CHAPTER 1

INTRODUCTION

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With the introduction of deregulation in power industry, many challenges have been faced by the participants in the emerging electricity market. Forecasting electricity parameters such as load and price have become a major issue in deregulated power systems [1]. The fundamental objective of electric power industry deregulation is efficient generation, consumption of electricity, and reduction in energy prices. To achieve these goals, accurate and efficient electricity load and price forecasting has become more important [2].

Accurate forecasting of electricity demand not only will help in optimizing the start-up of generating units it also save the investment in the construction of required number of power facilities and help to check the risky operation and unmet demand, demand of spinning reserve, and vulnerability to failures [3]-[4].

Price forecasting provide crucial information for power producers and consumers to develop bidding strategies in order to maximize profit. It plays an important role in power system planning and operation, risk assessment and other decision making. Its main objective is to reduce the cost of electricity through competition, and maximize efficient generation and consumption of electricity. Because of the non-storable nature of electricity, all generated electricity must be consumed. Therefore, both producers and consumers need accurate price forecasts in order to establish their own strategies for benefit or utility maximization [5].

In general, electricity demand and price in the wholesale markets are mutually intertwined activities. Short-term load forecasting is mainly affected by weather parameters. However, in short-term price forecasting, prices fluctuate cyclically in response to the variation of the demand. Many factors which influence the electricity price, such as hour of the day, day of the week, month, year, historical prices and demand, natural gas price etc. The restructured power market is co-ordinated by an independent system operator (ISO). In these deregulated power market, it is observed that daily power demand curves having similar pattern, but the daily price curves are volatile. Therefore, forecasting of locational marginal price (LMPs) become more important as it helps market participants not only to determine the bidding strategies of their generators, but also in risk management.

Various AI techniques used in load and price forecasting problem are expert systems, fuzzy inference, fuzzy-neural models, artificial neural network (ANN). Among the different techniques of forecasting, application of ANN for forecasting in power system has received much attention in recent years [6]-[9]. The main reason of ANN becoming so popular lies in its ability to learn complex and nonlinear relationships that are difficult to model with conventional techniques [10].

Here, artificial neural network designed using MATLAB R12 & R13 has been used to compute the short-term load forecast of different power market i.e. ISO New England market, PJM electricity market, Ontario electricity market & Toronto city of Ontario market, Canada. Also, short-term price forecast in ISO New England market has been performed. Both the hourly temperature and hourly electricity load, historical data have been used in forecasting. The temperature variable is included because temperature has a high degree of correlation with electricity load. In price forecasting hourly natural gas data has been also considered as an input for forecast. The neural network models are trained on hourly data from the ISO New England, PJM market, Ontario market & Toronto of Ontario market from 2007 to 2011 and tested on out-of-sample data from 2012. The simulation results obtained have shown that artificial neural network (ANN) is able to make very accurate short-term load and price forecast. Box plots of the error distribution of forecasted load and price have been plotted as a function of hour of the day, day of the week [11].

Optimization is a mathematical technique that concerns the finding of maxima or minima of functions in some feasible region. Here, different optimization techniques like genetic algorithm, pattern search, minimax optimization, hybrid of genetic & pattern search algorithm, hybrid of genetic algorithm & fmincon & Particle Swarm Optimization have been successfully applied to solve the ELD problem & day ahead economic load forecast (DAELF) problems using IEEE 30-bus (06 machine) & standard 26-bus (06 thermal units & 46 transmission line) system for satisfying the demand [12]-[13].

This thesis has been organized in eight chapters. Chapter 2 shows the literature survey. Chapter 3 presents the overview of neural network used**.** Chapter 4 discusses the selection of various data and model of ANN for day-ahead load and price forecasting. Results of simulation are presented in Chapter 5. Application of optimization technique in power market is discussed in Chapter 6. Chapter 7 discusses the conclusion. The future scope of work is discussed in Chapter 8.

CHAPTER 2

LITERATURE SURVEY

CHAPTER 2

LITERATURE SURVEY

Electric supply industry is changing from the monopoly to a competitive market environment with vertical as well as horizontal disintegrations of businesses. The emerging power system faces various challenges associated with uncertainly in the system information/data, complexity and time-line pressure of system operation and planning, etc. In the vertically integrated electricity supply industry, load forecasting has been a very important activity in the power system planning but due to introduction of competition in the electricity sector, the forecasting of several variables such as electric load, electric price, spinning reserves, bid prices, etc. is difficult task. The forecasting of these variables is challenging not only due to several market payers but also due to imperfect competition in the electricity markets such as energy market, ancillary service market, transmission market, etc. Moreover, various trading arrangements [14] such as pool model, bilateral dispatch model, pool plus bilateral model and multilateral model have different degree of uncertainties. Based on the number of suppliers, market may be classified as perfectly competitive market, oligopoly market or monopoly

Load forecasting in a power system can normally be segregated into three categories (i) short-term forecasting with a lead-time of up to a few days ahead, (ii) medium-term forecasting over a six month or one year period and (iii) long-term forecasting of the power system. Many activities in the competitive electricity markets, such as trading and risk management, are directly dependent on the quality of the price forecasting in order to evaluate derivatives and devise hedging strategies. Accurate price forecasting helps utilities, independent power producers and customers to submit effective bids with low risks in order to maximize their benefits.

2.1 Forecasting Methods

A range of methods for the load price, bid and SR forecasting have been suggested in the literature, Some conventional methods of forecasting are time-of-day method, regression method, stochastic time series methods like auto-regressive moving average (ARMA), integrated auto-regressive moving average (ARIMA), box-Jenkins method, linear time series models, multivariate adaptive regression splines (MARS), generalized auto-regressive conditional hetero-scedasticity (GARCH), etc. these forecasting approaches are having their own limitations in predicting the non-stationary, highly volatile signals. Artificial intelligence (AI) techniques such as fuzzy logic (FL), expert system, evolutionary computation (EC), genetic algorithm (GA), ant colony search (ACS), simulated annealing (SA), Tabu search (TS), Particle swarm optimization (PSO) and artificial neural network (ANN) promise a good predictability or nearly so and have been emerged in recent years in power systems' variables forecasting problems in power system area. However, these methods have main limitations of their sensitivity to the choice of parameters, such as the crossover and mutation probabilities in GA, temperature in SA, scaling factor in EP and inertia weight and learning factors in PSO. However, AI relies heavily on good problem description and extensive domain knowledge.

Many researchers have applied wavelet transformation as a preprocessor to decompose the ill-behaved series into better behaved consecutive series and then forecasting models like ARIMA and ANN have been applied for forecasting. To take care of high-frequency changes, fuzzy model has been applied to forecast the possible ranges of variations in the electricity load and price. Dynamic fuzzy system (DFS), extended Kalman filter (EKF) and an input/output hidden Markov model (IOHMM) have been applied for the forecasting of variables in electricity markets. A probabilistic methodology based on the integration of the loss of load cost (LOLC) concept in the capacity bidding process has been used to determine the operating reserve requirements and pricing.

ANN can acquire knowledge though adaptive training and generalization, hence, will be most useful AI technique for load, price, bid and SR forecasting. A feed forward multi-layer perception (MLP) model with back propagation (BP) training algorithms (Gradient descent/ conjugate gradient method) has been applied for electricity load, price and bid forecasting. Cascaded architecture of multiple ANNs and committee machine replace the single neural network for complex nonlinear mapping functions. Radial basis function neural network (RBFNN) and recurrent neural network (RNN) have also been proposed for forecasting due to several advantages. A new fuzzy-neural network (FNN) technique with higher learning capability has been proposed to forecast market parameters.

2.2 Load Forecasting Methods

Many conventional methods such as time-series method, regression method, stochastic time series methods, and state space methods have been used for load forecasting. Expert system models are usually able to take both quantitative and qualitative factors into account. Many models of this type have been proposed since mid-1980. A typical approach is to imitate the reasoning of a human operator and to reduce the analogical thinking behind the intuitive forecasting to formal steps of logic [15]. A possible method for a human expert to forecast is to search in historical database for a day that corresponds to the target day with factors like day are taken as the basis for the forecast. An expert system can thereby be an automated version of this kind of a search process [16]. On the other hand, the expert system can consist of a rule base defining relationships between external factors and daily load shapes. A popular approach to develop rules on the basis of fuzzy logic has been reported in reference [17]. The heuristic approach in arriving at solutions makes the expert system methods attractive for the system operators [18].

In recent years, artificial neural networks (ANNs) have been applied to many areas of power system analysis and control such as load forecasting [19], static and dynamic security assessment, dynamic load modeling, alarm processing and fault diagnosis [20]. These applications take advantage of the powerful mapping ability of ANNs and their inherently parallel and distributed processing characteristics for performing ultra-high-speed computation. Artificial neural network (ANN), whose operation is based on certain known properties of biological neurons, comprises various architectures of highly interconnected processing elements that offer an alternative to conventional computing approaches. They can achieve complicated input-output mappings without explicit programming and extract relationships (both linear and nonlinear) among data sets presented during a learning process. Furthermore, the redundancy of their inter connections ensures robustness and fault tolerance and they can be designed to self-adapt and learn [21]-[22].

The application of ANNs to the short-term load forecasting has gained a lot of attention. Dillon et al. [23] used adaptive pattern recognition and self-organizing techniques for short term load forecasting. Later, they used an adaptive neural network for short term load forecasting [24]. The availability of historical load data in the utility databases makes this area highly suitable for ANN implementation. ANNs are able to learn the relationship among weather variables and loads. As in the time series approach, the ANN traces previous load patterns and predicts (i.e., extrapolates) a load pattern using recent load data [25]. The ANN is able to perform non-linear modeling and adaptation. Their ability to perform better than traditional methods especially during rapidly changing weather conditions and the less time, have made ANN based load forecasting models very attractive for on-line implementation in energy control centers.

2.3 Price Forecasting Methods

Market simulation methods, which, generally, utilize several hypotheses, consider the generators' operation cost with the generator and transmission constraints. This approach is suitable for long-term price forecasting. Statistical methodology, which is based on the assumption of historical price characteristics, can be categorized in to the time series models, intelligent system methods and volatility analysis. Many of these methods are used for the short term load forecasting (STLF).

Time-series models provide a trade-off between underlying price behavior and accurate forecasting. Contreras et al. [26] have developed auto regressive integrated moving average (ARIMA) model to forecast electricity market prices of the Spanish and Californian markets. Multivariate dynamic regression (DR) and transfer function

(TF) models have been applied to forecast the Spanish and California market prices [27] and the PJM market prices [28]. DR relates current price to the past prices and past demand whereas TF relates current price to past prices, past demands and past errors. Time series models have been also applied to forecast commodity prices [29] such as oil [30] and natural gas [31]. Early applications of the time series models in the power system were for STLF. Simple auto regressive (AR) models are also being used to predict weekly prices in the Norwegian system [32]. A Bayesian-based classification method combined with an AR model is presented in [33] to predict the discrete probability density functions (PDF) of the market clearing prices (MCP). In [34], the performance of ARIMA model was improved by incorporating forecasted error.

The non-leaner multivariate adaptive regression splines (MARS) technique has been applied to forecast hourly energy price [35]. Generalized auto-regressive conditional hetero-scedasticity (GARCH) uses past variances and past variance forecasts to forecast future variance and has been applied to forecast day-ahead electricity price for Spain and California market. [36]

A typical artificial neural network (ANN) for electricity price forecasting is feed forward multi-layer perceptron (MLP) model with back propagation (BP) training algorithm (gradient descent) [37]-[38] or with conjugate gradient algorithm [39]. A single neural network with traditional learning algorithms may not be suitable for complex nonlinear mapping function of the price signal. Cascaded architecture of multiple ANNs [40] and committee machine [41] replace the single neural network. Radial basis function neural network (RBNN) [42] and recurrent neural network (RNN) [43] have also been proposed for forecasting due to several advantages.

CHAPTER 3

ARTIFICIAL NEURAL NETWORK FOR LOAD AND PRICE FORECASTING

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ARTIFICIAL NEURAL NETWORK FOR LOAD AND PRICE FORECASTING

3.1 Overview of Electricity Load Forecasting Problems & Methods

Forecasting electricity loads had reached the state of maturity. Short-term (a few minutes, hours, or days ahead) to the long term (up to 20 years ahead) forecasts, in particular have become increasingly important since the restructuring of power systems. Many countries have recently privatized and deregulated their power systems, and electricity has been turned into a commodity to be sold and bought at market prices. Since the load forecasts play a crucial role in the composition of these prices, they have become vital for the electricity industry. Load forecasting is however a difficult task. First, because the load series is complex and exhibits several levels of seasonality: the load at a given hour is dependent not only on the load at the previous hour, but also on the load at the same hour on the previous day, and on the load at the same hour on the day with the same denomination in the previous week. Secondly, because there are many important exogenous variables that must be considered, specially weather related variables.

Most forecasting models and methods have already been tried out on load forecasting, with varying degrees of success. Some of the models reported in literatures are multiplicative autoregressive models, dynamic linear or nonlinear models, autoregressive models, and methods based on Kalman filtering, Box and Jenkins transfer functions ARMAX models, optimization techniques, nonparametric regression. Despite this large number of alternatives, however, the most popular causal models are still the linear regression ones and the models that decompose the load, usually into basic and weather dependent components. These models are attractive because some physical interpretation may be attached to their components, allowing engineers and system operators to understand their behavior. However, they are basically linear models, and the load series they try to explain are known to be distinctly nonlinear functions of the exogenous variables. Several research works have been carried out on the application of artificial intelligence (AI) techniques to the load forecasting problem. Various AI techniques reported in literatures are expert systems, fuzzy inference, fuzzy-neural models, neural network (NN). Among the different techniques on load forecasting, application of NN technology for load forecasting in power system has received much attention in recent years. The main reason of NN becoming so popular lies in its ability to learn complex and nonlinear relationships that are difficult to model with conventional techniques

3.2 Overview of Electricity Price Forecasting Problems & Methods

The main objective of electricity market is to maximize profits. Forecasting loads and prices in electricity markets are mutually intertwined activities, and error in load forecasting will propagate to price forecasting. Electricity price has its special characteristics. The main features that make it so specific are at least three. One of them is its non-storability of power, which implies that prices are strongly dependent on the power demand. Another characteristic is the seasonal behavior of the electricity price at different level (daily, weekly and annual seasonality) and the third one is related to the question of its transportability. Furthermore, electricity price can rise by tens of or even hundreds of times of its normal value showing one of the greatest volatilities among all commodities. Electricity cannot be transported from one region to another one because of existing bottle-necks or limited transportation capacity. Application of forecasting methods common in other commodity markets, can have a large error in forecasting the price of electricity.

In most competitive electricity markets, the hourly price series have the characteristics such as volatility, non-stationary properties, multiple seasonality, spikes and high frequency. These characteristics are due to events that may occur alternatively in a market. For instance, a price spike that is a randomized event can be caused by market power, and also by unexpected incidents such as transmission congestion, transmission contingency and generation contingencies. It can also be influenced by other factors such as fuel prices, generation unit operation costs, weather conditions, and probably the most theoretically significant factor, the balance between overall system supply and demand.

Applications of electricity price forecasting fall into different time horizons: short-term forecasting, medium-term forecasting and long-term forecasting. Market participants need to forecast short-term (mainly one day-ahead) prices to maximize their profits in spot markets. Accurate medium term price forecasts are necessary for successful negotiations of bilateral contracts between suppliers and consumer. Long-term price forecasts influence the decisions on transmission expansion and enhancement, generation augmentation, distribution planning and regional energy exchange.

Electricity price forecasting models include statistical and non-statistical models. Time-series models, econometric models and intelligent system methods are the three main categories of statistical methods. Non-statistical methods include equilibrium analysis and simulation methods. Methods based on time-series or NN is more common for electricity price forecasting due to their flexibility and ease of implementation. Data mining technique has been used to forecast electricity price and price spikes in and, respectively. Nogales have proposed time-series models, including dynamic regression and linear transfer function models for short-term price forecasting. The main drawback of time-series model is that they are usually based on the hypothesis of stationarity; however, the price series violate this assumption. Another kind of time-series models like Generalized Autoregressive Conditional Heteroskedastic (GARCH) and Input-Output Hidden Markov models (IOHMM) have been developed in order to solve this problem. However, their application to electricity price prediction encounters difficulty. A rapid variation in load can have a sudden impact on the hourly price. The time-series techniques are successful in the areas where the frequency of the data is low, such as weekly patterns, but they can be problematic when there are rapid variations and high-frequency changes of the target signal. Hence, there is a need of more efficient forecast tool capable of learning complex and non-linear relationships that are difficult to model with conventional techniques.

Neural networks are composed of simple elements called neuron, operating in parallel. A neuron is an information processing unit that is fundamental to the operation of a neural network. The three basic elements of the neuron model are-

- A set of weights.
- An adder for summing the input signals.
- Activation function for limiting the amplitude of the output of a neuron.

Artificial neural network is inspired by biological nervous systems. As in nature, the connections between elements largely determine the network function. The Fig. 3.1 illustrates such a situation. A neural network can be trained to perform a particular function by adjusting the values of the connections (weights) between elements. In load forecasting, typically, many input/ target pairs are needed to train a neural network.

Typically, neural networks are adjusted, or trained, so that a particular input leads to a specific target output. The Fig. 3.2 illustrates such a situation. Here, the network is adjusted, based on a comparison of the output and the target, until the network output matches the target. Typically, many such input/target pairs are needed to train a network. Neural networks have been trained to perform complex functions in various fields, including pattern recognition, identification, classification, speech, vision, and control systems. Neural networks can also be trained to solve problems that are difficult for conventional computers or human beings. In fitting problems, neural network is mapped between data set of numeric inputs and a set of numeric targets. The neural network fitting tool consists of two-layer feed-forward network with sigmoid hidden neurons and linear output neurons. It can fit multi-dimensional mapping problems arbitrarily well, given consistent data and enough neurons in its hidden layer. The neural network is trained with Levenberg-marquardt back propagation algorithm.

For a perfect fit, the data should lie along a 45 degree line, where the neural network outputs are equal to the targets. If the performance on the training set is good, but the test set performance is significantly worse, which could indicate over fitting, and then by reducing the number of neurons can give good results. Regression R Values measure the correlation between outputs and targets. If R value is 1 means a close relationship, 0 a random relationship. If training performance is worse, then increase the number of neurons. Mean squared error which is the average squared difference between outputs and targets indicates the accuracy of forecasting.

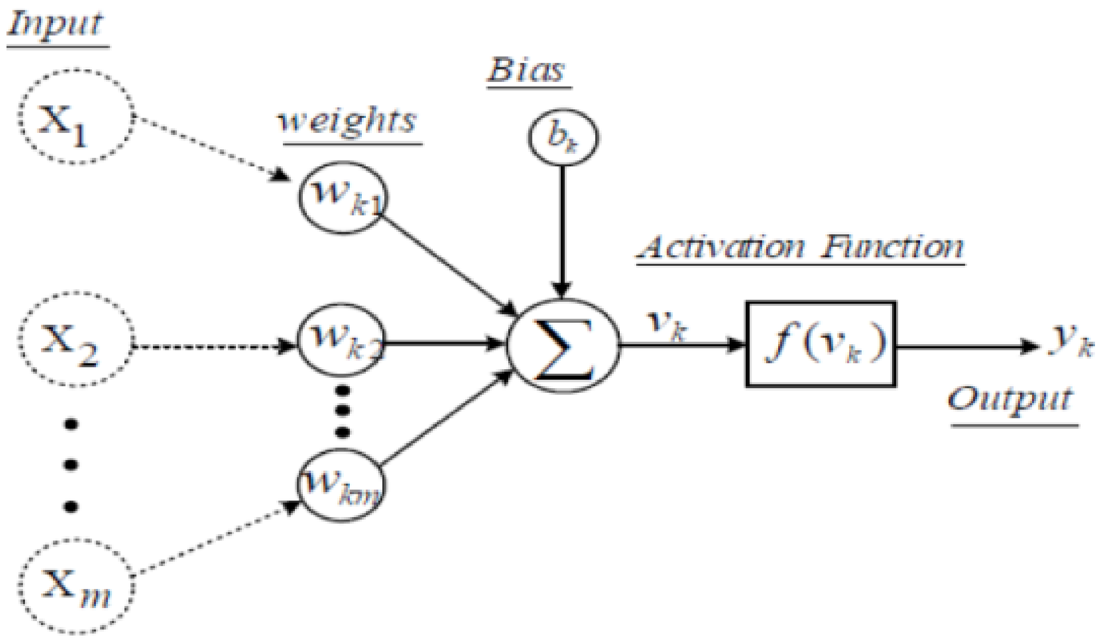

Figure 3.1. Model of an artificial neural network (ANN).

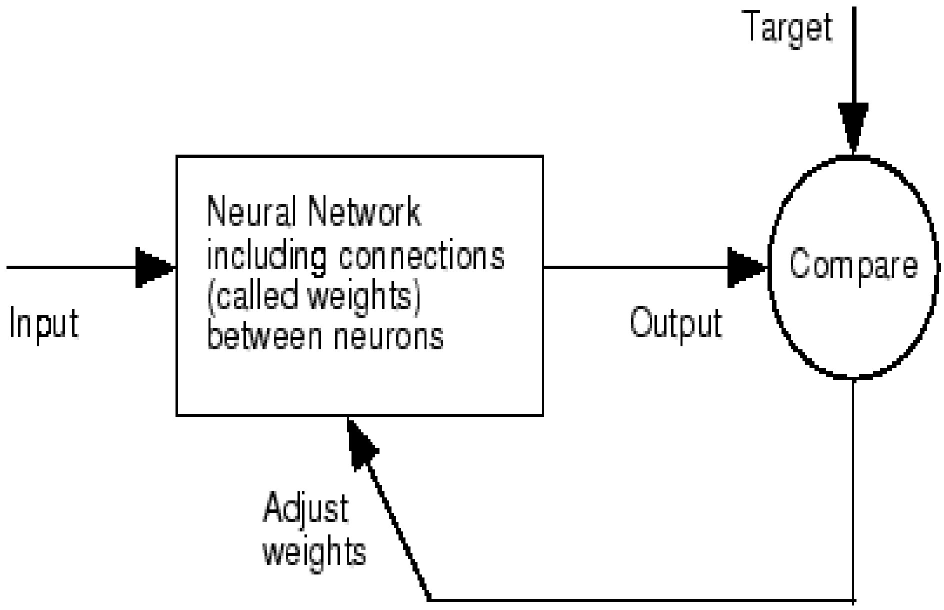

Figure 3.2. Working model of an ANN by adjusting it weights.

CHAPTER 4

DATA INPUTS AND ANN MODEL

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DATA INPUTS AND ANN MODEL

The models are trained on hourly data from the ISO New England market, PJM electricity market, Ontario electricity market & Toronto city of Ontario market from 2007 to 2011 and tested on out-of-sample data from 2012. The data used in the ANN model are historical data of both the temperature and hourly electricity load.

The relationship between demand and average temperature for ISO New England, Ontario electricity market & Toronto city of Ontario market is shown in Fig. 4.1, Fig. 4.2 & Fig. 4.3 respectively, where a close relationship between load and temperature can be observed.

Hourly temperature data for location in high demand area of has been considered in this thesis. Relationship between LMP and system load for ISO New England market in year 2012 is shown by Fig. 4.4. It shows that as the system load increases with LMP and both are highly correlated. Fig. 4.5 shows the effect of natural gas price on LMP for ISO New England market and both are interdependent.

