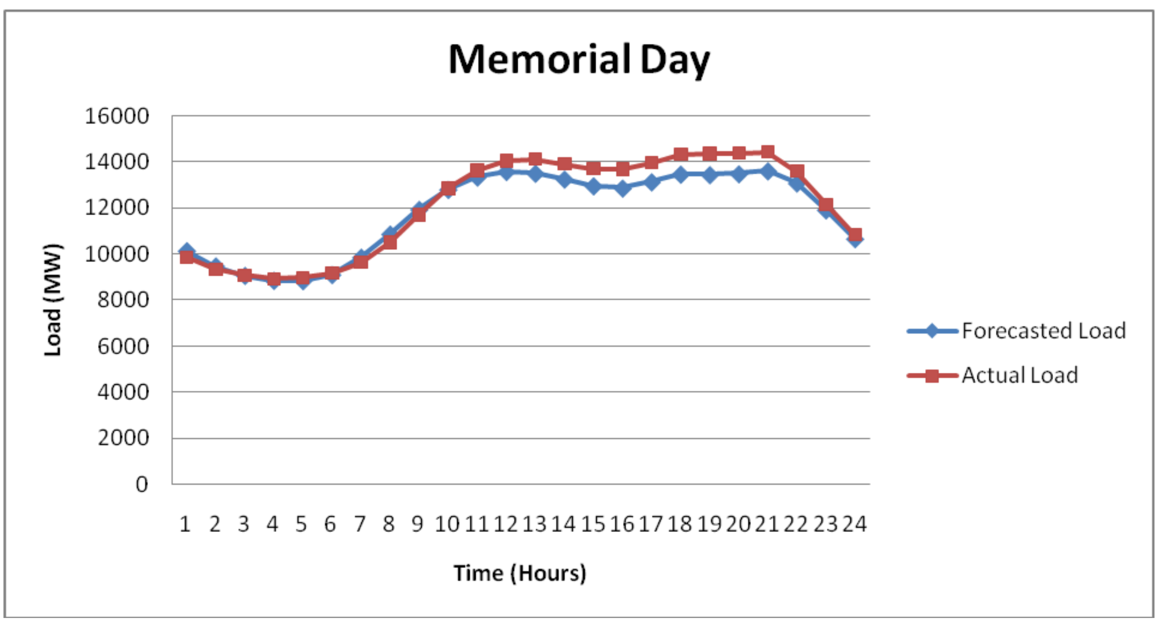

Fig. 79 Forecasted Load and Actual Load curves for Memorial Day

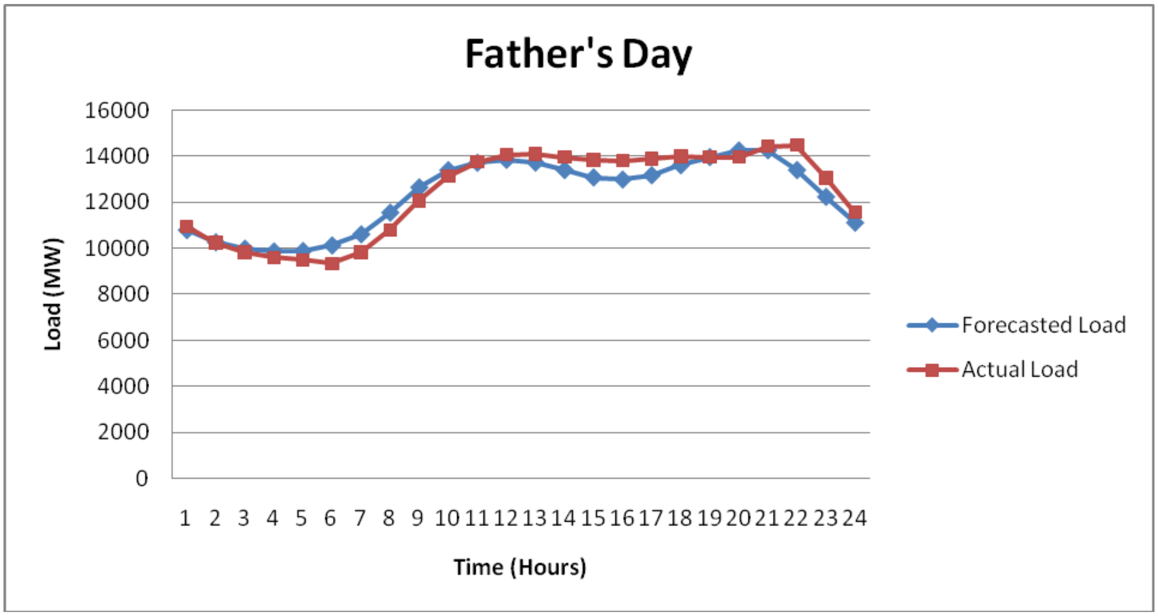

Fig. 80 Forecasted Load and Actual Load curves for Father's Day