The ANN model includes creating a matrix of inputs from the historical data, selecting and calibrating the chosen model and then running the model. For the load forecast, the inputs include

- Dry bulb temperature
- Dew point temperature
- Hour of day
- Day of the week
- Holiday/weekend indicator (0 or 1)
- Previous 24-hr average load
- 24-hr lagged load

- 168-hr (previous week) lagged load

Similarly for price forecast, the inputs include

- Dry bulb temperature
- Dew point temperature
- Hour of day
- Day of the week
- Holiday/weekend indicator (0 or 1)
- System load
- Previous day's average load
- Load from the same hour the previous day
- Load from the same hour and same day from the previous week
- Previous day's average price
- Price from the same hour the previous day
- Price from the same hour and same day from the previous week
- Previous day's natural gas price
- Previous week's average natural gas price

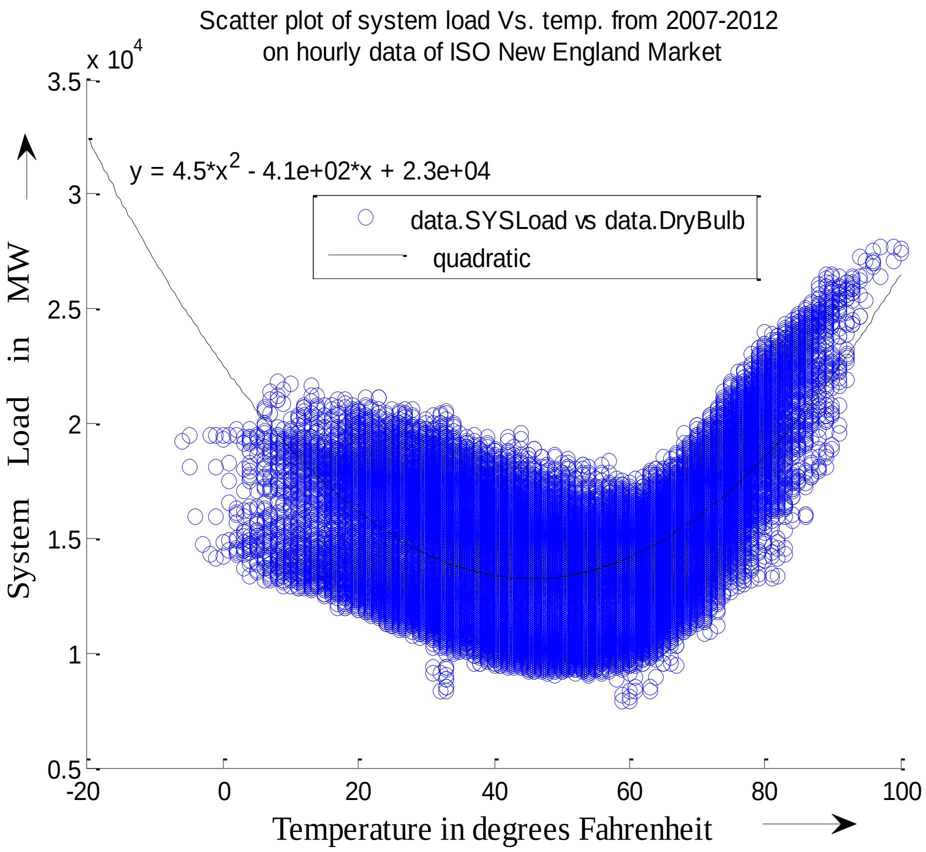

Fig. 4.1. Scatter plot of system load vs. temperature with quadratic fitting equation.

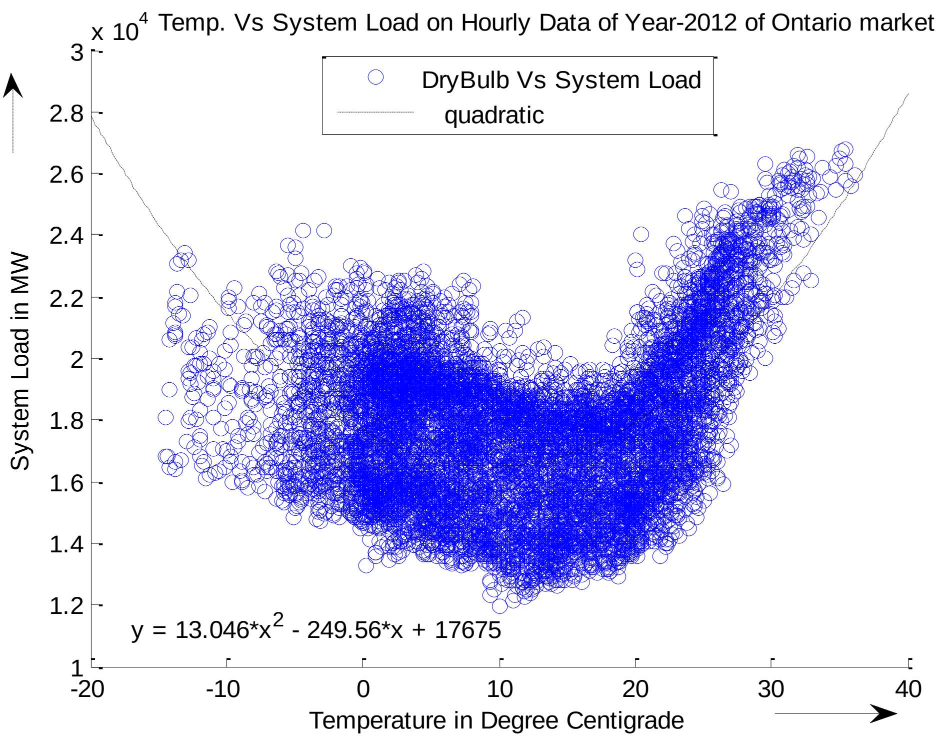

Fig. 4.2. Scatter plot of system load vs. temperature with quadratic fitting equation.

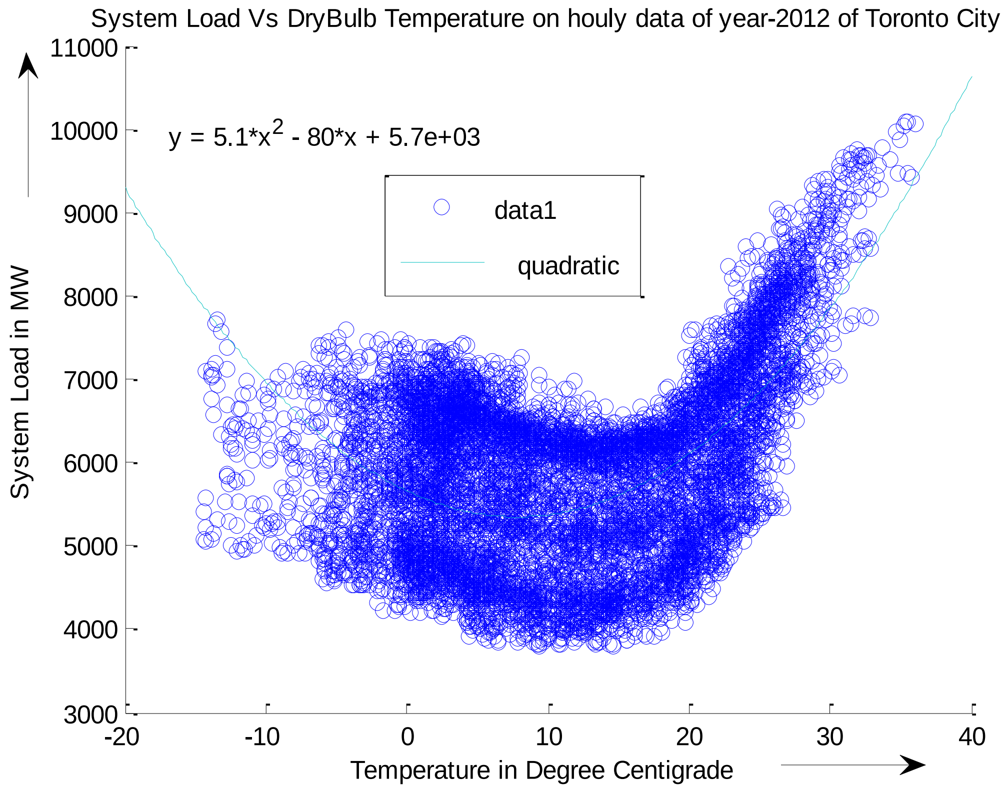

Fig. 4.3. Scatter plot of system load vs. temperature with quadratic fitting equation.

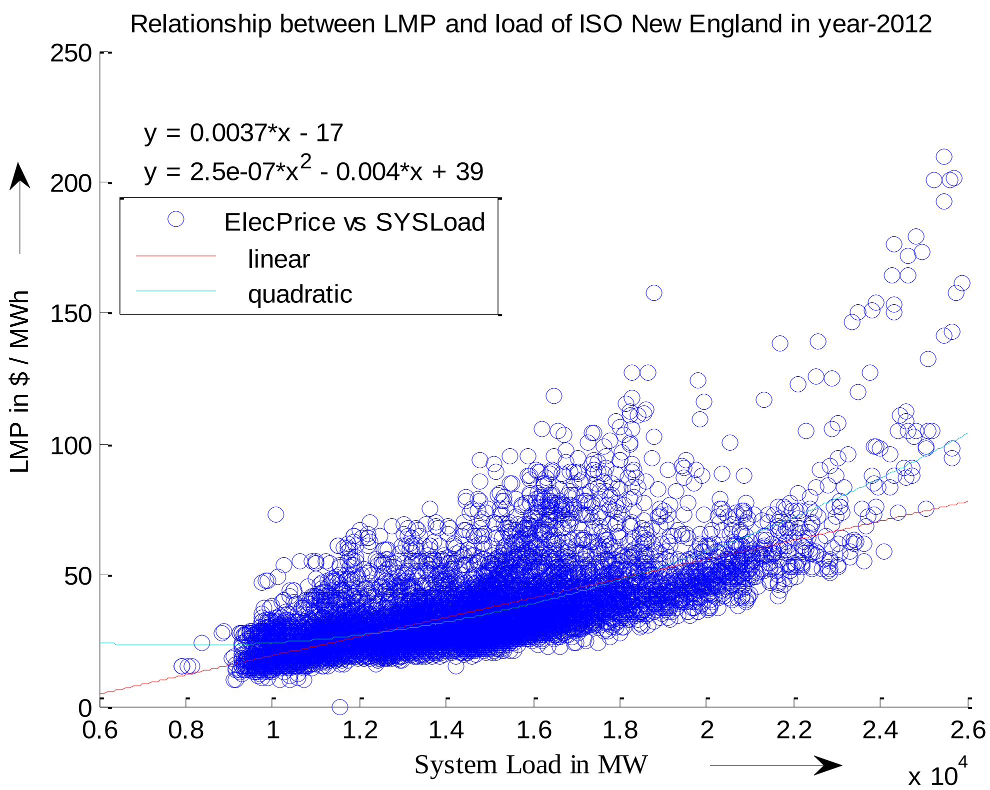

Fig. 4.4. Scatter plot between LMP and load with linear and quadratic fitting equation.

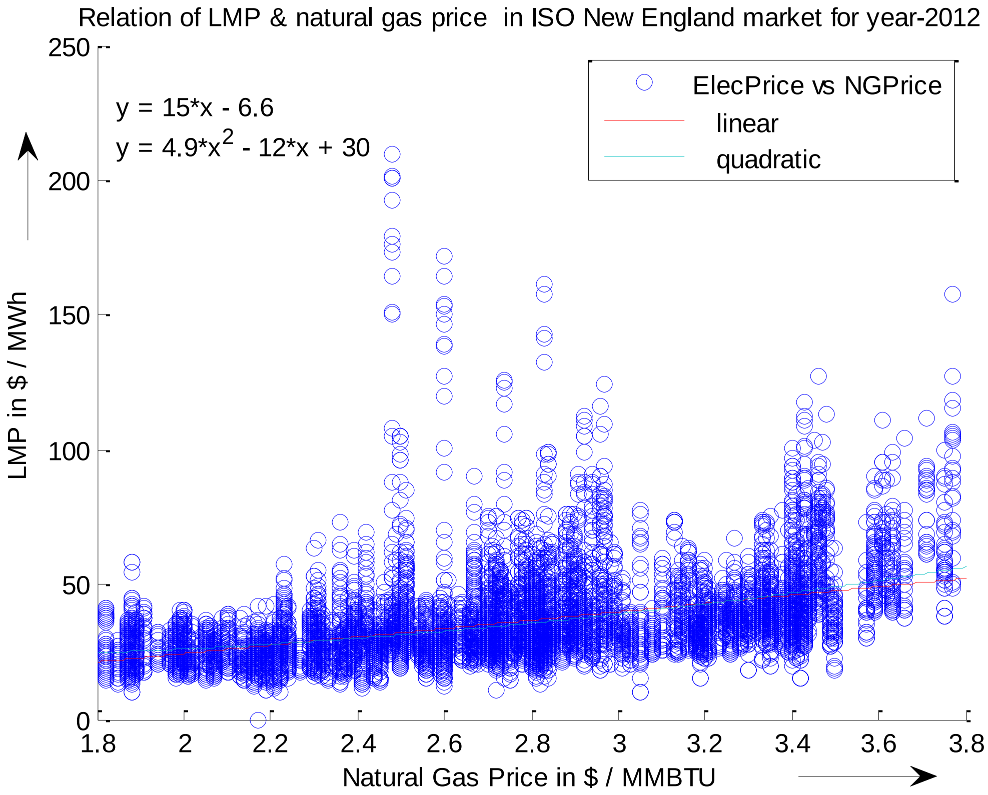

Fig. 4.5. Scatter plot between LMP and natural gas price with fitting equations.

CHAPTER 5

SIMULATION RESULTS

CHAPTER 5

SIMULATION RESULTS

5.1 Overview

Hourly day-ahead load forecasting has been done for each day, sample of each week & month of data of year 2012 using neural network tool box of MATLAB R12 & R13. The ANNs are trained with data from 2007 to 2011 and tested on out-of-sample data from 2012 of ISO New England market, PJM electricity market, Ontario electricity market & Toronto of Ontario market.

Also hourly day-ahead price forecasting has been done for each day, sample of each week & month of data of year 2012 using neural network tool box of MATLAB R12a. The ANNs are trained with data from 2007 to 2011 & and tested on out-of-sample data from 2012 of ISO New England market.

The test sets are completely separate from the training sets and are not used for model estimation or variable selection. Various plots of the error distribution as a function of hour of the day, day of the week are generated. Also, the various plots comparing the day ahead hourly actual and forecasted load and price for each day, each week for the testing year 2012 are also generated. Simulation results of ISO New England market, PJM electricity market, Ontario electricity market & Toronto city of Ontario Market is discussed below.

In the ANN's accuracy on out-of-sample periods is computed with the Mean Absolute Percent Error (MAPE) metrics. The principal statistics used to evaluate the performance of these models, mean absolute percentage error (MAPE), is defined in eq. 5.1 below

$$MAPE\,[\%] = \frac{1}{N}\sum_{i=1}^{N}\frac{\left|L_A^i - L_F^i\right|}{L_A^i}\times 100 \tag{5.1}$$

Where L_A & L_F are actual & forecasted load respectively & N is the number of data inputs.

MAPE has been taken as a matric as a measure of error to show the effectiveness of the ANN over an average span of time. Most of time ANN is forecasting with minimum possible error and high absolute error at one or two instances may occur but effectiveness of ANN remains good most of the time. These errors may also be checked with more modifications in the ANN.

For price forecasting the accuracy of forecast is accomplished by MAPE, this is computed as in eq. 5.2 below

$$MAPE\,[\%] = \frac{1}{N}\sum_{i=1}^{N}\frac{\left|P_A^i - P_F^i\right|}{P_A^i}\times 100 \tag{5.2}$$

Where P_A and P_F are the actual and forecasted hourly prices, N is the number of hours, and i is the hour index.

Also, the ANN’s accuracy on out-of-sample periods is computed with the Mean Absolute Error (MAE) metrics. It is defined in eq. 5.3 below

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left|P_i^{\mathrm{true}} - P_i^{\mathrm{forecast}}\right| \tag{5.3}$$

Where P_i^{true} & $P_i^{forecast}$ are the actual & forecasted hourly load or price, N is the number of hours, and i is the hour index.

5.2 Load Forecasting of ISO New England Market

The ANN model used in the forecasting is shown below in Fig. 5.2.1. It has input, output and one hidden layers. Hidden layer has 48 neurons. Inputs to the neurons are as listed above for load forecasting model. After simulation the MAPE obtained is 1.59% for load forecasting for testing year 2012, as shown in Fig. 5.2.2.

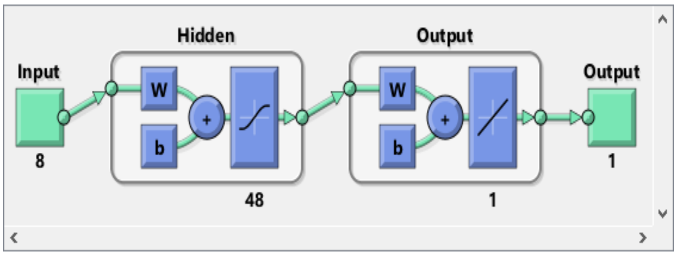

Fig. 5.2.1 Showing eight different input data for one target data with 48 neurons.

The box-plot of the error distribution of forecasted load as a function of hour of the day is presented in Fig. 5.2.3. It shows the percentage error statistics of hour of the day in year 2012. It is also evident that the maximum error is for the 21st hour of the day and minimum error for 14th hour of the day in year 2012. The box-plot of the error distribution of forecasted load as a function of day of the week is evaluated in Fig. 5.2.4 which shows the percentage error statistics of day of the week in year 2012. The maximum error is for the Monday and minimum error for Saturday in year 2012.

Multiple series plots between actual load & forecasted load from 29 January, 2012 to 04 February, 2012 & from 28 October, 2012 to 03 November, 2012 for ISO New England market and also plots of MAPE with maximum error (3.87%) and minimum error (0.90%) for weekly testing samples have been shown in Fig. 5.2.5 and Fig. 5.2.6.

From the results obtained from Table 5.7, it is clear that maximum MAPE (2.10%) is for October, 2012 and minimum MAPE (1.18%) is for February, 2012 for day ahead monthly load forecast in ISO New England market, as shown in Fig. 5.2.7 & Fig 5.2.8. Multiple series plots between actual load & forecasted load on 24 December, 2012 for ISO New England market and also plots of MAPE with maximum error (6.23 %) for day ahead hourly forecast in year 2012 have been shown in Fig. 5.2.9. Also there is least error for daily load forecast on 28 Sep., 2012 in the year 2012 with MAPE (0.48%) for ISO New England market is shown in Fig. 5.2.10. Result for daily MAPE for day ahead hourly load of ISO New England market for whole year is discussed in Table 5.1.

Comparison of MAPE (%) using different methods of load forecast has been shown in Table 5.2.1 with their maximum & minimum MAPE in their testing interval [1]-[10].Also, from Table 5.2.1 it is clear that average MAPE is 1.59% for load forecast in the testing year 2012 by using ANN proposed. This is much better than the existing models of load forecast.

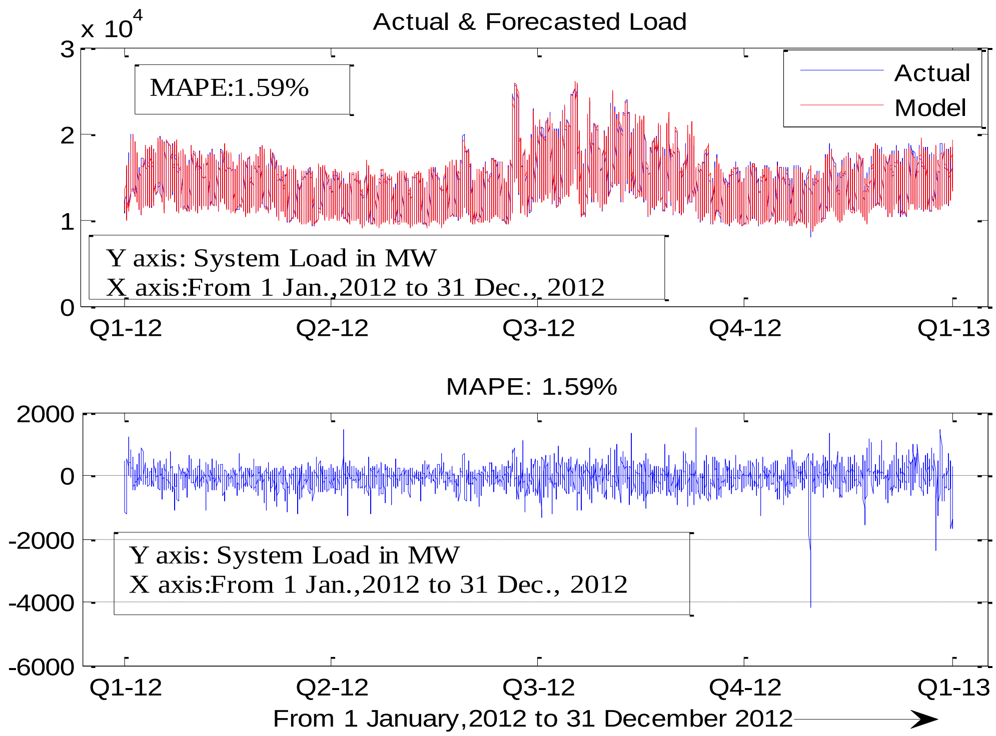

Figure 5.2.2. Plot between actual & forecasted load for ISO New England market.

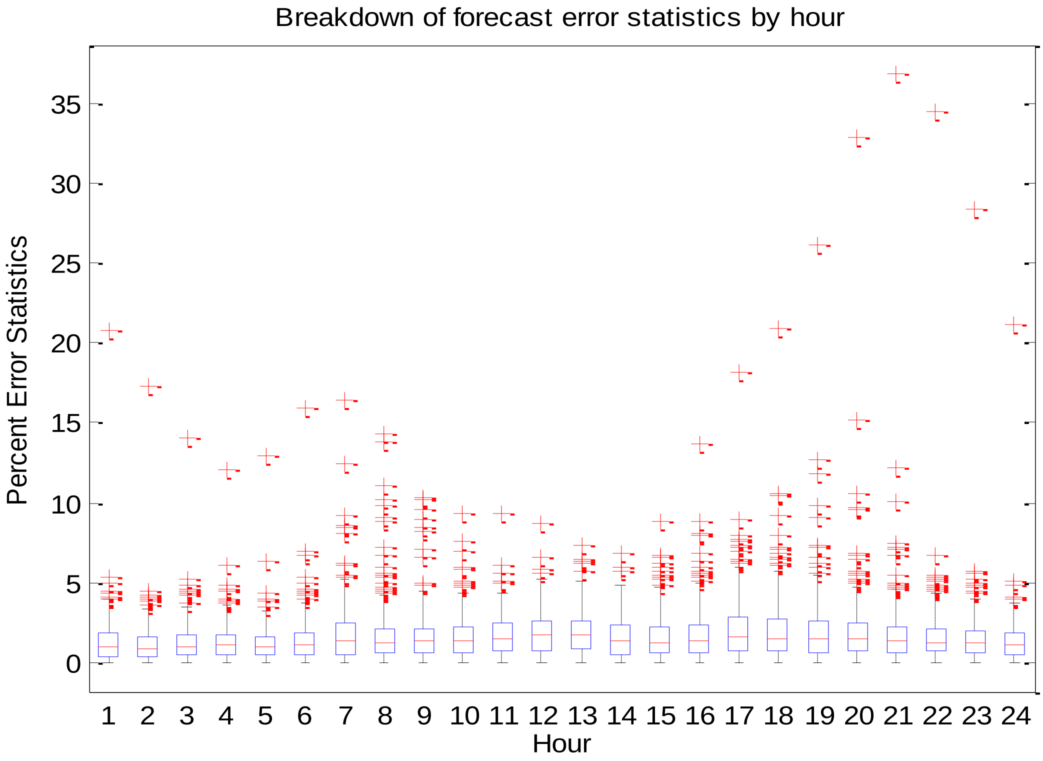

Figure 5.2.3. Box-plot of the error distribution of forecasted load as a function of hour of the day for year 2012.

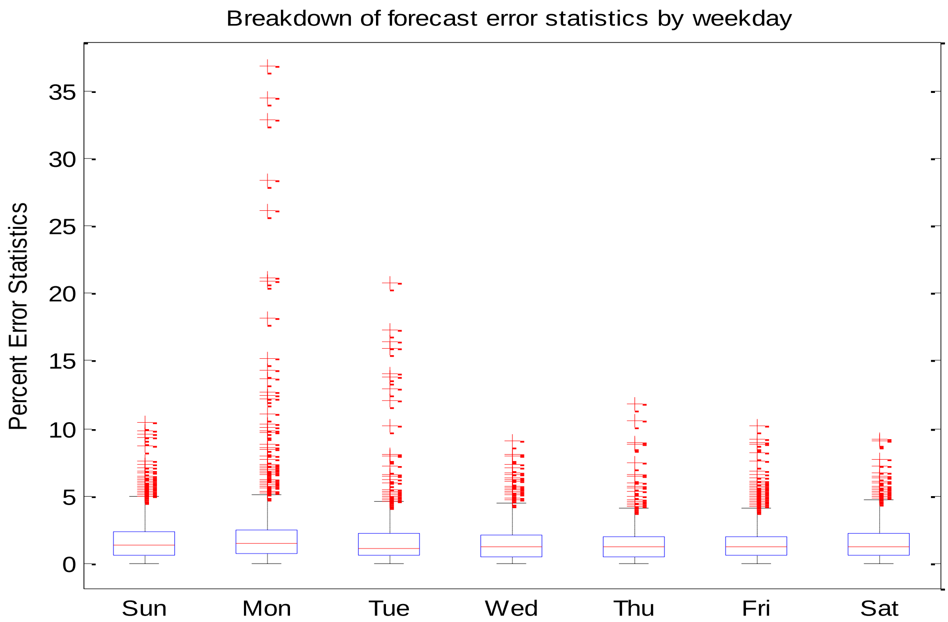

Figure 5.2.4. Box-plot of the error distribution for the forecasted load as a function of day of the week in the year 2012.

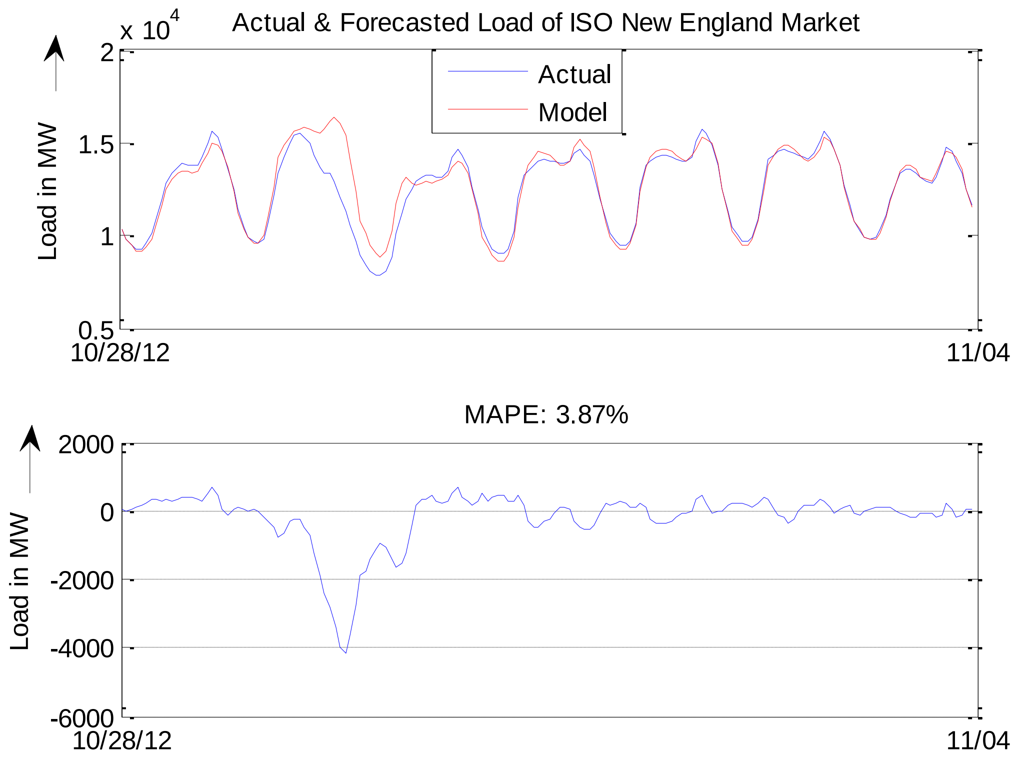

Figure 5.2.5. Maximum MAPE is 3.87% for the load forecast of 28 October, 2012 to 03 November, 2012.

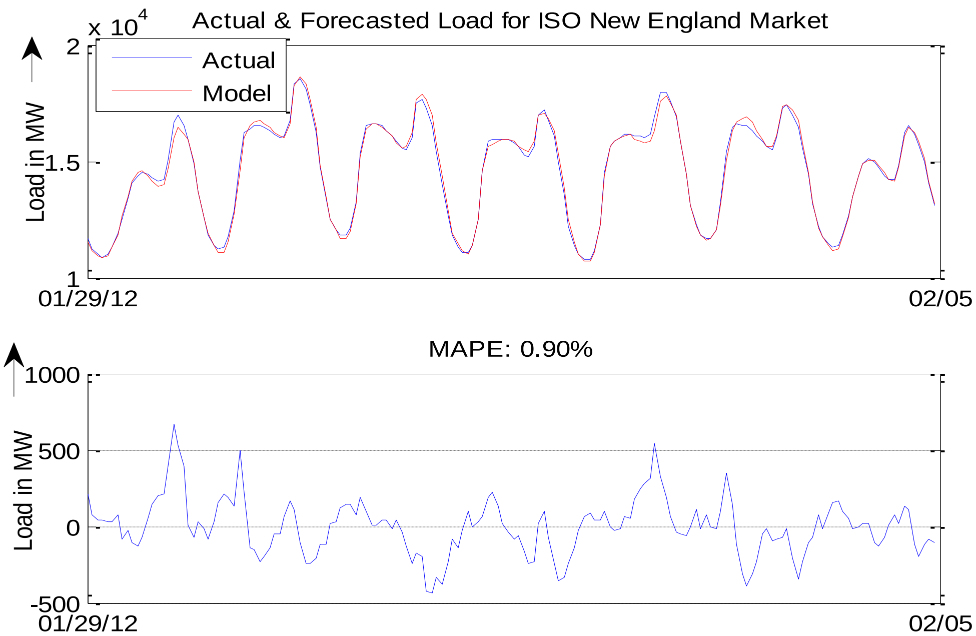

Figure 5.2.6. Minimum MAPE is 0.90% for the load forecast of 29 January, 2012 to 04 February, 2012.

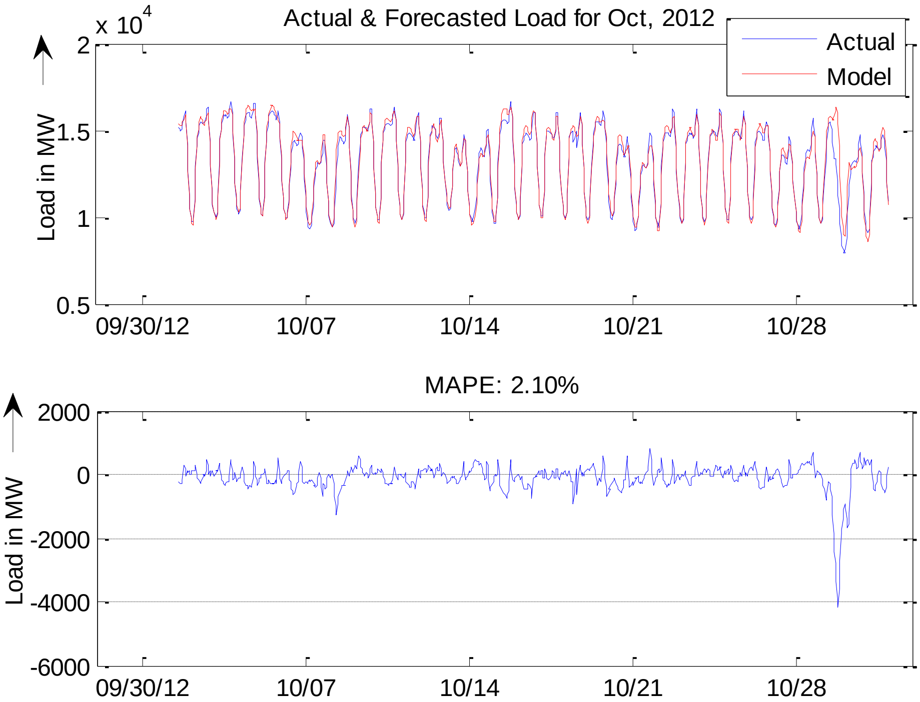

Fig. 5.2.7. Maximum MAPE is 2.10% for day ahead hourly-monthly forecast for the forecast of Oct., 2012 of ISO New England market in year 2012.

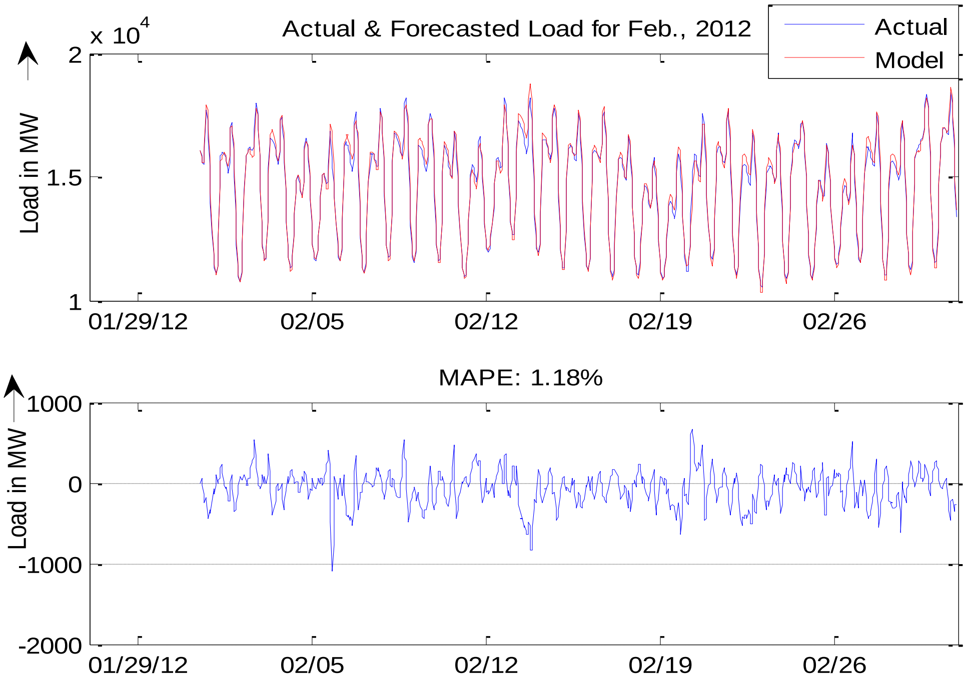

Fig. 5.2.8. Minimum MAPE is 1.18% for day ahead hourly-monthly forecast for the forecast of Feb., 2012 of ISO New England market in year 2012.

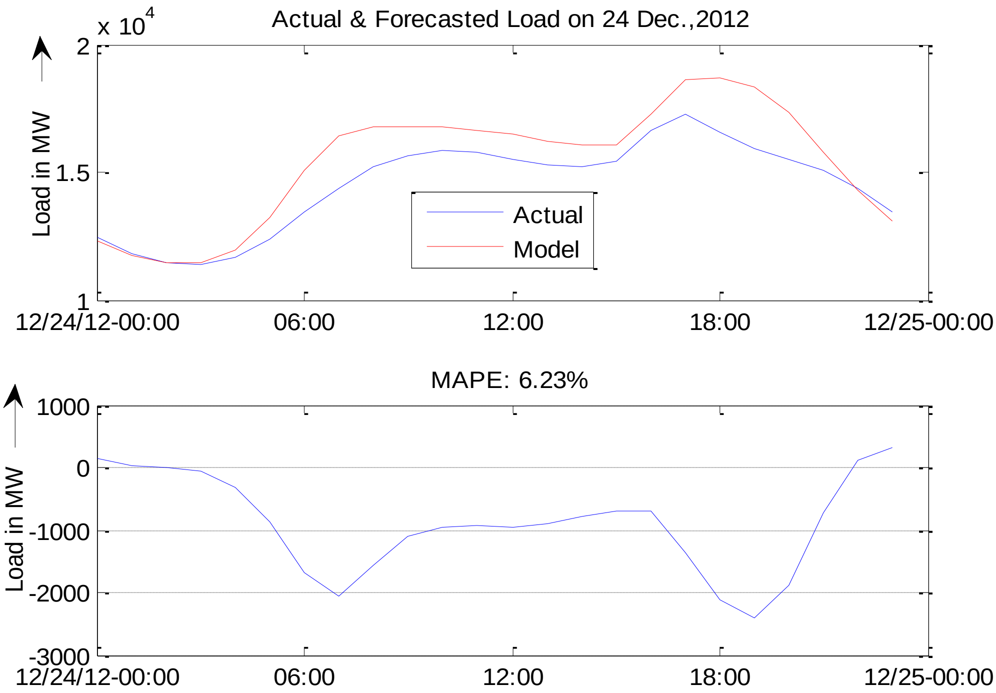

Fig. 5.2.9. MAPE is maximum (6.23%) for day ahead hourly forecast for the forecast on 24 Dec., 2012 of ISO New England market in year 2012.

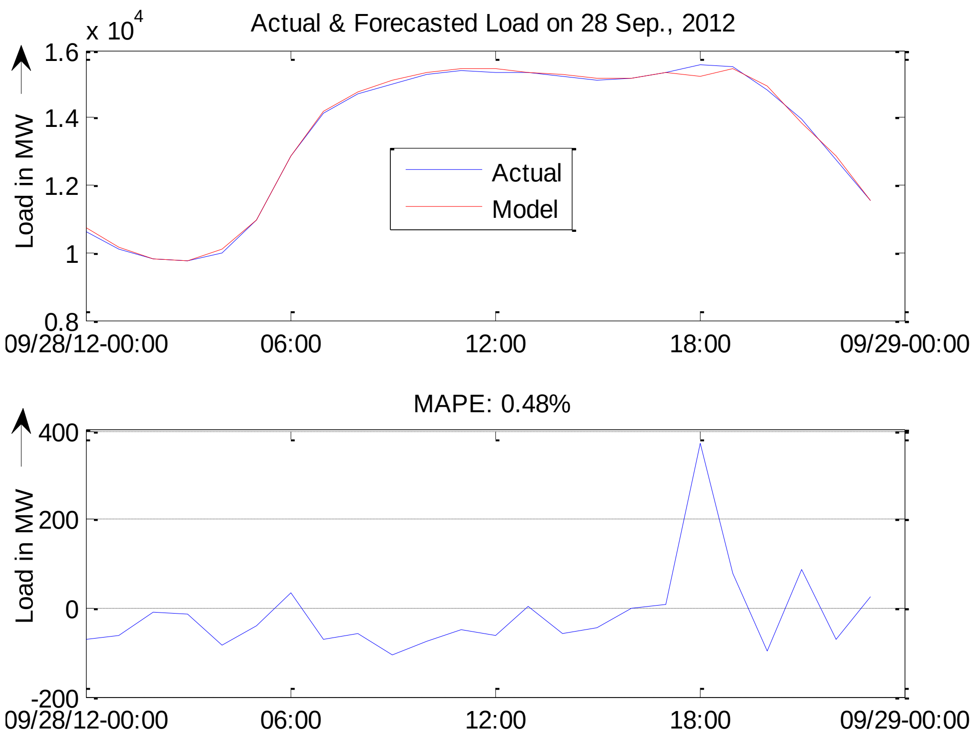

Fig. 5.2.10. MAPE is minimum (0.48%) for day ahead hourly load forecast.

TABLE 5.1

RESULTS FOR OUT-OF-SAMPLE DAILY TEST FROM JANUARY TO DECEMBER IN YEAR 2012

Day	MAPE (%) for Each Day of the Month of Year 2012 During Day-Ahead Load Forecast of ISO New England Market											
	Jan.	Feb.	Mar	Apri	May	Jun.	July	Aug	Sep	Oct.	Nov	Dec
1	4.3	0.91	1.17	1.56	1.05	1.6	1.0	0.78	1.5	1.34	1.58	1.25
2	2.6	0.79	2.26	1.31	1.59	1.0	2.7	1.44	1.5	0.91	1.44	2.16
3	2.6	0.93	2.11	1.52	1.59	1.1	1.7	1.19	1.5	1.29	0.79	2.39
4	1.2	0.59	0.78	1.11	1.21	1.3	1.1	1.21	1.3	1.64	2.67	1.23
5	1.1	1.48	1.91	0.96	2.03	2.1	1.5	1.7	1.7	1.36	1.34	1.89
6	0.8	1.71	1.17	3.61	1.09	1.4	1.3	1.54	1.5	1.94	1.38	2.08
7	1.2	0.52	2.59	1.19	0.8	1.2	2.7	2.38	1.3	2.23	3.19	1.24
8	2.3	1.17	2.54	2.35	0.6	0.8	1.1	1.43	1.7	2.74	0.88	1.18
9	1.1	1.55	1.05	1.59	0.61	0.9	1.6	1.33	2.4	1.18	1.55	1.46
10	0.8	1.1	1.11	1.04	1.23	1.3	1.9	1.2	2.3	1.14	2.03	1.34
11	1.1	1.01	2.11	0.81	0.82	1.1	1.1	2.3	2.1	1.37	2.33	1.95
12	0.9	0.88	3.23	0.95	1.33	0.6	1.0	1.47	1.6	0.97	2.54	1.89
13	1.2	2.35	2.54	1.12	1.01	0.6	1.3	1.46	1.4	1.27	0.93	1.78
14	1.1	1.17	0.94	1.55	0.94	0.8	1.7	1.24	2.0	2.21	1.32	1.96
15	1.0	0.9	1.22	1.13	0.59	0.8	1.1	1.18	2.4	2.22	1.31	1.98
16	1.2	0.68	1.4	2.06	0.5	1	0.8	1.12	1.9	1.62	1.12	2.85
17	1.9	0.93	2.29	2.1	1.44	1.1	0.9	1.77	1.0	0.75	1.57	1.21
18	1.3	1.02	2.02	3.6	1	1.5	2.2	2.93	1.4	1.35	1.9	1.8
19	1.4	1.57	1.76	1.17	1.58	1.2	1.2	1.37	2.6	1.75	1.62	1.52
20	1.2	2	1.18	1.04	1.08	2.5	2.5	1.47	2.4	2.67	0.99	1.83
21	1.4	1.03	1	1.49	1.14	1.8	1.0	1.17	1.0	1.85	1.25	1.46
22	3.6	2.01	1.94	1.93	0.81	1.2	1.2	1.13	1.4	1.54	4.03	2.23
23	2.2	1.13	2.03	1.98	0.56	1.5	1.2	1.24	1.3	0.96	3.96	1.47
24	2.3	0.76	2.16	2.07	0.94	1.7	1.3	1.25	1.6	0.9	2.18	6.23
25	0.7	1.02	1.42	1.27	1.05	2.7	2.9	1.12	1.8	0.89	2.05	2.71
26	1.0	1.23	1.15	0.91	2.48	1.6	1.3	1.74	1.0	1.82	1.48	3.12
27	1.1	1.55	1.69	1.62	2.31	1.3	1.2	1.25	1.3	1.49	0.63	1.36
28	1.4	1.34	1.42	0.97	1.06	1.2	0.9	1.48	0.4	2.04	0.74	1.71
29	1.0	0.75	0.7	1.64	2.65	1.3	1.1	2.12	1.3	11.4	1.48	1.41
30	1.0	-----	1.71	1.03	2.12	1.7	1.0	1.59	1.1	7.23	1.34	1.37
31	0.9	-----	1.12	-----	1.48	-----	1.8	1.77	-----	2.59	-----	4.72

TABLE 5.2.1

COMPARISON OF MAPE (%) USING DIFFERENT METHODS OF LOAD FORECASTING

S.N.	Methods	Max. MAPE	Min. MAPE	Avg. MAPE
1	GRNN	4.00	1.80	2.90
2	Back Propagation	3.27	1.73	2.53
3	SVM	6.10	1.50	2.71
4	Dual SVM Hybrid	3.62	1.21	2.10
5	ARMA	10.34	1.53	4.77
6	Recurrent ANN	4.10	1.39	2.08
7	Modified ANN	3.90	1.82	2.81
8	Hybrid ANN	2.79	1.58	2.14
9	Similar Day Approach	4.95	0.65	--------
10	Multi stage ANN STLF Engine	6.39	2.81	4.85
11	SOM-SVM Hybrid	2.68	1.34	2.06
12	**Proposed ANN for load forecast of ISO New England market**	**3.87**	**0.90**	**1.59**

5.3 Load Forecasting of PJM Electricity Market

The ANN model used in the forecasting is shown below in Fig. 5.3.1. It has input, output and one hidden layers. Hidden layer has 42 neurons. Inputs to the input layer are as listed above for load forecast ignoring temperature data (dry bulb & dew point temperature). After simulation the MAPE obtained is 3.14% for load forecasting for the year 2012, as shown in Fig. 5.3.2.

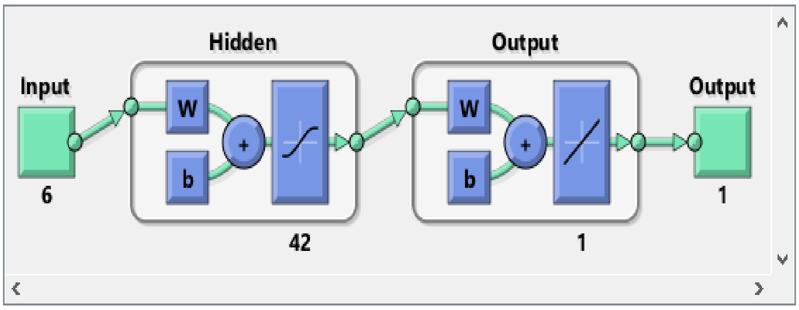

Fig. 5.3.1. Showing six different input data for one target data with 42 neurons.

The box-plot of the error distribution of forecasted load as a function of hour of the day is presented in Fig. 5.3.3. It shows the percentage error statistics of hour of the day in year 2012. It is also evident that the maximum error is for the 9^{th} hour of the day and minimum error for 23^{rd} hour of the day in year 2012. The box-plot of the error distribution of forecasted load as a function of day of the week is evaluated in Fig. 5.3.4 which shows the percentage error statistics of day of the week in year 2012. The maximum error is for the Saturday and minimum error for Friday in year 2012.

Multiple series plots between actual load & forecasted load from 24 June, 2012 to 30 June, 2012 & from 21 October, 2012 to 27 October, 2012 for PJM electricity market and also plots of MAPE with maximum error (5.87%) and minimum error (1.66%) for weekly testing sample have been shown in Fig. 5.3.5 and Fig. 5.3.6. The Mean Absolute Percentage Error (MAPE) between the forecasted and actual loads for each week & month has been calculated and presented in the Table 5.6 & Table 5.7 respectively for the year 2012.