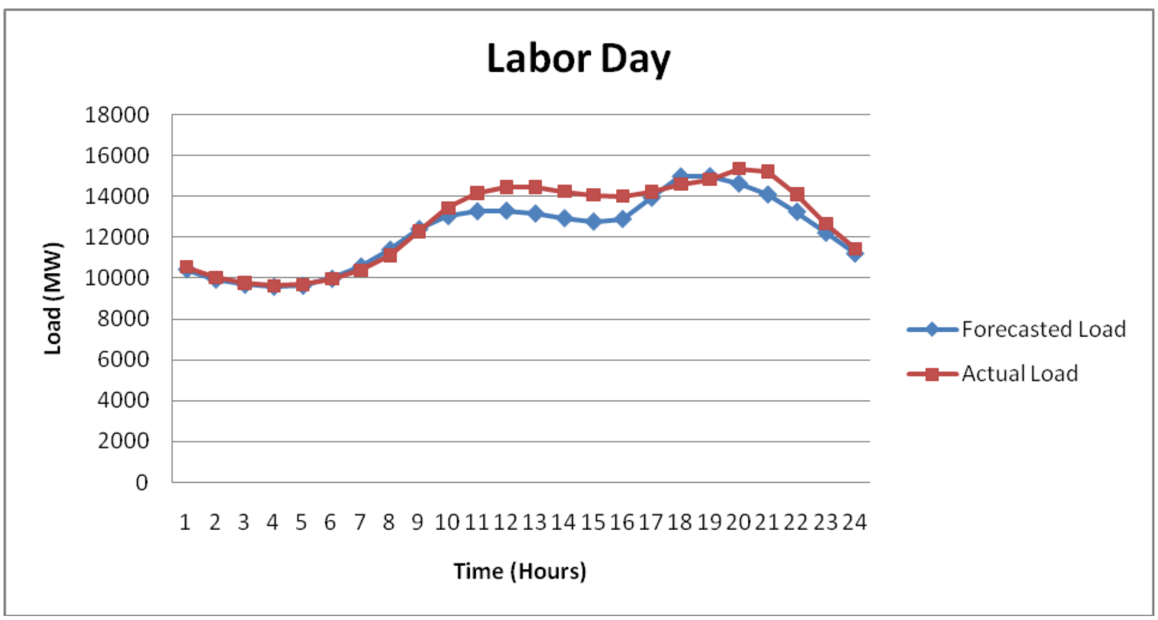

Fig. 81 Forecasted Load and Actual Load curves for Labor Day

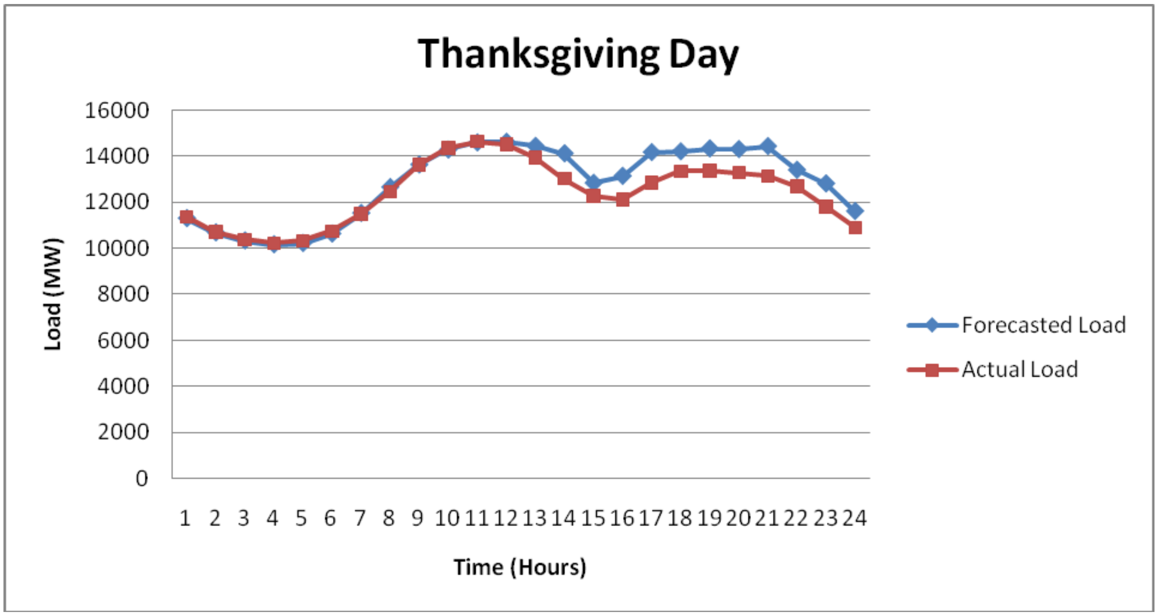

Fig. 82 Forecasted Load and Actual Load curves for Thanks giving Day