From the results in Table 5.6 & Table 5.7 it is observed that MAPE for ISO New England market is much better than MAPE for PJM electricity market (RTO region). This is due to the fact that temperature and weather data is not been taken as input in PJM electricity market but it is considered for input in ISO New England. This indicates that temperature data is a very important parameter for load forecasting using ANN.

From the results obtained from Table 5.7, it is clear that MAPE is highest (4.24%) is for January and minimum MAPE (2.23%) is for October, 2012 for PJM electricity market from samples of monthly test, as shown in Fig. 5.3.7 & Fig 5.3.8. Multiple series plots between actual load & forecasted load on 30 June, 2012 & on 25 October, 2012 for PJM electricity market and also plots of MAPE with maximum error (12.34%) and minimum error (0.70%) for day ahead hourly forecast in year 2012 have been shown in Fig. 5.3.9 and Fig. 5.3.10.

Result for daily MAPE for day ahead hourly forecast for whole year is discussed in Table 5.2. The MAPE for ISO New England Market are far better than that of PJM electricity market. This is because the temperature data has been considered as an input to ANN for Load forecast in case of ISO New England market.

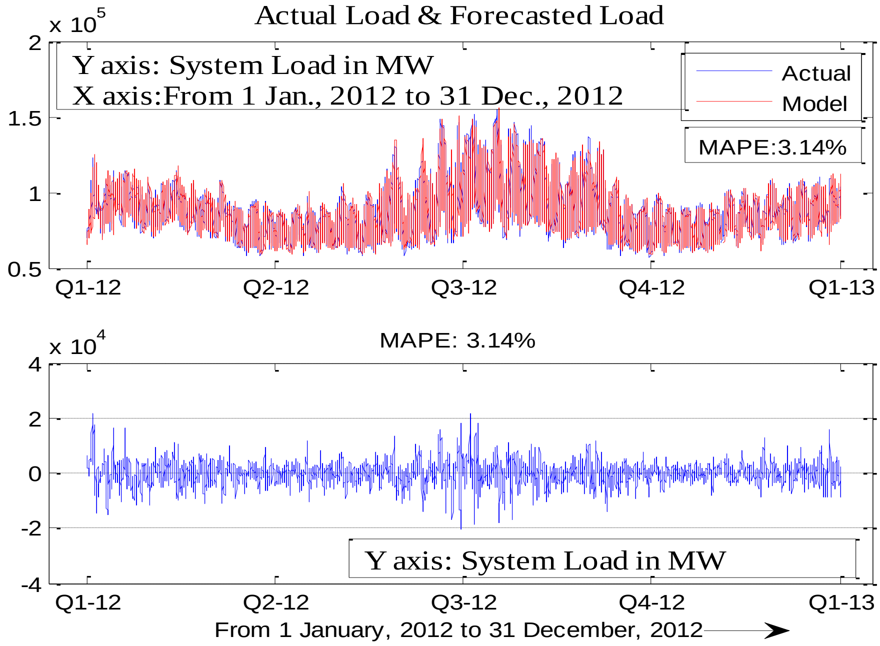

Figure 5.3.2. Multiple series plot between actual & forecasted load for PJM market.

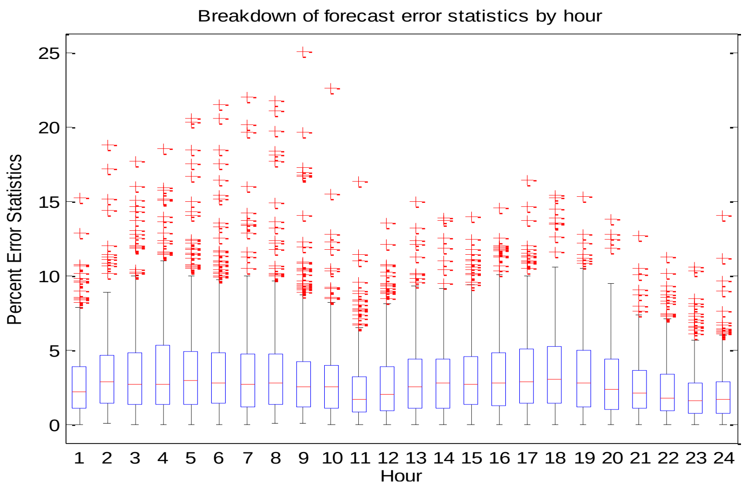

Fig. 5.3.3. Box-plot of the error distribution of forecasted load as a function of hour of the day for year 2012.

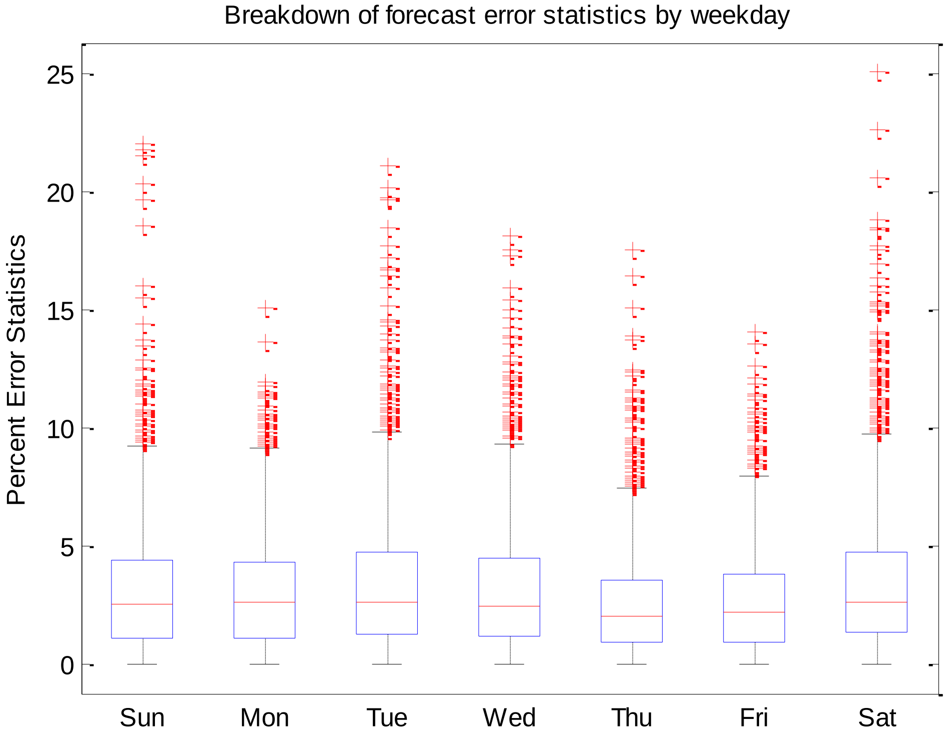

Fig. 5.3.4. Box-plot of the error distribution for the forecasted load as a function of day of the week in the year 2012.

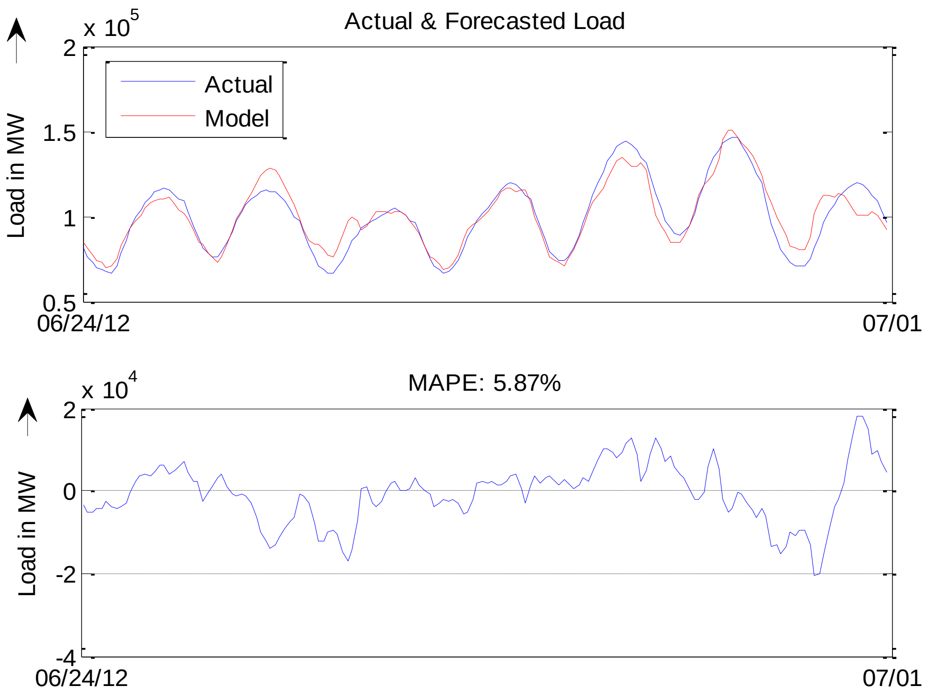

Fig. 5.3.5. MAPE is maximum 5.87% for the forecast of 24-30 June, 2012.

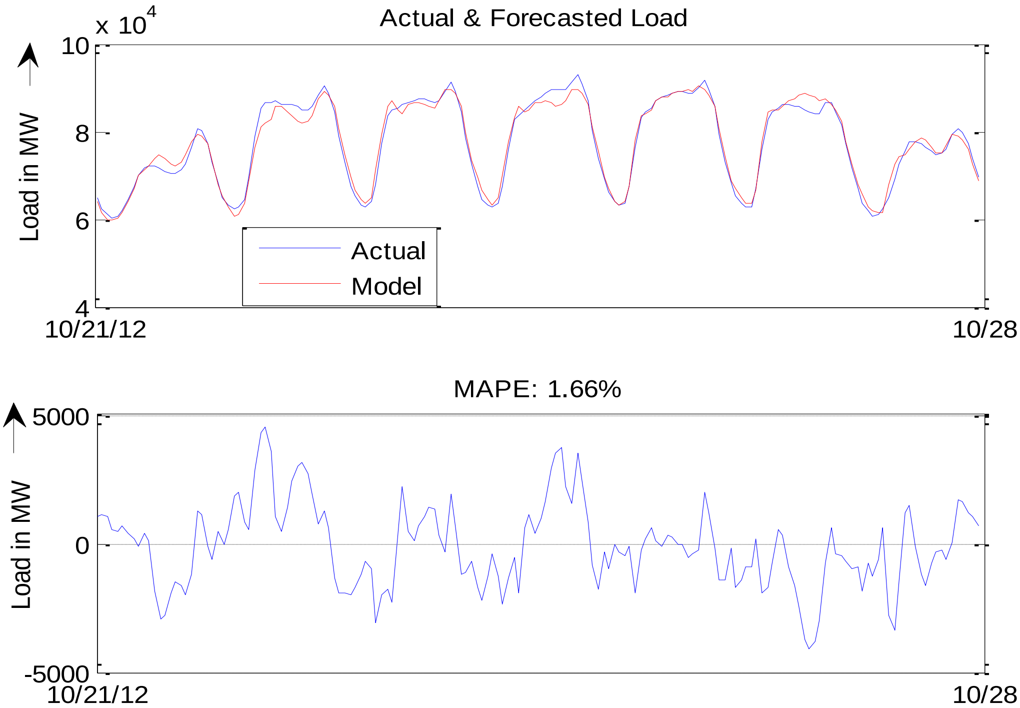

Fig. 5.3.6. MAPE is least 1.66% for the forecast of 21-27 October, 2012.

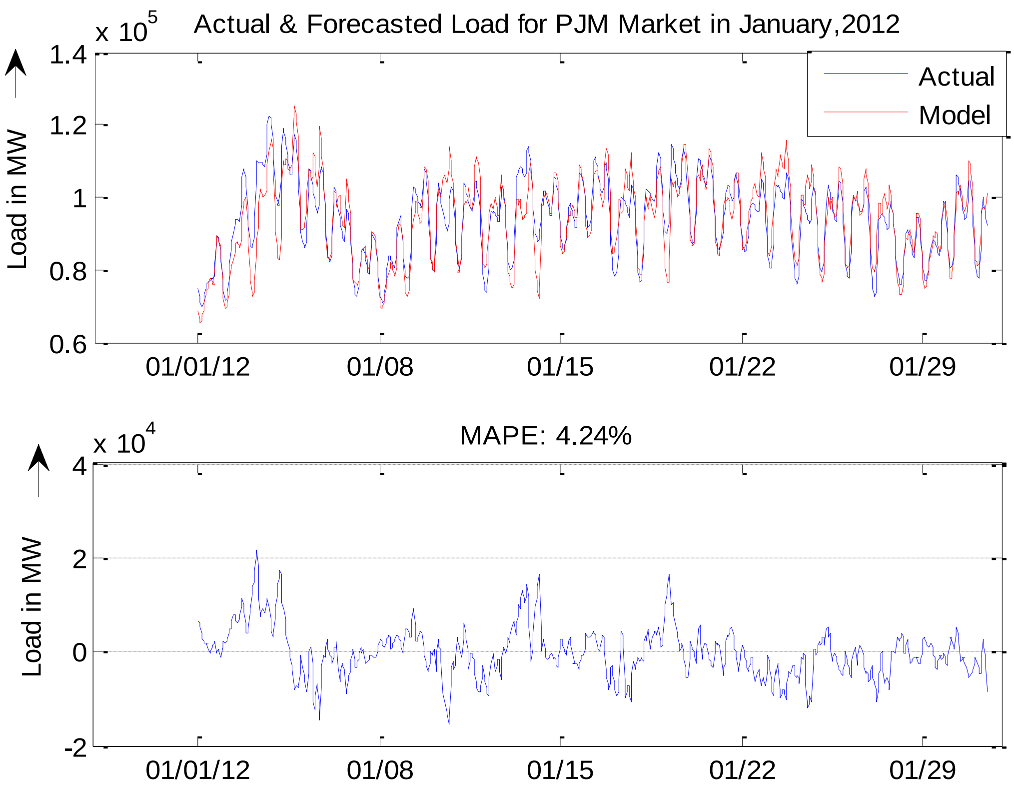

Fig. 5.3.7. Maximum MAPE is 4.24% for the forecast of Jan., 2012.

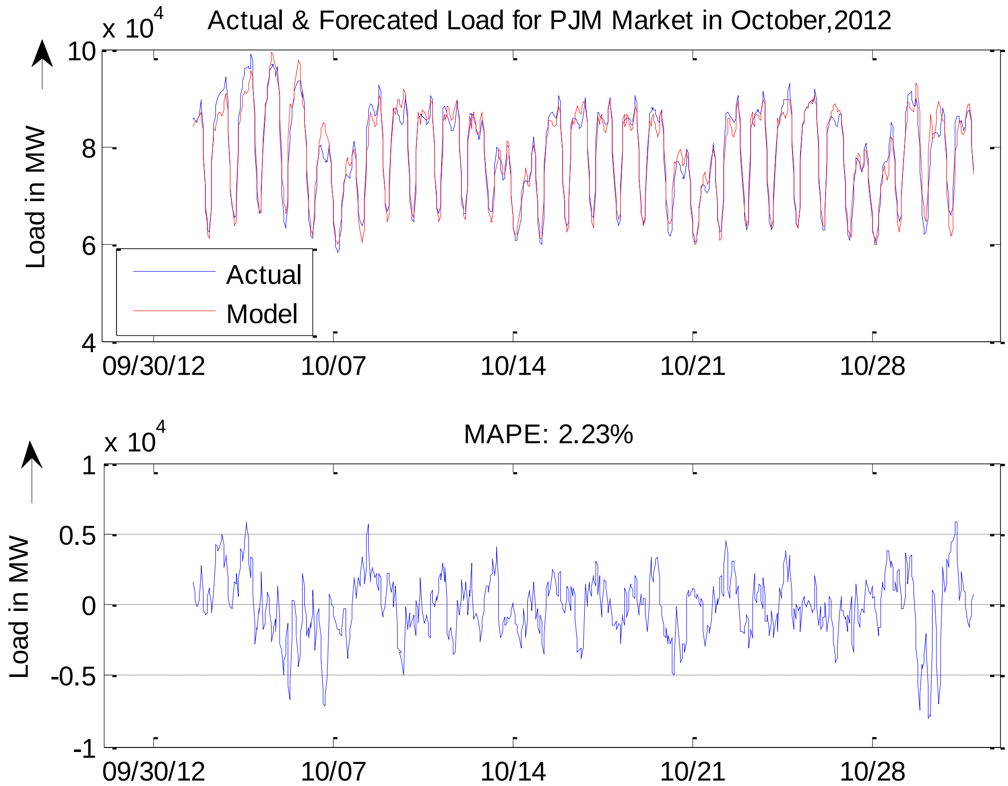

Fig. 5.3.8. MAPE is minimum (2.23%) for the forecast of Oct., 2012.

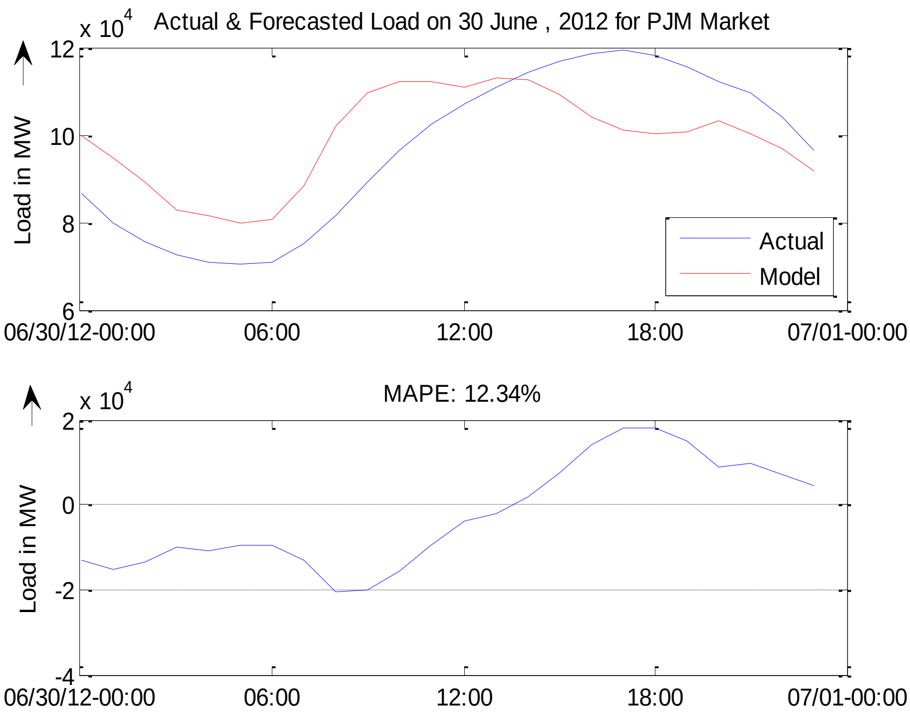

Fig. 5.3.9. MAPE is highest (12.34%) for the forecast of 30 June, 2012.

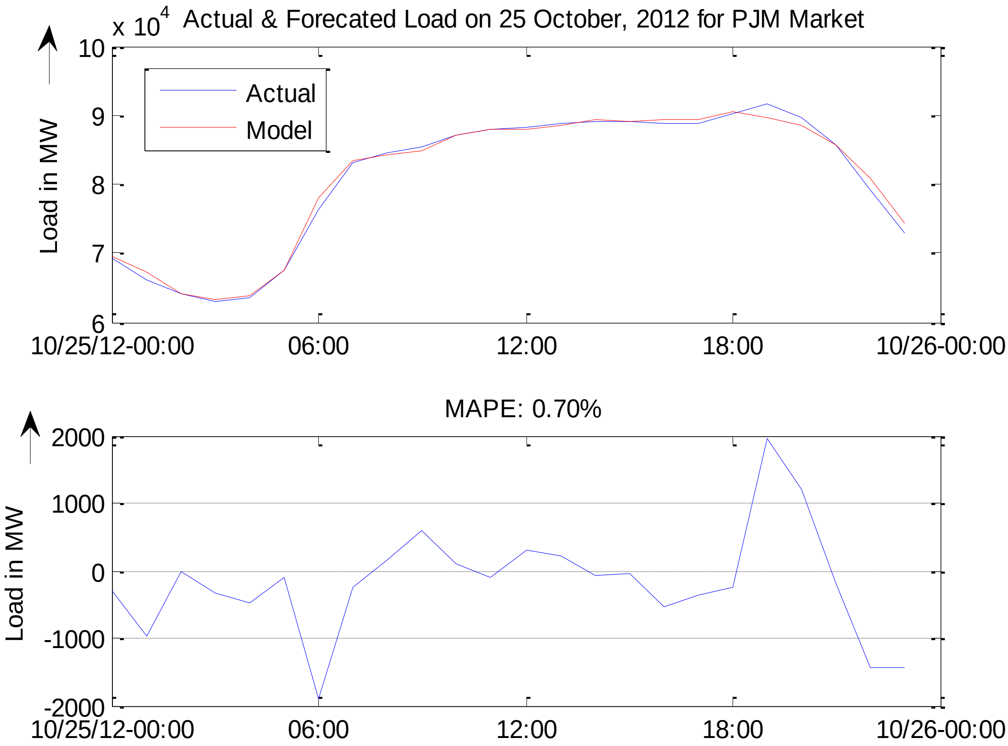

Fig. 5.3.10. MAPE is least (0.70%) for the forecast of 25 Oct., 2012.

TABLE 5.2

RESULTS FOR OUT-OF-SAMPLE DAILY TEST FROM JANUARY TO DECEMBER IN YEAR 2012

Day	MAPE (%) for Each Day of the Month of Year 2012 During Day-Ahead Load Forecast of PJM Electricity Market											
	Jan.	Feb.	Mar.	April	May	Jun.	July	Aug.	Sep.	Oct.	Nov.	Dec.
1	2.54	3.07	2.93	2.4	2.65	4.43	2.15	1.08	3.45	1.25	1.51	1.88
2	6.23	1.95	3.28	1.53	3.23	6.18	2.82	2.73	4.03	2.66	1.83	2.22
3	10.29	3.52	2.74	1.56	3.19	3.55	2.59	2.66	5.62	2.98	2.45	4.36
4	7.31	2.78	2.15	1.93	1.93	2.56	8.5	3.18	3.67	1.63	0.9	2.78
5	5.5	2.33	3.52	1.94	5.14	6.2	3.71	2.48	2.77	3.42	2.39	2.52
6	3.39	4.47	5.01	2.01	4.45	2.54	3.3	2.62	2.54	3.2	2.91	4.42
7	1.69	1.89	4.22	2.81	1.94	2.02	6.93	4.1	1.72	2.19	2.31	2.63
8	2.54	4.14	2.78	3.56	2.11	3.39	4.32	1.5	4.9	2.81	1.53	4.46
9	4.19	2.36	1.92	2.27	2.17	3.5	4.34	1.52	9.14	2.35	2.26	2.68
10	5.45	2.23	4.9	2.11	3.65	5.1	2.12	3.04	3.37	1.34	2.37	1.9
11	3.66	4.08	4.32	3.4	1.17	3.58	1.94	5.56	4.5	2.07	2.31	2.44
12	4.07	5.62	3.22	2.75	2.56	4.1	1.81	5.39	2.85	1.39	2.07	3.7

13	6.9	4.78	3.78	1.72	2.04	4.3	2.2	1.94	2.48	2.32	2.22	2.3
14	4.75	4.32	2.03	1.54	2.35	2.49	2.47	2.19	4.21	1.63	3.33	3.34
15	1.98	3.41	1.28	3.68	2.57	2.67	2.22	2.22	6.02	1.92	1.37	1.83
16	3.36	2.42	1.56	4.74	1.33	1.63	3.24	1.67	3.66	1.85	1.41	3.53
17	6	4.26	3.52	4.4	3.79	3.25	3.09	1.74	2.24	1.55	2.75	1.64
18	2.81	2.96	3.27	3.48	1.93	1.58	5.84	3.27	3.56	1.43	2.01	2.71
19	6.34	1.73	2.08	1.24	3.75	4.8	4.5	5.73	4.89	1.83	1.51	2.36
20	1.85	3.1	1.6	1.97	3.12	5.51	4.63	1.08	1.86	3.39	1.56	1.86
21	2.78	3.72	1.05	2.36	2.58	2.4	6.14	2.16	1.21	1.51	2.01	4.46
22	4.21	4.69	1.37	1.15	3.19	2.42	2.32	2.22	2.1	2.32	2.68	3.67
23	6.16	1.74	1.82	3.26	2.54	6.12	4.88	2.28	5.29	1.59	2.86	3.83
24	5.27	2.95	4.34	3.53	3.48	4.56	4.32	1.88	1.21	2.11	6.61	4.98
25	2.86	4.41	1.83	1.41	2.99	4.61	6.74	1.26	1.03	0.7	3.37	4.63
26	2.93	5.42	2.26	2.02	1.53	7.36	3.15	2.28	3.15	1.79	2.17	8.96
27	5.14	3.13	5.21	2.13	2.54	2.87	1.59	3.32	1.34	1.62	2.8	3.05
28	2.26	3.03	1.72	2.44	4.67	4.95	3.23	2.33	2.03	2.37	2.49	2.83
29	2.02	2.96	3.2	3.32	4.46	4.38	5.1	3.47	5.57	3.29	2.67	2.82
30	3.1	----	2.65	1.84	4.32	12.34	1.85	3.65	2.01	5.01	2.16	1.97
31	5.48	-----	1.79	-----	3.73	----	1.49	3.55	-----	3.1	-----	4.54

5.4 Load Forecasting of Ontario Electricity Market

Here hourly day-ahead load forecasting has been done for sample of each day, week & month of data of year 2012 using neural network tool box of MATLAB R13a. The ANNs are trained with data from 2007 to 2011 and tested on out-of-sample data from 2012. The test sets are completely separate from the training sets and are not used for model estimation or variable selection.

The model accuracy on out-of-sample periods is computed with the Mean Absolute Percent Error (MAPE) metrics. The principal statistics used to evaluate the performance of these models, mean absolute percentage error (MAPE).

Various plots comparing the day ahead hourly actual and forecasted load for every weeks for the year 2012 are also generated. Simulation results of Ontario Electricity Market is discussed below.

5.4.1. Load Forecast by Ignoring Temperature Data

The ANN model used in the forecasting is shown below in Fig. 5.4.1. It has input, output and one hidden layers. Hidden layer has 60 neurons. Inputs to the input layer are as listed above for load forecast without considering temperature data. After simulation the MAPE obtained is 2.91% during load forecasting of year-2012.

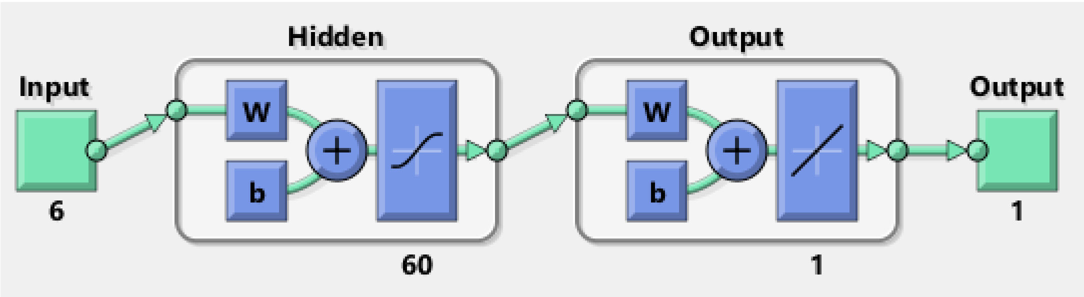

Fig. 5.4.1. Showing six different input data for one target data with 60 neurons.

Multiple series plots between actual load & forecasted load from 06-12 May, 2012 & from 05-11 August, 2012 and also plots of MAPE with maximum error (4.87%) and minimum error (1.68%) for day ahead hourly weekly forecast in year 2012 have been shown in Fig. 5.4.2 and Fig. 5.4.3. The simulation results show that the highest & least error occurred with MAPE of 9.98% & 1.09% for day-ahead forecast of 06 August & 23 October, 2012 respectively.

The box-plot of the error distribution of forecasted load as a function of hour of the day is presented in Fig. 5.4.4. It shows the percentage error statistics of hour of the day in year 2012. It is also evident that the maximum error is for the 6th hour of the day and minimum error for 21th hour of the day in year 2012. The box-plot of the error distribution of forecasted load as a function of day of the week is evaluated in Fig. 5.4.5 which shows the percentage error statistics of day of the week in year 2012. The maximum error is for the Monday and minimum error for Friday in year 2012.

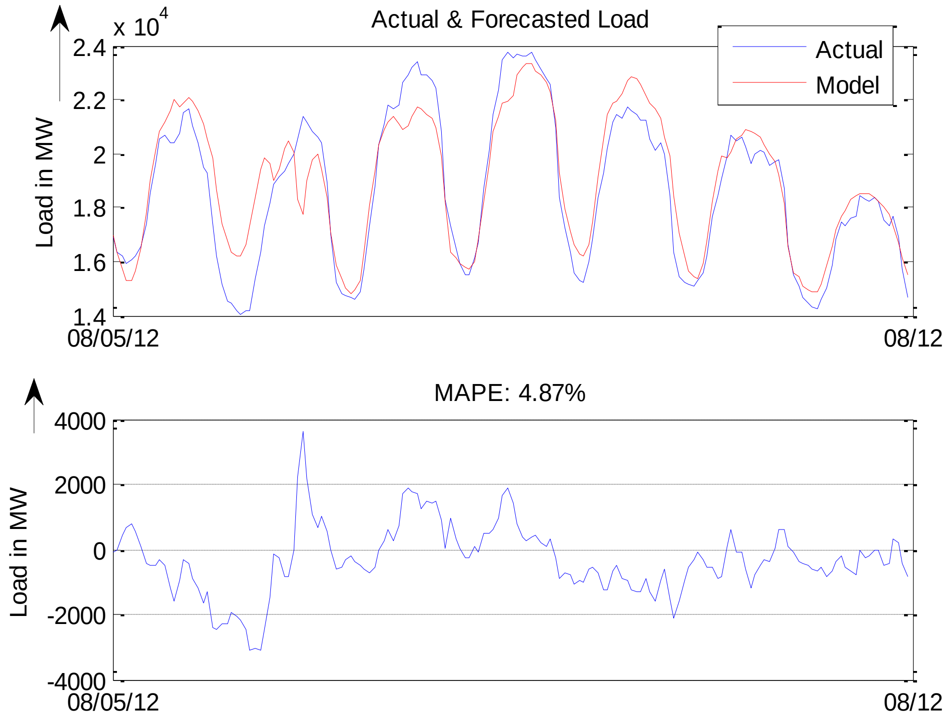

Fig. 5.4.2. MAPE is maximum (4.87 %) for the forecast of 05-11 August, 2012 for day ahead hourly weekly forecast.

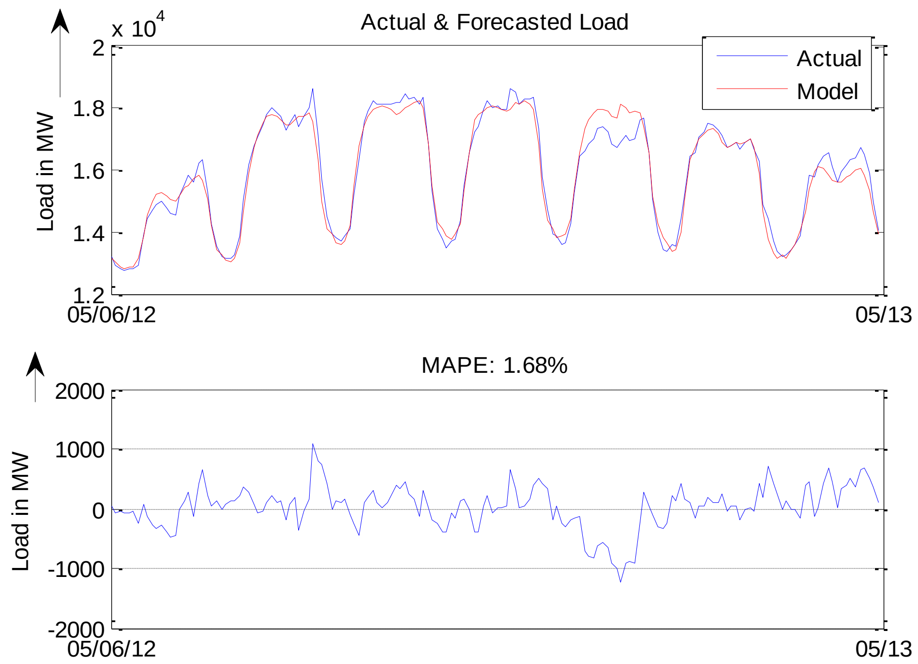

Fig. 5.4.3. MAPE is least (1.68%) for the forecast of 06-12 May, 2012 for day ahead hourly weekly forecast in the year 2012.

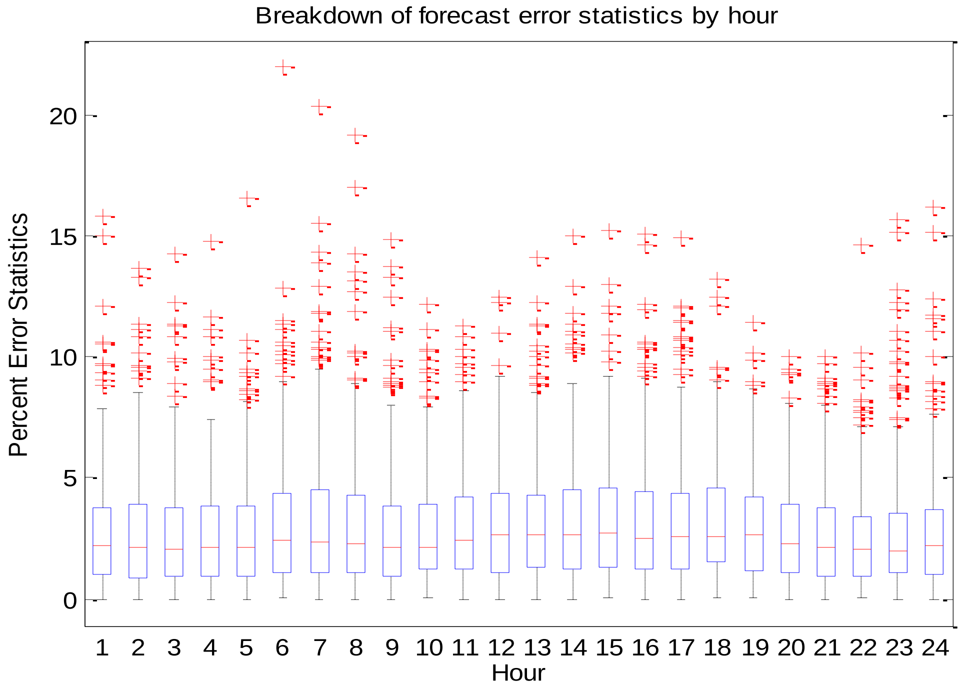

Fig. 5.4.4. Error distribution of forecasted load as a function of hour of the day in year-2012 for Ontario electricity market without temperature data as input.

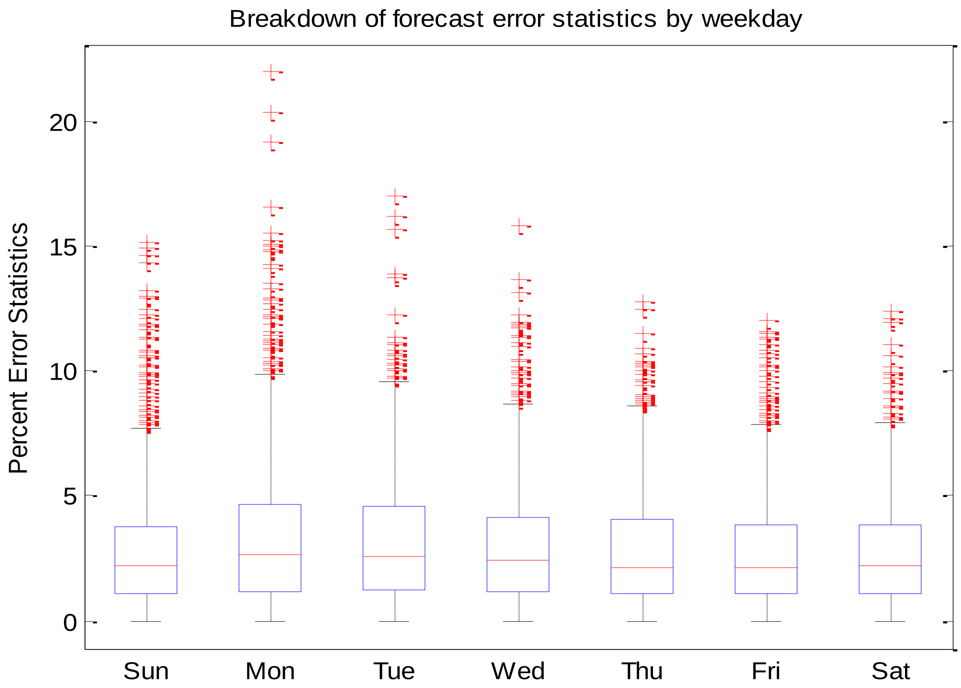

Fig. 5.4.5. Error distribution for the forecasted load as a function of day of the week in year-2012 for Ontario market without temperature data as input.

5.4.2. Load Forecasting by Considering Temperature Effect

The ANN model used in the forecasting is shown below in Fig. 5.4.6. It has input, output and one hidden layers. Hidden layer has 60 neurons. Inputs to the input layer as listed above for load forecast by taking temperature data as input variable. After simulation the MAPE obtained is 2.38% for load forecasting of year-2012 as shown in Fig. 5.4.7.

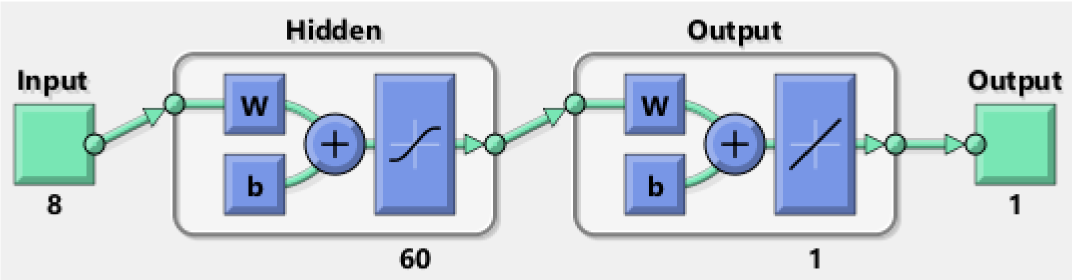

Fig. 5.4.6. Showing eight different input data for one target data with 60 neurons.

Multiple series plots between actual load & forecasted load from 06-12 May, 2012 & from 05-11 August, 2012 and also plots of MAPE with maximum error (3.83%) and minimum error (1.54%) for day ahead hourly weekly forecast in year 2012 have been shown in Fig. 5.4.8 and Fig. 5.4.9. It has been observed that the maximum & minimum error occurred with MAPE of 8.16% & 0.85% for day-ahead forecast of 06 August & 03 February, 2012 respectively. Multiple series plots between actual load & forecasted load for 03 February, 2012 and also plot of MAPE with minimum error (0.85%) for day-ahead forecast in year 2012 have been shown in Fig. 5.4.10.

The box-plot of the error distribution of forecasted load as a function of hour of the day is presented in Fig. 5.4.11. It shows the percentage error statistics of hour of the day in year 2012. It is also evident that the maximum error is for the 6th hour of the day and minimum error for 19th hour of the day in year 2012. The box-plot of the error distribution of forecasted load as a function of day of the week is evaluated in Fig. 5.4.12 which shows the percentage error statistics of day of the week in year 2012. The maximum error is for the Monday and minimum error for Friday in year 2012.

The Mean Absolute Percentage Error (MAPE) & Mean Absolute Error (MAE) between the forecasted and actual loads for each week & month has been calculated and presented in the Table 5.6 & Table 5.7 respectively for the year 2012. Result for daily MAPE for day ahead hourly forecast from January-December, 2012 is discussed in Table 5.3 & 5.4. From the results in Table 5.3, 5.4, 5.6 & 5.7 it is observed that MAPE with temperature data is much better than MAPE without considering temperature as input. This indicates that temperature data is a very important parameter for load forecasting using ANN. From the results obtained from Table 5.7, it is clear that maximum MAPE (3.83%) is for July, 2012 and minimum MAPE (2.23%) is for November, 2012 without considering the effect of temperature for Ontario electricity market. Also, it is clear that maximum MAPE (2.78%) is for July, 2012 and minimum MAPE (2.05%) is for February, 2012 for Ontario market with temperature data as input variable. Simulation result of day-ahead load forecast of 26 January, 2012 with temperature data as input variable to ANN is shown in Fig. 5.4.13 & the MAPE is 1.20%.

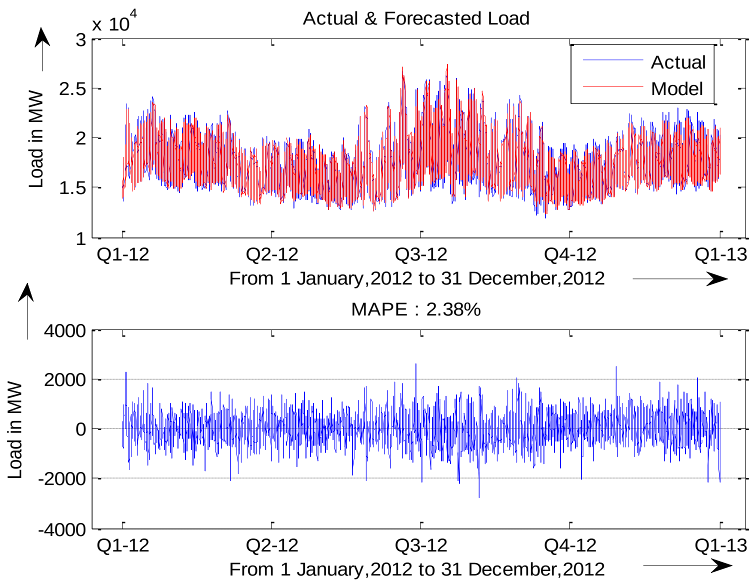

Fig. 5.4.7. Multiple series plot between actual load & forecasted load by ANN in year 2012 with temperature as input for Ontario electricity market.

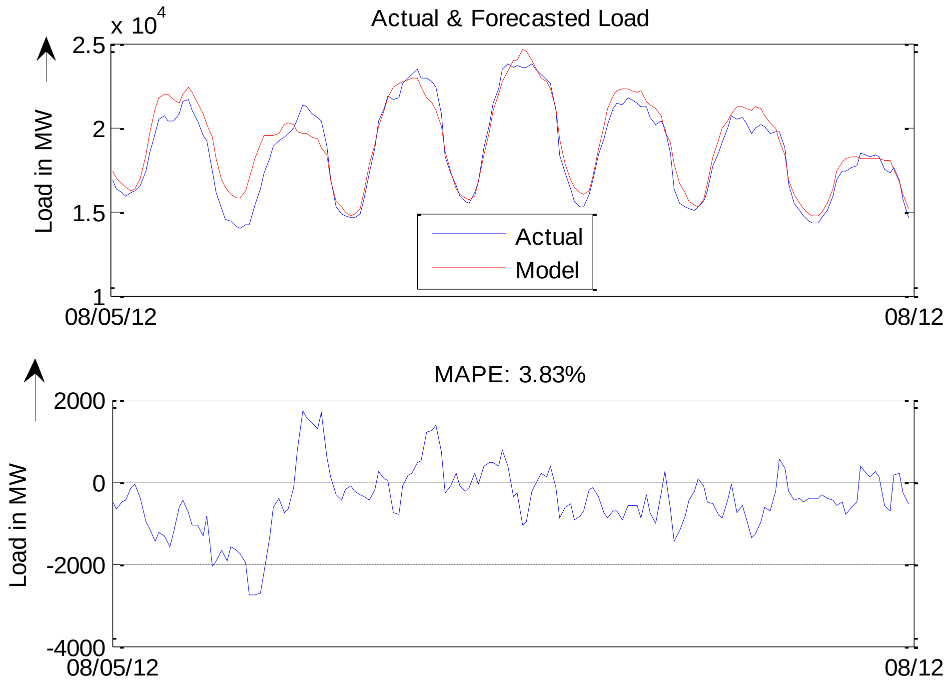

Fig. 5.4.8. MAPE is maximum (3.83 %) for the forecast of 05-11 August, 2012 for day ahead hourly weekly forecast.

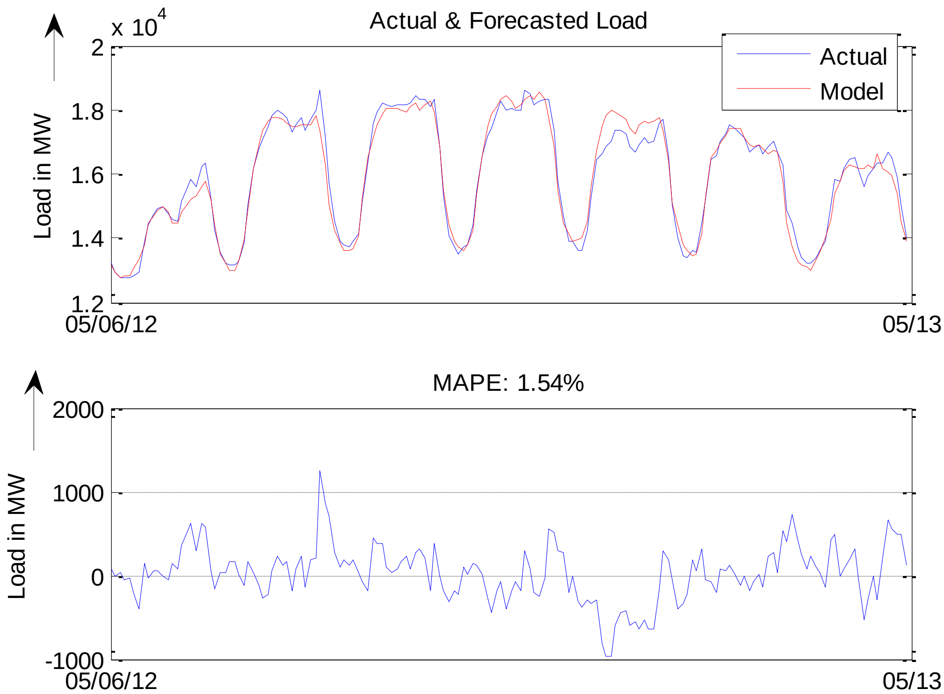

Fig. 5.4.9. MAPE is minimum (1.54%) for the forecast of 06-12 May, 2012 for day ahead hourly weekly forecast in the year 2012.