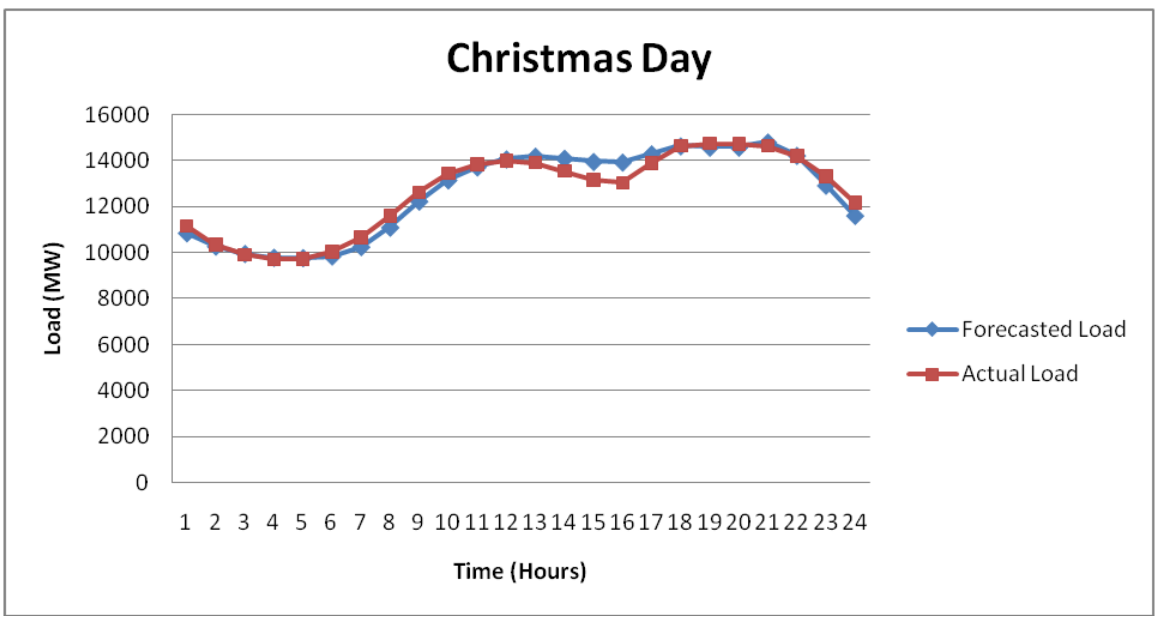

Fig. 83 Forecasted Load and Actual Load curves for Christmas Day

Summary of anomalous days MAPE results are shown in the Table 58.

TABLE 58
Summary of Anomalous Days results using Case Study IV

S.No	Name of Anomalous Day	Date	MAPE (%)
1	New Year Day	01-01-2003	2.685
2	President's Day	17-02-2003	2.864
3	Tax Day	15-04-2003	3.716
4	Memorial Day	26-05-2003	3.295
5	Father's Day	15-06-2003	3.696
6	Labor Day	01-09-2003	3.843
7	Thanksgiving Day	27-11-2003	3.932
8	Christmas Day	25-12-2003	2.265

7.6 Comparison and Discussion of Anomalous Days results using Case Study I, II, III, & IV

This section presents the comparison of anomalous days forecasting results by the proposed methodologies for case studies I, II, III, & IV for few anomalous days of the year 2003. In the Table 59, MAPE of anomalous days forecasting results using different case studies are compared. It can be seen from Table 59 that the results in case study IV are most reasonable and MAPE is in the range of 3% or somewhat higher but less than 4% in all cases, which still is quite good for STLF of anomalous days.

TABLE 59
Comparison of Anomalous Days results using Case Study I, II, III, & IV

S.No	Name of Anomalous Day	Date	CASE I	CASE II	CASE III	CASE IV
			MAPE (%)			
1	New Year Day	01-01-2003	6.154	5.562	4.635	2.685
2	President's Day	17-02-2003	7.934	4.795	4.018	2.864
3	Tax Day	15-04-2003	4.927	4.338	4.274	3.716
4	Memorial Day	26-05-2003	6.854	6.065	4.819	3.295
5	Father's Day	15-06-2003	5.389	4.564	3.945	3.696
6	Labor Day	01-09-2003	6.811	6.597	5.584	3.843
7	Thanksgiving Day	27-11-2003	7.141	6.298	5.044	3.932
8	Christmas Day	25-12-2003	5.139	4.555	2.899	2.265

7.7 Impact of Error in Weather Variables on STLF for Anomalous days

The variation of MAPE (%) of anomalous days STLF results with and without error in weather parameters for these four case studies are shown in Tables 60-61.

Where

(T+1%) is Temperature with 1% error (addition). (H+3%) is Humidity with 3% error (addition), (T-1%) is Temperature with 1% error (subtraction), (H-3%) is Humidity with 3% error (subtraction) and percentage error in temperature applied on Kelvin scale.

TABLE 60

COMPARISON OF STLF FOR ANOMALOUS DAYS RESULTS WITH AND WITHOUT ERROR IN WEATHER PARAMETERS FOR CASE STUDY 1 & CASE STUDY II

S. No	Name of Anomalous Day	Date	Case Study I			Case Study II		
			Without Weather Forecast Error	With Weather Forecast Error		Without Weather Forecast Error	With Weather Forecast Error	
				T+ 1%, H+3%	T-1%, H-3%		T+1%, H+3%	T-1%, H-3%
			MAPE (%)					
1	New Year Day	01-01-2003	6.154	7.809	6.002	5.562	6.063	7.408
2	President's Day	17-02-2003	7.934	6.601	8.797	4.795	4.533	5.067
3	Tax Day	15-04-2003	4.927	4.632	5.483	4.338	5.148	5.083
4	Memorial Day	26-05-2003	6.854	7.052	6.743	6.065	6.672	6.375
5	Father's Day	15-06-2003	5.389	5.636	5.287	4.564	5.124	5.922
6	Labor Day	01-09-2003	6.811	6.806	7.442	6.597	7.963	6.810
7	Thanksgiving Day	27-11-2003	7.141	6.938	5.956	6.298	6.856	6.732
8	Christmas Day	25-12-2003	5.139	5.086	5.222	4.555	6.155	6.132