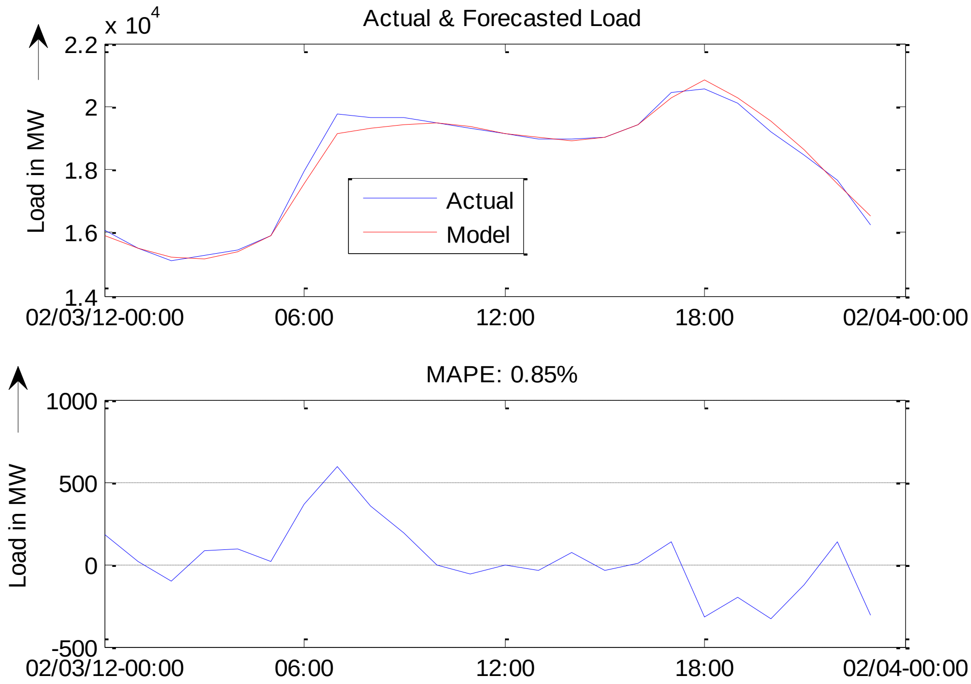

Fig. 5.4.10. MAPE is minimum (0.85%) for the forecast of 03 February, 2012 for day ahead hourly forecast in the year 2012.

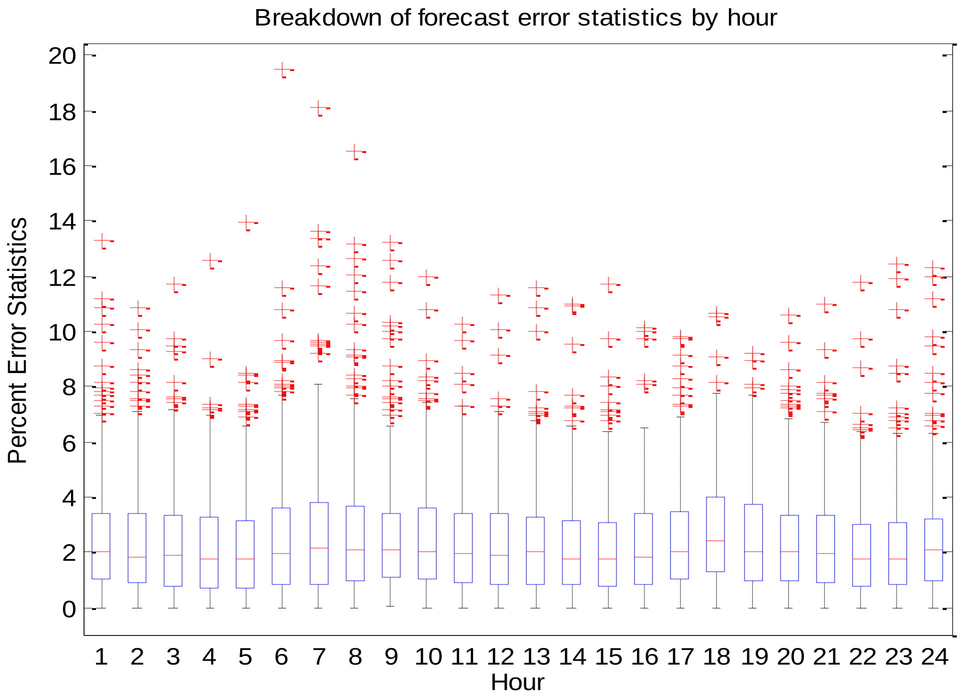

Fig. 5.4.11. Error distribution of forecasted load as a function of hour of the day in year-2012 of Ontario market with temperature data as input to ANN.

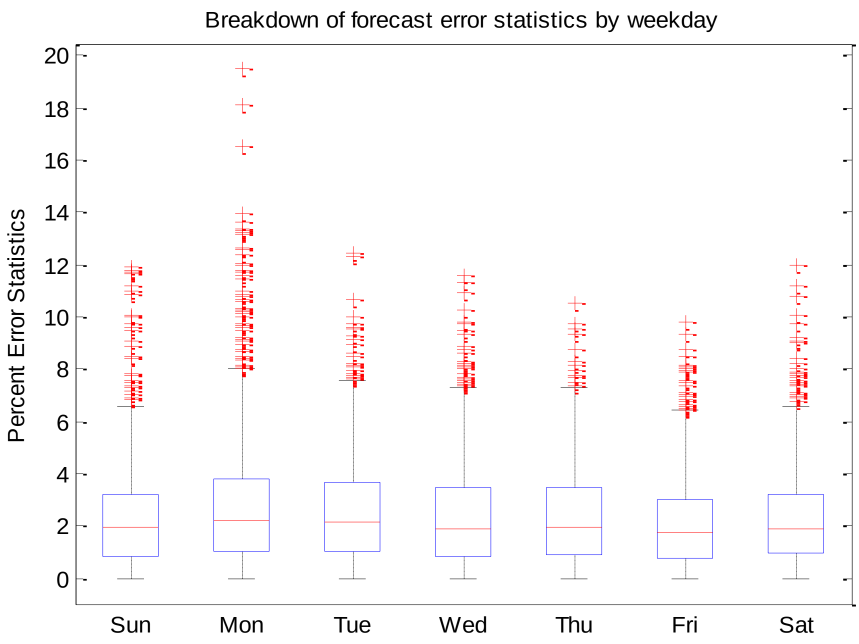

Fig. 5.4.12. Error distribution for forecasted load as a function of day of the week in year-2012 for Ontario market with temperature data as input to ANN.

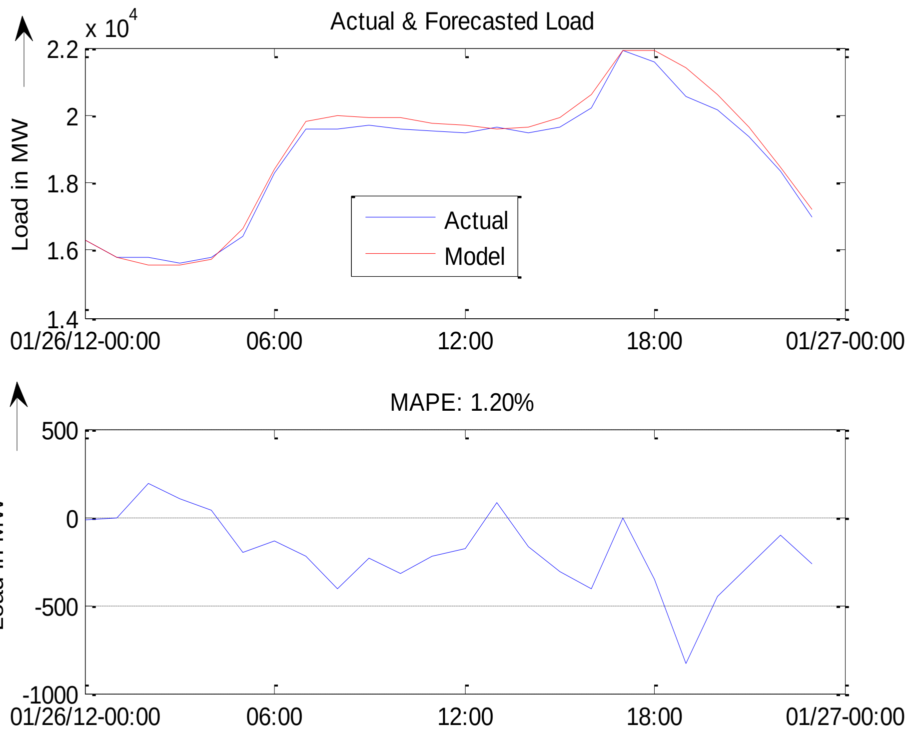

Fig. 5.4.13. Day-ahead hourly load forecast of 26 January, 2012 with temperature parameter as input.

TABLE 5.3

RESULTS FOR OUT-OF-SAMPLE DAILY TEST FROM JANUARY TO JUNE IN YEAR 2012

Day	MAPE (%) for Each Day of the Month in Year 2012 During Day-Ahead Load Forecast for Ontario Electricity Market											
	Without Temperature data						With Temperature data					
	Jan.	Feb.	Mar.	April	May	June	Jan.	Feb.	March	April	May	June
1	2.24	1.82	1.75	3.35	2.96	2.73	2.33	1.17	1.45	2.76	2.26	2.29
2	5.47	1.8	2.57	3.48	1.45	2.25	3.39	1.45	2.14	1.46	1.74	2.11
3	8.16	1.28	2.08	1.59	1.31	1.25	4.5	**0.85**	2.15	1.6	1.37	1.25
4	2.72	1.87	2.36	3.03	1.56	1.86	1.94	2.02	1.56	2.27	2.24	1.86
5	3.85	1.41	4.52	2.78	2.55	2.89	3.58	0.94	1.91	2.48	2.15	2.02
6	2.35	2.26	2.49	2.37	1.65	3.29	2.46	1.87	1.58	1.29	1.27	1.77
7	3	3.21	5.87	2.55	1.63	3.11	2.53	2.02	5.59	3.09	1.48	2.28
8	2.89	3.69	2.71	2.29	1.29	2.66	1.9	2.67	2.03	2.52	1.13	1.79
9	1.86	3.15	2.39	2.05	1.43	1.8	1.66	2.19	2.02	2.1	1.25	2.54
10	3.43	3.12	3.16	2.41	2.85	6.96	2.46	2.11	2.28	2.8	2.74	3.9
11	1.7	3.63	5.09	2.44	1.09	2.72	1.49	1.45	5.32	1.46	1.19	1.48
12	1.48	3.52	2.13	2.83	1.83	4.61	1.4	2.15	2.04	2.51	1.74	3.95
13	2.86	4	4.98	1.95	2.09	5.23	2.38	3.12	4.01	1.96	2.29	3.86
14	3.11	3.28	1.33	1.84	2.7	2.91	1.34	3.48	1.17	2.19	3.03	2.65
15	3.09	2.88	1.54	3.04	2.33	5.79	1.93	2.46	1.21	2.55	1.25	4.27
16	4	1.86	1.42	2.39	3.67	2.08	2.89	1.95	2.48	3.53	2.45	1.28
17	3.86	2.46	2.58	2.19	2.11	1.97	2.7	1.33	3.01	2.78	3.01	2.23
18	2.67	1.56	2.12	2.12	2.53	3.48	1.37	1.26	2.42	1.85	2.59	2.11
19	3.03	2.17	3.58	1.85	2.36	6.02	2.49	1.32	3.91	1.79	1.47	2.5
20	1.77	6.04	2.32	1.58	1.92	5.08	1.58	3.67	2.07	1.83	0.95	2.83
21	1.39	2.71	3.36	3.68	4.33	3.86	1.74	2.82	3.51	3.61	3.69	1.29
22	2.73	2.58	2.35	2.58	1.83	5.24	1.66	1.71	3.17	2.26	1.67	2.39
23	2.41	1.95	3.17	2.25	2.04	2.84	2.2	1.84	2.54	2.34	1.7	2
24	1.86	3.87	1.91	2.47	5.04	1.55	1.5	2.94	2.61	2.12	2.76	1.66
25	2.12	2.7	2.46	3.84	3.79	4.36	1.64	1.16	2.32	3.39	1.41	3.03
26	1.55	2.85	3.17	2.66	2.68	4.27	1.2	1.64	2.02	3.08	1.56	4.24
27	2.2	2.7	2.54	1.65	2.4	2.14	2.41	2.25	2.5	1.43	1.86	3.14
28	1.39	2.38	1.73	1.97	6.53	5.27	1.65	2.04	1.35	1.87	4.36	3.73
29	3.56	3.65	2.32	3.43	4.8	3.86	1.92	3.56	2.14	2.93	4.74	1.82
30	2.91	----	2.37	2.07	5.58	3.04	2.23	-----	1.89	1.88	3.26	2.19
31	3.83	-----	2.81	-----	3.2	-----	3.42	------	2.53	-----	2.65	-----

TABLE 5.4

RESULTS FOR OUT-OF-SAMPLE DAILY TEST FROM JULY TO DECEMBER IN YEAR 2012

Day	MAPE (%) for Each Day of the Month in Year 2012 During Day-Ahead Load Forecast for Ontario Electicity Market											
	Without Temperature data						With Temperature data					
	July	Aug.	Sep.	Oct.	Nov.	Dec.	July	Aug.	Sep.	Oct.	Nov.	Dec.
1	2.1	3.86	3.38	2.36	2.77	3.86	2.76	3.38	2.79	2.25	2.2	3.28
2	5.08	4.15	3.66	2.43	1.74	1.48	4.54	2.31	3.14	2.34	1.49	1.51
3	4.14	2.61	4.93	1.92	2.41	2.78	2.16	2.17	4.39	1.61	1.82	2.64
4	3.68	3.16	2.85	1.47	1.12	1.71	2.14	2.15	2.52	2.37	1.59	2.13
5	1.68	5.35	3.27	1.78	2.95	3.33	1.32	5.31	2.02	1.79	3.29	2.74
6	3.78	**9.98**	2.01	1.61	2.32	2.45	1.44	**8.16**	2.76	1.76	2.85	1.9
7	4.55	4.25	3.63	2.21	2.94	2.17	3.53	2.17	3.38	1.86	2.11	2.91
8	4.72	2.7	4.18	4.95	1.87	2.44	3.17	1.8	3.58	4.55	1.51	1.88
9	2.39	5.96	5.79	3.25	1.65	3.25	3	3.69	4.99	3.04	2.18	2.53
10	2.61	3.12	2.75	2.72	1.97	3.21	2.28	3.14	2.71	2.24	1.7	2.88
11	2.54	2.7	4.19	1.53	1.92	2.89	3.05	2.52	4.11	1.66	2.93	1.93
12	4	1.61	4.8	2.19	1.79	2.48	3.04	1.23	3.27	1.83	2.81	1.86
13	2.63	3.08	4.1	4.06	2.17	3.13	2.35	1.27	3.18	3.87	2.24	2.64
14	2.67	3.1	3.8	2.11	1.61	2.05	2.69	2.33	2.73	1.75	1.87	1.86
15	2.11	3.42	4.94	4.43	2.39	1.82	3.05	2.75	4.69	3.28	1.99	1.17
16	4.41	3.84	2.92	1.74	1.5	1.84	1.86	2.46	2.22	1.46	1.76	1.64
17	3.32	3.01	2.63	1.4	2.19	3.66	2.73	2.32	2.24	1.46	1.95	4.22
18	4.18	3.83	2.04	1.52	1.39	2.68	2.54	2.81	1.68	1.55	1.48	2.23
19	6.87	1.33	2.01	2.06	1.7	3.03	3.49	2.01	1.94	1.87	1.54	2.5
20	5.82	2.41	1.82	1.73	2.04	2.05	3.49	1.11	2.03	1.41	1.75	2.18
21	4.47	2.47	2.15	2.68	2.47	2.48	3.09	2	1.63	2.59	2.08	1.55
22	7.1	3.05	1.96	1.36	1.48	3	3.05	1.45	2.59	1.56	1.81	1.96
23	4.49	4.02	2.56	**1.09**	2.51	2.59	1.81	2.29	1.86	1.51	2.39	1.88
24	6.26	3.26	1.56	1.97	3.82	6.62	5.14	2.31	1.54	1.83	3.19	6.99
25	5.64	3.17	3.63	1.57	1.95	4.78	4.6	2.93	3.96	2	1.54	1.87
26	1.22	3.54	1.55	2.11	2.33	4.37	1.98	3.03	1.76	2.1	1.83	3.29
27	2.19	2.39	2.44	1.9	2.6	3.8	1.79	2.35	3.18	2.25	2.47	2.74
28	1.7	4.01	1.56	2.96	2.24	2.33	1.77	2.53	1.66	2.78	1.64	1.56
29	2.6	4.96	2.17	2.99	2.73	2.78	2.18	5.08	2.03	3.68	2.22	1.5
30	4.16	4.7	1.64	2.52	4.02	2.23	2.65	2.89	1.22	2.58	3.14	2.02
31	3.62	4.45	-----	1.29	-----	5.32	2.86	1.69	-----	1.32	-----	4.76

5.5 Price Forecast of ISO New England Market

The ANN model used in the forecasting is shown below in Fig. 5.5.1. It has input, output and one hidden layers. Hidden layer has 22 neurons. The 14 different inputs to the input layer are same as specified above for price forecast. We were able to obtain an MAPE 9.25% for price forecasting in the year 2012, which is shown in Fig. 5.5.2.

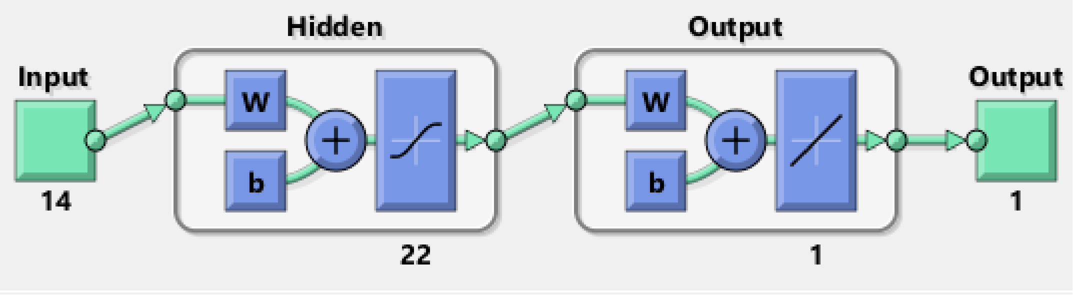

Fig. 5.5.1 Showing fourteen different input data for one target data with 22 neurons in hidden layer.

The box-plot of the error distribution of forecasted price as a function of hour of the day is evaluated in Fig. 5.5.3. It shows the percentage error statistics of hour of the day in year 2012. It is clear that the highest error is for the 8^{th} hour of the day and least error for 1^{st} hour of the day in year 2012. The box-plot of the error distribution of forecasted price as a function of day of the week is evaluated in Fig. 5.5.4. It shows the percentage error statistics of day of the week in year 2012. The highest error is for the Saturday and least error for Monday in year 2012.

Multiple series plots between actual price & forecasted price from 17-23 June, 2012 & from 07-13 October, 2012 and also plots of their corresponding MAPE with highest error (19.87%) and least error (5.60%) for day-ahead hourly forecast from weekly testing sets in year-2012 have been shown in Fig. 5.5.5 and Fig. 5.5.6 and also in Table 5.6.

Also, it is clear that maximum MAPE (12.27%) is for June, 2012 and minimum MAPE (6.90%) is for October, 2012 for day ahead monthly price forecast as shown in Fig. 5.5.7 & Fig. 5.5.8. Also there is least error for daily price forecast on 15 Feb., 2012 in the year 2012 with MAPE (3.14%) is shown in Fig. 5.5.9.

Result for daily MAPE for day ahead hourly price forecast of ISO New England market for whole year is discussed in Table 5.5. It has been observed that the MAPE for load forecasting are far better than that of price forecasting. This is because price curves of ISO New England power market is highly volatile & depends on also many other factors which must also be taken care off.

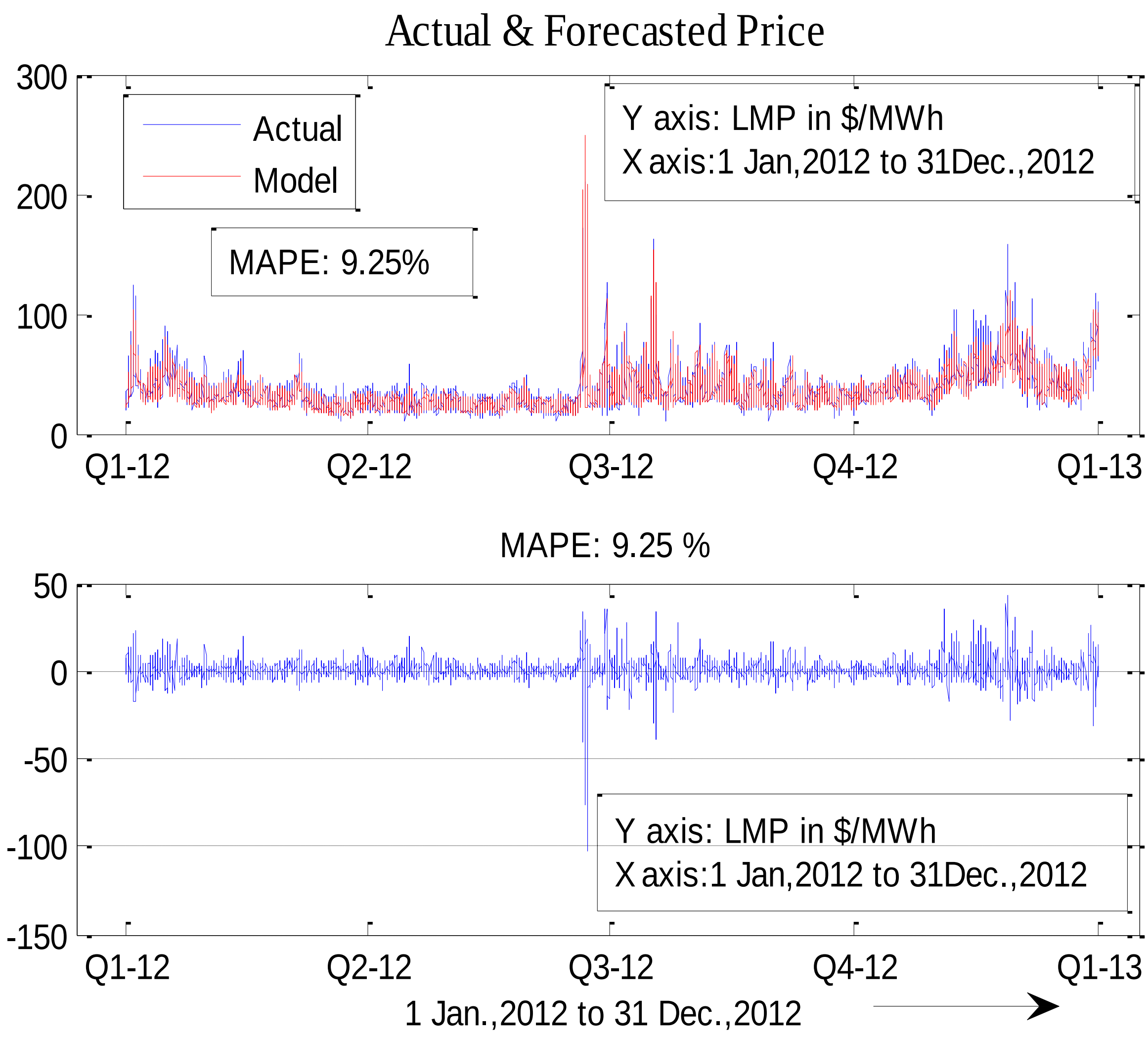

Fig. 5.5.2. Plot between actual & forecasted price by using ANN in the year 2012.