TABLE 61

COMPARISON OF STLF FOR ANOMALOUS DAYS RESULTS WITH AND WITHOUT ERROR IN WEATHER PARAMETERS FOR CASE STUDY III & CASE STUDY IV

S. No	Name of Anomalous Day	Date	Case Study III			Case Study IV		
			Without Weather Forecast Error	With Weather Forecast Error		Without Weather Forecast Error	With Weather Forecast Error	
				T+1%, H+3%	T-1%, H-3%		T+1%, H+3%	T-1%, H-3%
			MAPE (%)					
1	New Year Day	01-01-2003	4.635	5.502	6.816	2.685	2.857	2.924
2	President's Day	17-02-2003	4.018	4.432	4.657	2.864	2.982	3.142
3	Tax Day	15-04-2003	4.274	4.282	4.403	3.716	4.893	4.887
4	Memorial Day	26-05-2003	4.819	5.270	6.221	3.295	4.803	5.430
5	Father's Day	15-06-2003	3.945	3.836	3.981	3.696	3.954	4.026
6	Labor Day	01-09-2003	5.584	6.453	7.038	3.843	3.885	3.802
7	Thanksgiving Day	27-11-2003	5.044	6.728	6.125	3.932	4.126	4.265
8	Christmas Day	25-12-2003	2.899	2.917	2.588	2.265	2.538	2.602

7.8 Summary and Observations

STLF results are presented for anomalous days for four different case studies for four different proposed methodologies and MAPE results are compared. Case Study IV: Forecasting using Season wise Previous Anomalous Days and Weekends before Anomalous Days shows better results for the considered anomalous days when compared with the results by other case studies and MAPE by Case Study IV has been in the range of 2% to 4% only for the selected anomalous days. Variations in MAPE (%) of proposed case studies with and without weather forecast errors are also shown.

Assessment of impact of error possibilities in weather parameter on STLF has been done and results tables showed that the proposed methodology for anomalous days STLF using season wise previous anomalous days and weekend before anomalous days and Mahalanobis distance norm for similar day is robust and errors in input weather parameters do not have large impact on the quality of STLF results.

Chapter 8
Conclusions

The electrical load is having non linear behavior and soft computing methods have the ability to deal with the non linearity. In this research thesis, fuzzy logic with optimization is chosen for short term load forecasting. A fuzzy logic system gives better forms of rule expressions and reasoning logic like the human thought process. Proposed work presented the fuzzy logic based STLF by selecting similar days where Mahalanobis distance norm is proposed to be used to find out these similar days from previous data. The average of the corrected hourly loads of the similar days of the forecast day is then considered as the hourly load of the forecast day. STLF results show that proposed use of Mahalanobis distance norm gives better results than the use of Euclidean distance norm that has been used in previous literature.

The fuzzy membership functions parameter limits are optimized through four different optimization techniques. 1) Heuristic, 2) Particle Swarm Optimization (PSO), 3) New Particle Swarm Optimization (NPSO) and 4) Evolutionary Particle Swarm Optimization (EPSO).

In Heuristic Approach, fuzzy membership parameter values are tuned heuristically. Step by step increment/decrement of parameters is adopted. It takes fewer number iterations and less time to the tuning of parameters but MAPE could be high.

PSO simulates the bird flocking behavior. In PSO, each particle fitness value can be evaluated in a search space by using the fitness function. The particle direction of flying can be decided by its velocity and position. PSO function modifies the latest particle position by using an optimization equation based on the global best of the previous iteration. The optimization of fuzzy parameter values is done by using PSO and these optimized fuzzy parameters are used for STLF. This approach has taken the large number of iterations and more time to get the optimal solutions but the accuracy of forecasted results is better than the heuristic approach.

In NPSO, each particle leaves its previous worst position and also leaves from the previous worst position of its group. NPSO function modifies the latest particle position by using optimization equations based on the global worst of the previous iteration. The optimization of fuzzy parameter values is done by using NPSO and these optimized fuzzy parameters are used to get the forecasted load values. This approach has worked similar to PSO and also takes large number of iterations and more time to get the optimal solution but performance in accuracy of results is slightly better than PSO.