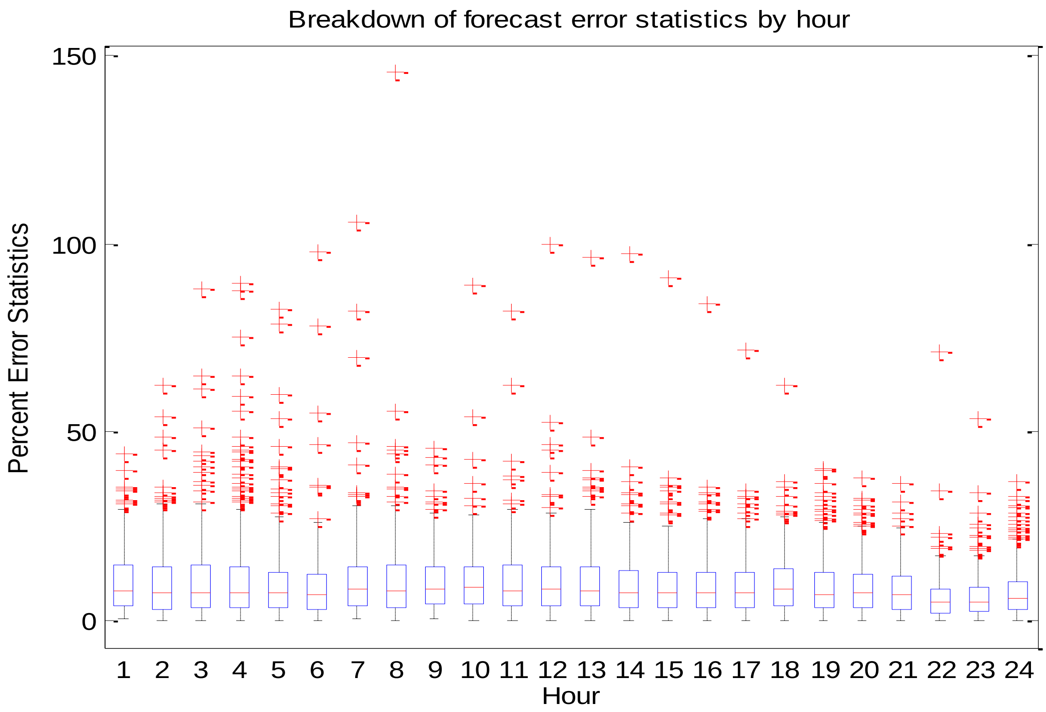

Fig. 5.5.3. Box-plot of the error distribution of forecasted price as a function of hour of the day for year 2012.

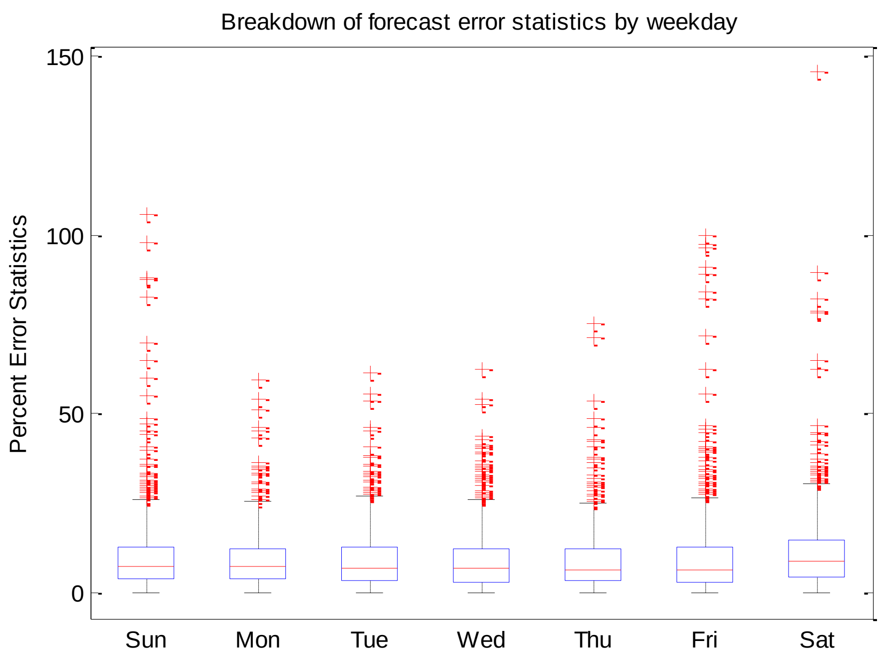

Fig. 5.5.4. Box-plot of the error distribution for the forecasted price as a function of day of the week in the year 2012.

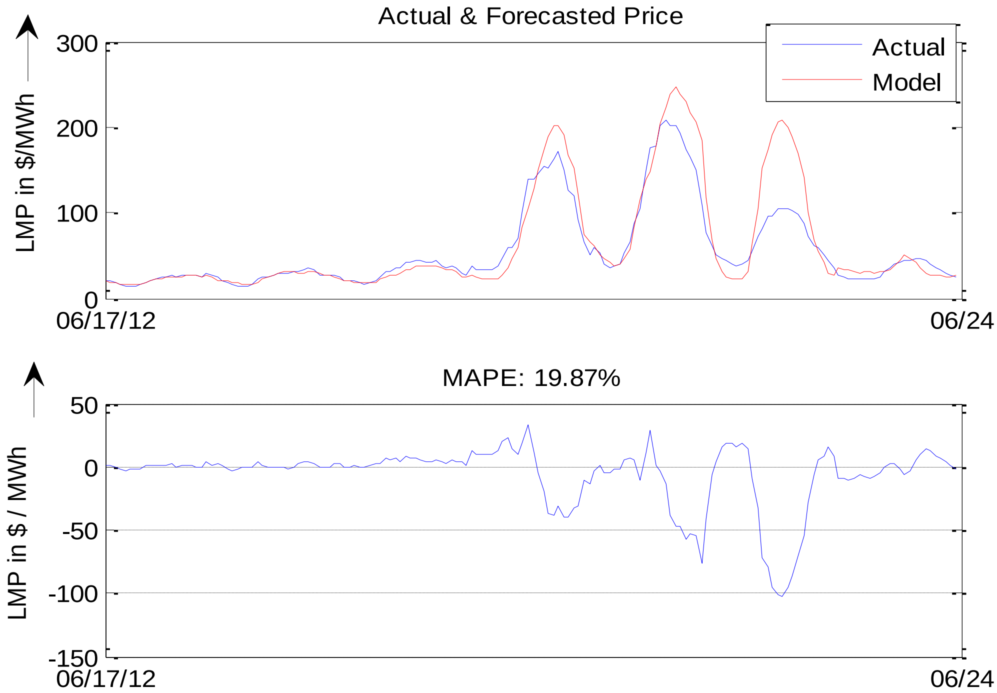

Fig. 5.5.5. MAPE is highest (19.87%) during the price forecast of 17-23 June, 2012 from weekly testing sets in year 2012.

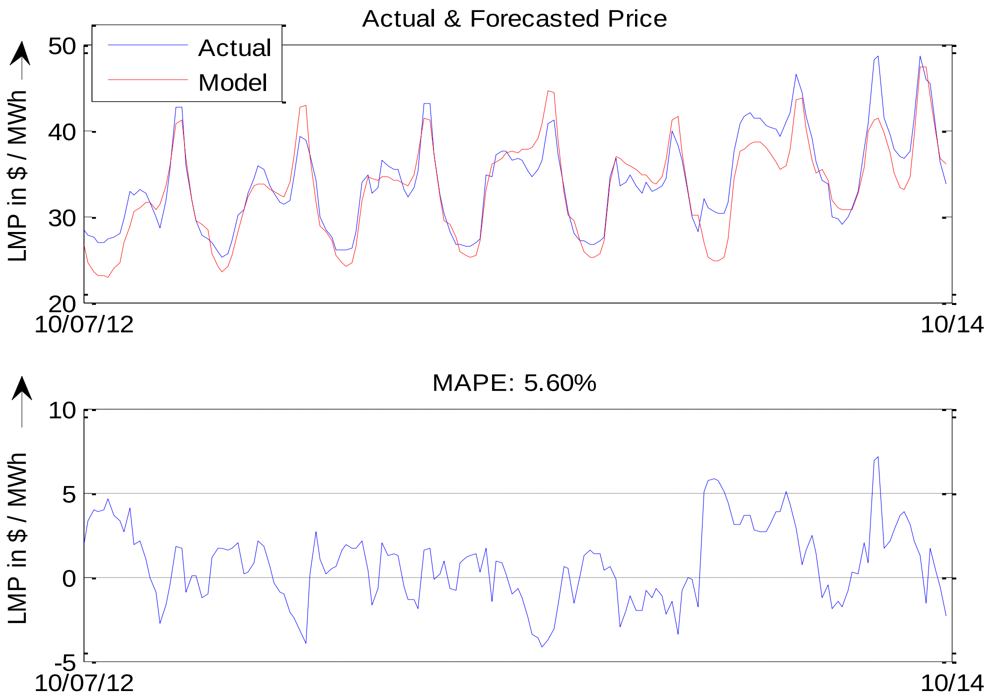

Fig. 5.5.6. MAPE is least (5.60%) during the price forecast of 7-13 October, 2012 from weekly testing sets in year 2012.

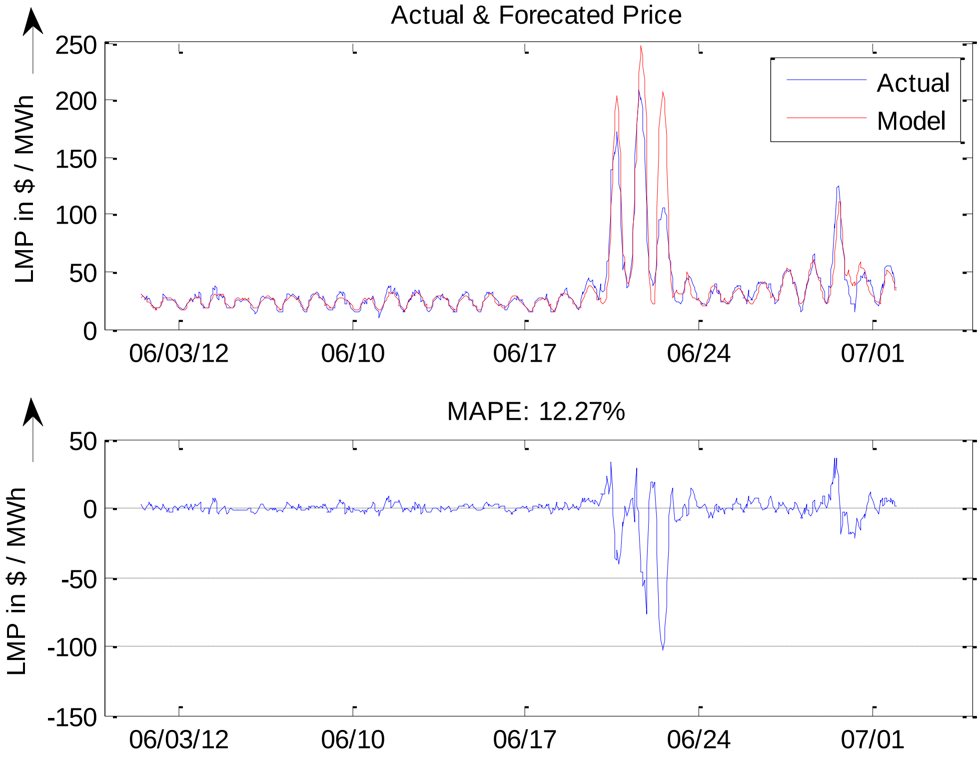

Fig. 5.5.7. MAPE is highest 12.27% for the month of June during price forecast.

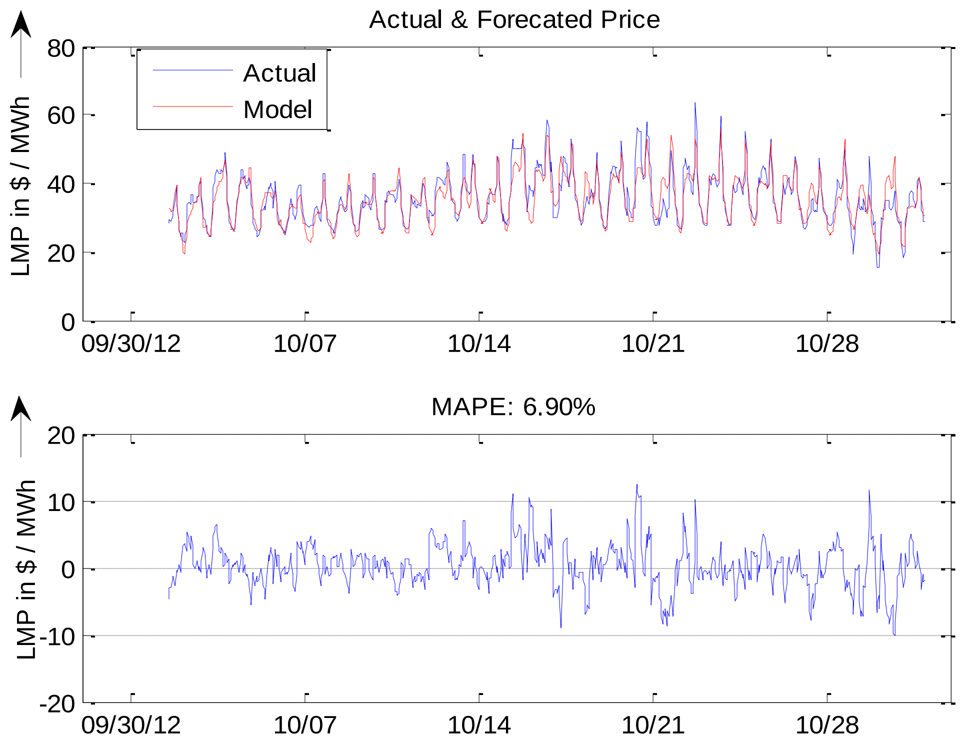

Fig. 5.5.8. MAPE is least 6.90% for the month of October during price forecast.

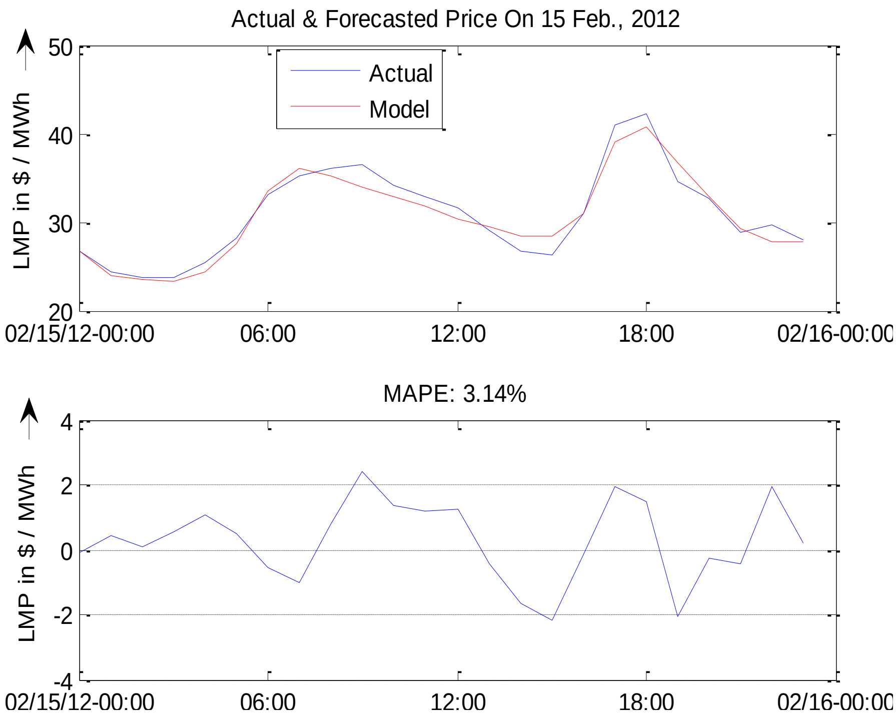

Fig. 5.5.9. MAPE is least 3.14% for the forecast on 24 Dec., 2012 in year 2012.

The Mean Absolute Percentage Error (MAPE) between the forecasted and actual loads and prices for each week has been calculated and presented in the Table 5.6 for ISO New England market in the testing year-2012.

TABLE 5.5

RESULTS FOR OUT-OF-SAMPLE DAILY TEST FROM JANUARY-DECEMBER

Da y	MAPE (%) for Each Day of the Month of Year 2012 During Day-Ahead Price Forecast of ISO New England Market											
	Jan.	Feb.	Mar.	Apri	May	Jun.	July	Aug	Sep.	Oct.	Nov	Dec.
1	18.4	5.06	8.55	15.6	9.59	6.4	10.3	6.35	16.8	10.2	9.53	14.2
2	9.55	6.2	12.6	7.52	13.4	6.25	12.0	6.52	11.6	7.21	6.3	17.8
3	9.43	10.8	8.57	4.83	11.5	6.25	11.3	8.8	7.84	6.14	15.8	5.27
4	14.5	5.56	7.87	6.56	11.2	9.08	13.9	8.52	9.25	4.18	8.34	15
5	12.2	4.67	8.83	8.56	6.64	6.14	12.7	7.03	7.91	5.72	13.6	10.0
6	6.78	6.24	6.95	9.89	6.51	8.7	6.55	10.3	10.2	5.16	17.0	12.8
7	7.5	6.07	10.8	7.87	6.29	7	14.1	5.64	8.58	7.31	14.6	21.8
8	7.94	5.57	7.24	7.84	9.05	5.65	16.1	3.77	12.4	4.49	7.89	13.0

9	6.69	6.47	9.1	8.73	11	10.4	8.74	4.42	7.26	3.78	8.3	7.92
10	11.7	5.83	6.38	9.64	5.72	8.43	4.76	4.72	7.98	4.65	9.93	11.6
11	9.93	11.0	7.94	14.2	12.8	14.1	9.36	5.91	4.01	3.96	4.95	7.2
12	5.21	8.48	5	12.4	9.98	6.29	7.34	4.44	11.1	9.63	6.57	13.0
13	6.17	7.63	12.7	10.0	10.6	6.78	11.1	7.57	10.2	5.36	6.11	4.43
14	13.3	10.0	8.21	16.6	7.84	8.22	9.96	5.93	4.72	3.65	10	7.21
15	8.28	3.14	6.39	23.5	5.37	7.1	8.6	4.35	9.6	7.62	5.62	7.91
16	11.7	5.19	6.66	11.4	5.69	7.78	6.87	4.08	8.77	9.6	6.34	5.46
17	12.7	6.48	8.28	8.11	12.4	6.35	16.2	6.41	7.91	8.23	11.5	6.12
18	15.7	7.17	7.64	10.6	5.64	6.86	20.5	13.3	13.1	6.4	10.8	5.46
19	7.57	7.58	11.8	10.8	6.11	11.1	7.25	7.66	4.14	3.82	12.7	6.59
20	8.95	7.57	7.83	6.44	6.76	24.9	9.09	13.5	4.36	10.2	7.88	4.91
21	9.18	5.98	12.0	17	9.78	17.2	4.45	10.1	4.31	13.2	5.49	6.58
22	9.41	3.11	12.4	9.29	5.8	50.5	16.5	4.39	6.21	6.72	6.08	7.96
23	7	5.15	8.29	14.1	8.55	21.9	12.7	9.04	9.17	3.15	7.15	7.76
24	8.83	5.29	8.02	5.37	9.41	8.63	13.5	5.03	6.95	4.3	11.4	6.6
25	3.92	10.7	8.3	11.9	9.21	6.66	9.23	11.7	11.1	5.25	9.27	19.6
26	7.19	9.98	7.66	16.1	14.0	12.1	13.0	10.4	2.51	3.75	9.99	7.34
27	3.77	9.23	8.22	18.8	10.0	5.62	8.07	8.52	3.99	8.15	13.7	7.16
28	5.06	8.25	13.0	9.25	6.8	11.9	11.2	7.5	4.02	7.83	8.04	19.8
29	6.23	6.68	14.3	9.48	6.57	18.1	8.57	6.8	7.64	12.9	9.13	8.3
30	10.3	----	16.5	6.56	11.2	39.8	5.42	15.5	7.71	18.3	13.2	23.4
31	6.46	-----	13.2	-----	15.1	----	7.59	6.86	-----	6.32	-----	9.82

TABLE 5.6

RESULTS FOR OUT-OF-SAMPLE TEST FOR YEAR 2012

S. N.	Duration (Year 2012) mm/dd - mm/dd	Load of Ontario electricity market				ISO New England		PJM
		Without Temp. data		With Temp. data		MAPE (%)		MAPE (%)
		MAPE (%)	MAE (MW)	MAPE (%)	MAE (MW)	Load	Price	Load
1	01/01-01/07	3.97	733.84	2.96	540.2	2.03	11.23	5.28
2	01/08-01/14	2.48	466.22	1.8	342.26	1.24	8.72	4.51
3	01/15-01/21	2.83	553.77	2.1	411.57	1.39	10.61	3.59
4	01/22-01/28	2.04	375.7	1.75	316.5	1.79	6.46	4.12
5	01/29-02/04	2.44	439.09	1.87	328.37	**0.90 (min)**	7.25	3.13
6	02/05-02/11	2.92	552.34	1.89	359.91	1.22	6.57	3.07
7	02/12-02/18	2.79	513.81	2.25	413.02	1.13	6.88	3.97
8	02/19-02/25	3.14	570.96	2.21	399.15	1.36	6.49	3.19
9	02/26-03/03	2.57	475.49	2.18	397.25	1.49	9.13	3.36
10	03/04-03/10	3.36	610.92	2.42	441.33	1.59	8.19	3.50
11	03/11-03/17	2.72	448.39	2.75	451.5	1.96	7.71	2.58

12	03/18-03/24	2.69	426.87	2.89	467.96	1.73	9.64	2.21
13	03/25-03/31	2.49	426.55	2.11	359.75	1.32	11.64	2.67
14	04/01-04/07	2.74	468.34	2.14	361.16	1.61	8.70	2.03
15	04/08-04/14	2.26	385.52	2.22	378.52	1.34	11.37	2.48
16	04/15-04/21	2.41	400.15	2.56	434.41	1.80	12.58	3.12
17	04/22-04/28	2.49	429.58	2.36	401.09	1.53	12.15	2.28
18	04/29-05/05	2.19	345.81	2.08	330.35	1.45	9.79	3.04
19	05/06-05/12	**1.68 (min.)**	271.14	**1.54 (min.)**	249.12	0.93	8.78	2.58
20	05/13-05/19	2.54	426.17	2.3	381.01	1.01	7.68	2.54
21	05/20-05/26	3.09	547.48	1.96	330.22	1.15	9.08	2.78
22	05/27-06/02	3.93	692.9	3.04	532.95	1.76	8.92	4.33
23	06/03-06/09	2.41	415.03	1.93	321.4	1.29	7.61	3.39
24	06/10-06/16	4.33	795.98	3.06	551.08	0.94	8.39	3.41
25	06/17-06/23	4.07	838.2	2.19	435.4	1.58	**19.87 (max)**	3.73
26	06/24-06/30	3.5	675.87	2.83	542.79	1.68	14.73	**5.87 (max)**
27	07/01-07/07	3.57	741.41	2.55	512.19	1.78	11.59	4.28
28	07/08-07/14	3.08	592.61	2.8	552.78	1.43	9.64	2.75
29	07/15-07/21	4.45	866.46	2.9	550.01	1.43	10.44	4.24
30	07/22-07/28	4.09	813.74	2.88	561.02	1.47	12.07	3.75
31	07/29-08/04	3.45	701.21	2.53	488.58	1.23	7.40	2.58
32	08/05-08/11	**4.87 (max.)**	890.64	**3.83 (max.)**	690.72	1.70	5.98	2.98
33	08/12-08/18	3.13	569.49	2.17	385.39	1.60	6.59	2.63
34	08/19-08/25	2.82	542.74	2.02	369.53	1.25	8.79	2.37
35	08/26-09/01	3.92	740.82	2.91	534.1	1.64	10.73	3.15
36	09/02-09/08	3.5	603.63	3.11	534.05	1.53	9.70	3.61
37	09/09-09/15	4.34	691.02	3.67	560.46	2.08	7.87	4.65
38	09/16-09/22	2.22	361.39	2.05	330.51	1.70	6.99	2.79
39	09/23-09/29	2.21	354.29	2.29	370.79	1.28	6.49	2.80
40	09/30-10/06	1.89	304.71	1.9	307.52	1.37	6.63	2.45
41	10/07-10/13	2.99	482.02	2.73	437.82	1.56	**5.60 (min)**	2.07
42	10/14-10/20	2.14	360.67	1.83	307.51	1.80	7.08	1.94
43	10/21-10/27	1.81	299.55	1.98	329.1	1.35	6.37	**1.66 (min)**
44	10/28-11/03	2.38	411.03	2.27	396.97	**3.87 (max)**	11.01	2.79
45	11/04-11/10	2.12	394.9	2.18	407.69	1.86	11.41	2.28
46	11/11-11/17	1.94	351.72	2.22	405.67	1.59	7.31	2.21
47	11/18-11/24	2.2	394.36	2.03	364.55	2.27	8.81	2.75
48	11/25-12/01	2.82	532.86	2.3	438.33	1.28	11.11	2.51
49	12/02-12/08	2.33	425.96	2.24	408.36	1.74	13.72	3.34
50	12/09-12/15	2.69	503.46	2.12	401.76	1.76	8.47	2.60
51	12/16-12/22	2.68	497.49	2.33	431.3	1.84	6.16	2.89
52	12/23-12/29	3.9	684.51	2.83	496.91	2.57	10.95	4.44
53	**Average**	**2.91**	**526.90**	**2.38**	**424.07**	**1.59**	**9.25**	**3.14**