EPSO is a hybrid scheme with PSO with an explicit selection and self-adapting properties for its parameters. EPSO has the properties of Replication, Mutation, Reproduction, Evaluation and Selection. This approach can avoid the PSO problem of focusing on the optimal solution in the other regions. The optimization of fuzzy parameter values is done by using EPSO. These optimized parameter values are fed to the fuzzy inference system (FIS) for setting to input parameter limits and FIS is used to obtain the forecast the load of different days of a month.

Each chapter has presented a proposed short term forecasting method using the fuzzy inference system (FIS) that are optimized by different optimization techniques and simulation results are presented and discussed for the days that included weekdays as well as weekends also. The MAPE for hourly actual load and forecasted load results of the days of a week have been presented in tabular form. MAPE results for forecasting errors are compared for the proposed STLF techniques with and without using the optimization techniques. The graphical representations of forecasted and actual load curves for different days are also presented. Though forecasted load curves by the proposed techniques followed the similar pattern of actual load curve in all cases of proposed techniques with optimization, the proposed EPSO based technique for STLF shows better results compared with other proposed techniques.

STLF results are presented for anomalous days for four different case studies and MAPE results are compared. The MAPE for hourly actual load and forecasted load results of selected anomalous days are presented in tabular form. The graphical representations of forecasted and actual load curves are also shown for anomalous days. A methodology for forecasting the anomalous day load that uses the input data as the season wise previous anomalous days and weekends before anomalous days shows better results when compared to the forecasted load results by other methodologies.

For short term load forecasting for the next day load, next day data of temperature and humidity need to be used that is provided by weather forecasting and these forecasted weather variables like temperature and humidity may have some errors. The impact of error in weather variable inputs for the next day load forecasting is also analyzed in this research thesis by simulating the STLF with consideration of low and high extremities of temperature and humidity as inputs. The comparison of results of STLF considering the input weather variables with and without errors demonstrated that the proposed STLF methodologies for weekdays, weekend and anomalous days are robust and possible errors in input weather parameters are not affecting much the STLF results.

Novelty and major contributions of research work are:

- A Mahalanobis Distance norm is used for the selection of similar days has been proposed considering the temperature, humidity and day type as the similarity criteria parameters. The fuzzy logic is chosen in the correction of similar days of the forecast day.
- Optimization of the fuzzy input parameter limits for generation of better correction factors to improve the accuracy of the forecasted load has been done using Heuristic Approach, Particle Swarm Optimization (PSO), New Particle Swarm Optimization (NPSO) and Evolutionary Particle Swarm Optimization (EPSO).
- The short term load forecasting algorithms are developed for each optimization technique and these have been validated on real-time data.
- To overcome the small number of data availability for anomalous days, new methodologies have been proposed for anomalous day load forecasting and these have been validated on real-time data.
- The possibilities of errors in input weather parameters data are considered for week days and their impact has been analyzed.
- Impact of errors in weather variables on STLF for weekend days have been analyzed.
- In addition to weekdays and weekends, assessment of impact of error possibilities in weather parameters on STLF for anomalous days has been done in this research work.

Therefore, the research work presented in this thesis is providing a comprehensive solution for short term load forecasting for weekdays, weekend days and anomalous day and it will be very useful for power utilities.

Future Work

The new technologies like smart grid are going to have big impact on the performance of the power sector. With the proliferation of new generation smart meters in power sector, granular load consumption data is available in the sample of a few minutes time intervals. Soft computing techniques have shown great success in short term load forecasting but they are usually trained from offline data and need to be improved further to train its hyper-parameters from newly arriving data from smart meters. Researchers need to work further for developing improved models that also adapt online algorithms with more advanced hybrid optimization techniques that could be capable to train its hyperparameters with the granular data continuously arriving from smart meters. Therefore, research may further be taken for the development of short term load forecasting algorithms that may provide further improved forecasted results by utilizing the online data obtained from smart meters.

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