TABLE 5.7

RESULTS FOR OUT-OF-SAMPLE MONTHLY TEST IN YEAR 2012

S.N.	Month	Load of Ontario electricity market				ISO New England		PJM
		Without Temperature data		With Temperature data		MAPE (%)		MAPE (%)
		MAPE (%)	MAE (MW)	MAPE (%)	MAE (MW)	Price	Load	Load
1	January	2.86	536.31	2.17	402.98	9.21	1.56	**4.24 (max)**
2	February	2.76	511.52	**2.05 (min.)**	378.46	6.92	**1.18 (min)**	3.41
3	March	2.8	475.71	2.53	427.28	9.57	1.69	2.74
4	April	2.49	420.3	2.31	388.86	10.78	1.53	2.51
5	May	2.67	459.01	2.17	365.78	9.00	1.26	2.95
6	June	3.48	658.69	2.49	458.32	**12.27 (max)**	1.36	4.13
7	July	**3.83 (max.)**	759.45	**2.78 (max.)**	543.91	10.52	1.51	3.67
8	August	3.65	691.38	2.68	488.92	7.60	1.51	2.73
9	September	3.03	496.01	2.72	440.28	8.17	1.62	3.38
10	October	2.25	371.85	2.2	365.2	**6.90 (min)**	**2.10 (max)**	**2.23 (min)**
11	November	**2.23 (min.)**	409.26	2.11	388.85	9.63	1.71	2.40
12	December	2.99	543.41	2.48	452.62	10.39	2.04	3.29

5.6 Effect of Temperature on Load Forecast Using Improved ANN

A new artificial neural network (ANN) has been designed to compute the forecasted load. The data used in the modeling of ANN are hourly historical data of the temperature and electricity load. The ANN model is trained on hourly data from the ISO New England market and Ontario Electricity Market from 2007 to 2011 and tested on out-of-sample data from 2012. Simulation results obtained have shown that day-ahead hourly forecasts of load using proposed ANN is very accurate with very less error in both the markets.

However load forecast for ISO New England market & Ontario market is much better with temperature data as input than without taking it. This is due to the fact that temperature and weather data are having high degree of correlation with load of that particular region. This indicates that temperature data is a very important parameter for load forecasting using ANN.

5.6.1. Ontario Electricity Market Neglecting Temperature Effect

The ANN & improved ANN model used in the forecasting has input, output and one hidden layers. Hidden layer has 50 neurons in ANN, whereas improved ANN consists of a hybrid of 46 & 50 neurons in its hidden layer. Inputs to the input layer are as listed above for load forecast without considering temperature data. After simulation the MAPE obtained is 2.90% & 2.85 % for load forecasting for the year 2012 by using ANN & improved ANN respectively. Multiple series plot between actual load & forecasted load & also the plot of MAPE in testing year-2012 using improved ANN is shown in Fig. 5.6.1.

The box-plot of the error distribution of forecasted load as a function of hour of the day is presented in Fig. 5.6.2. It shows the percentage error statistics of hour of the day in year 2012. It is also evident that the maximum error is for the 6^{th} hour of the day and minimum error for 21^{th} hour of the day in year 2012. The box-plot of the error distribution of forecasted load as a function of day of the week is evaluated in Fig. 5.6.3 which shows the percentage error statistics of day of the week in year 2012. The maximum error is for the Monday and minimum error for Friday in year 2012.

Multiple series plots between actual load & forecasted load from 05-11 Aug., 2012 & from 06-12 May, 2012 for Ontario electricity market and also plots of MAPE with maximum error (4.60%) and minimum error (1.66%) for day ahead hourly weekly forecast in year 2012 have been shown in Fig. 5.6.4 and Fig. 5.6.5 by ANN & improved ANN respectively.

The MAPE between the forecasted and actual loads for each day, week & month has been calculated and presented in Table 5.8-5.11, 5.13 & also MAE for each week & month is presented in Table 5.12-5.13 for the testing year 2012.

From the results obtained from Table 5.8-5.9, it is clear that highest MAPE (9.14%) is on 06 August & least MAPE (1.01%) is on 26 July, 2012 in Ontario electricity market (without temperature data) for day ahead hourly forecast in testing year-2012 & also multiple series plots between actual load & forecasted load with plot of MAPE on 06 August is shown in Fig. 5.6.6.

From the results obtained from Table 5.13, it is clear that maximum MAPE (3.85%) is for July & minimum MAPE (2.17%) is for November, 2012 for Ontario electricity market (without temperature data) by using improved ANN model for day-ahead forecasting.

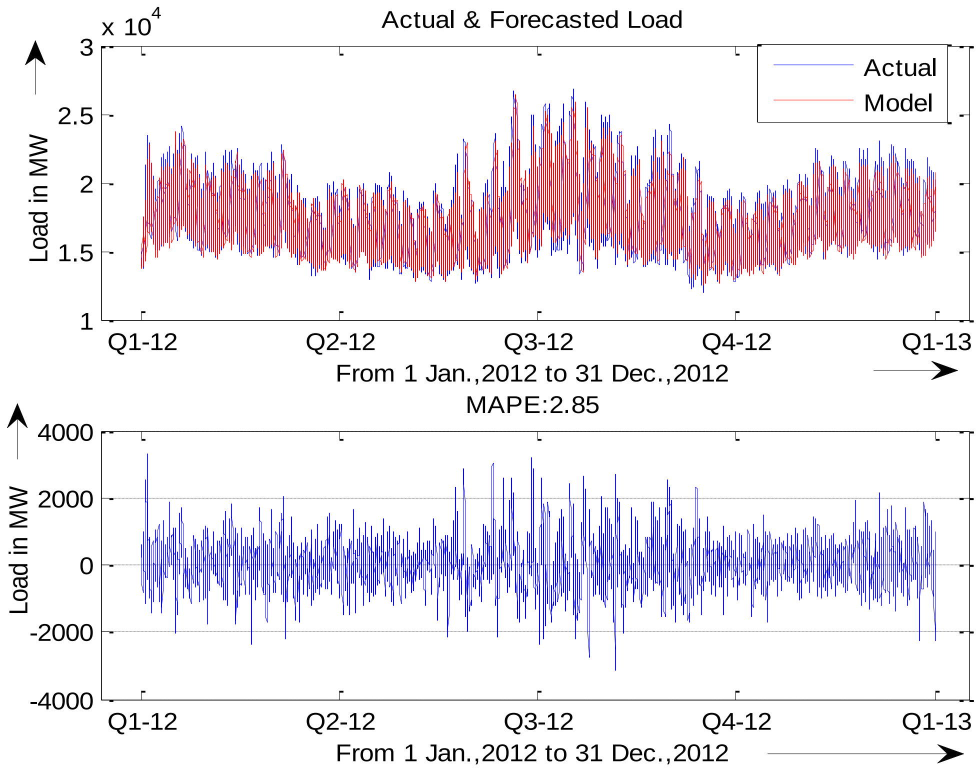

Fig. 5.6.1. Multiple series plot between actual load & forecasted load by improved ANN in year 2012 for Ontario electricity market.

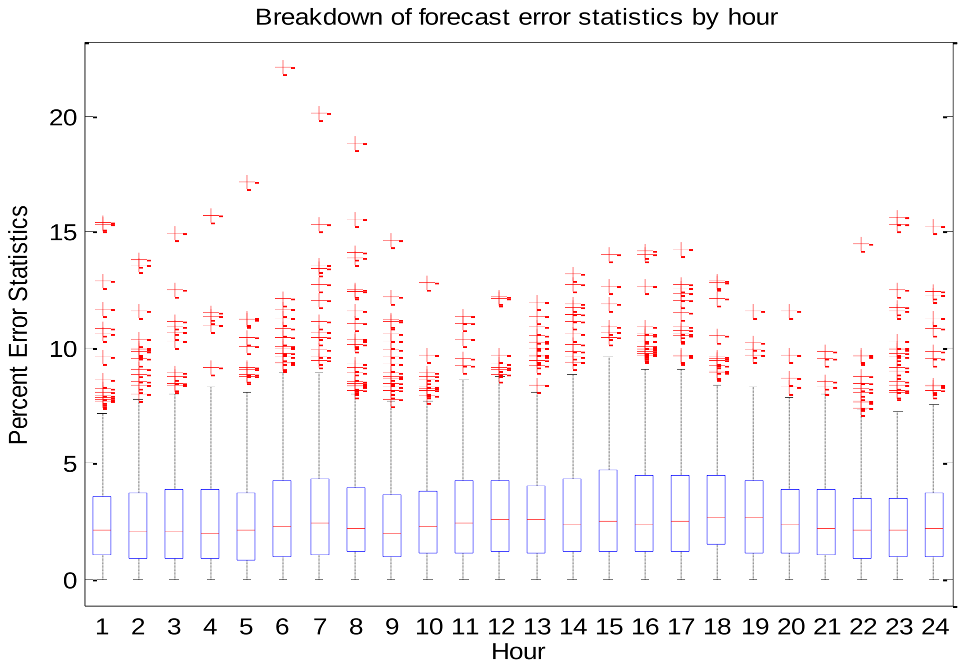

Fig. 5.6.2. Error distribution of forecasted load as a function of hour of the day in the year 2012 for Ontario electricity market by improved ANN.

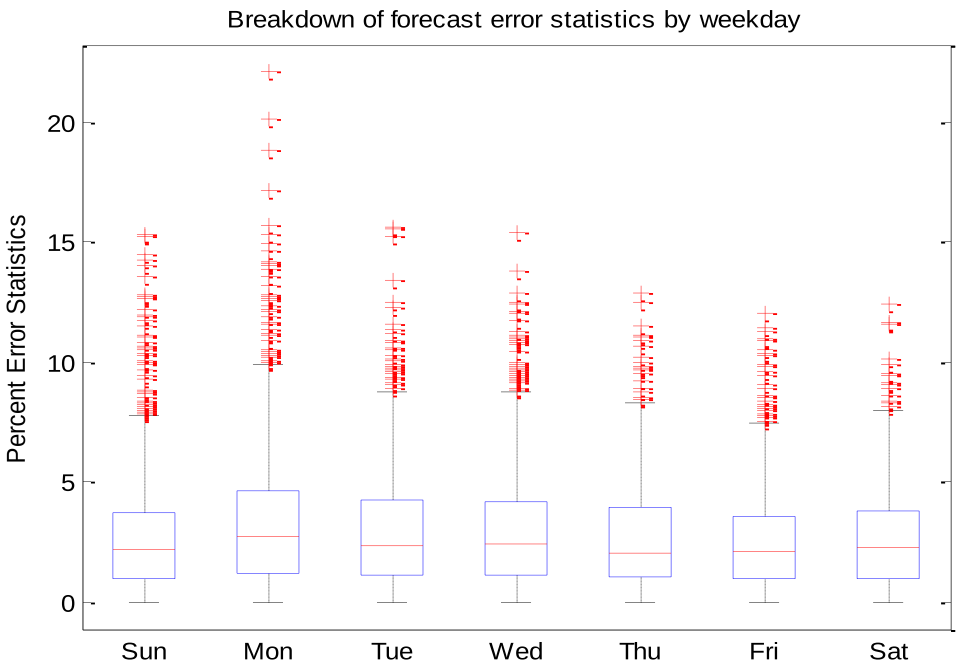

Fig. 5.6.3. Error distribution for the forecasted load as a function of day of the week in the year 2012 for Ontario electricity market by improved ANN.

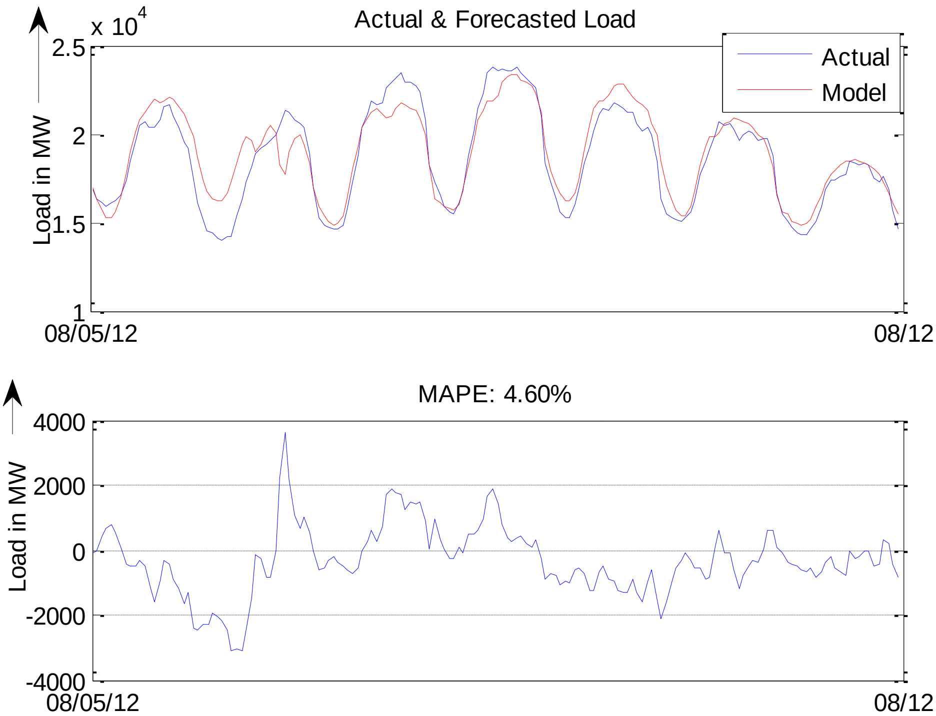

Fig. 5.6.4. Maximum MAPE is 4.60 % for the forecast of 05 -11 Aug., 2012 in year 2012 for day ahead hourly weekly forecast by using ANN.

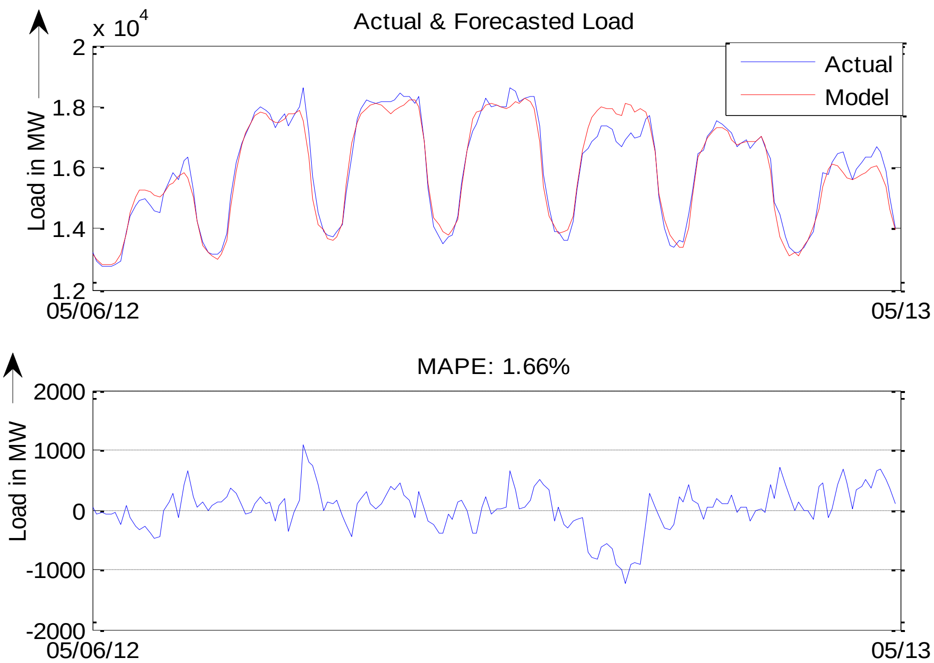

Fig. 5.6.5. Minimum MAPE is 1.66% for the forecast of 06-12 May, 2012 for day ahead hourly weekly forecast in the year 2012 by using improved ANN.

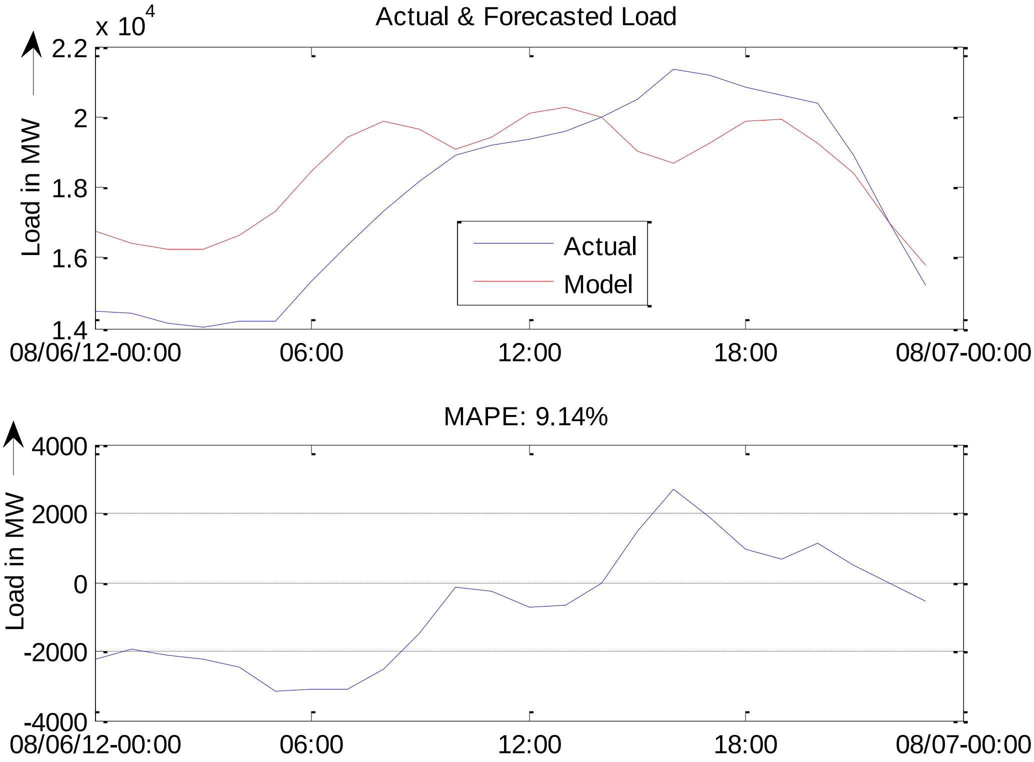

Fig. 5.6.6. MAPE is highest (9.14%) for the day ahead hourly forecast on 06 August, 2012 in Ontario electricity market in year 2012 by improved ANN.

5.6.2. ISO New England Market

The ANN & improved ANN model used in the forecasting has input, output and one hidden layers. Hidden layer has 52 neurons in ANN, whereas improved ANN has hybrid of 52 & 48 neurons in its hidden layer. Inputs to the input layer as listed above for load forecast with considering temperature data. After simulation the MAPE obtained is 1.55 % & 1.50 % for load forecasting for the year 2012 by ANN & improved ANN respectively. Multiple series plot between actual load & forecasted load & also the plot of MAPE in testing year-2012 using improved ANN is shown in Fig. 5.6.7.

The box-plot of the error distribution of forecasted load as a function of hour of the day is presented in Fig. 5.6.8. It shows the percentage error statistics of hour of the day in year 2012. It is also evident that the maximum error is for the 21st hour of the day and minimum error for 14th hour of the day in year 2012. The box-plot of the error distribution of forecasted load as a function of day of the week is evaluated in Fig. 5.6.9 which shows the percentage error statistics of day of the week in year 2012. The maximum error is for the Monday and minimum error for Thursday in year 2012.

Multiple series plots between actual load & forecasted load from 06-12 May, 2012 & from 28 October, 2012 to 03 November, 2012 for ISO New England market and also plots of MAPE with maximum error (3.85%) and minimum error (0.85%) for day ahead hourly weekly forecast in year 2012 have been shown in Fig. 5.6.10 and Fig. 5.6.11 by using improved ANN.

Also, an ANN & improved ANN model for forecasting has been developed without considering temperature data (dry bulb & dew point) as an input to input layer. This ANN & improved ANN model used in the forecasting has input, output and one hidden layers. Hidden layer has 38 neurons in ANN, while the improved ANN has hybrid of 42 & 50 neurons in its hidden layer. After simulation the MAPE obtained is 2.90 % & 2.81 % for load forecasting for the year 2012 by using ANN & improved ANN respectively. The MAPE obtained between actual load & forecasted load from 17-23 June & from 06-12 May, 2012 for ISO New England market shows maximum error (5.13%) & minimum error (1.19%) for day ahead hourly weekly forecast in year 2012 by using ANN & improved ANN respectively.

The MAPE between the forecasted and actual loads for each day, week & month has been calculated and presented in Table 5.8-5.11, 5.13 & also MAE for each week & month is presented in Table 5.12-5.13 for the testing year 2012, with & without considering temperature data as an input to ANN forecasting model for both the power markets (ISO New England & Ontario electricity market). From the results of Table 5.8-5.13 it is observed that MAPE & MAE for the power markets by considering temperature variable as an input to ANN for forecast is much better. This indicates that temperature data is a very important parameter for load forecasting using ANN. Also, the MAPE & MAE from Table 5.8-5.13 of ISO New England market with considering temperature data is much better than without considering temperature data as input to ANN in same market.

From the results obtained from Table 5.13, it is clear that maximum MAPE (2.02%) is for Dec., 2012 and minimum MAPE (1.4%) is for July, 2012 for ISO New England market (with temperature data), as soon in Fig. 5.6.12 using improved ANN.

Multiple series plots between actual load & forecasted load using improved ANN on 09 May, 2012 for ISO New England market and also plots of MAPE with least error (0.45%) for day ahead hourly forecast in year 2012 have been shown in Fig. 5.6.13. Also the highest error for daily forecast is on 29 Oct., 2012 in the year 2012 with MAPE (11.35%) for ISO New England market is presented in Table 5.9.

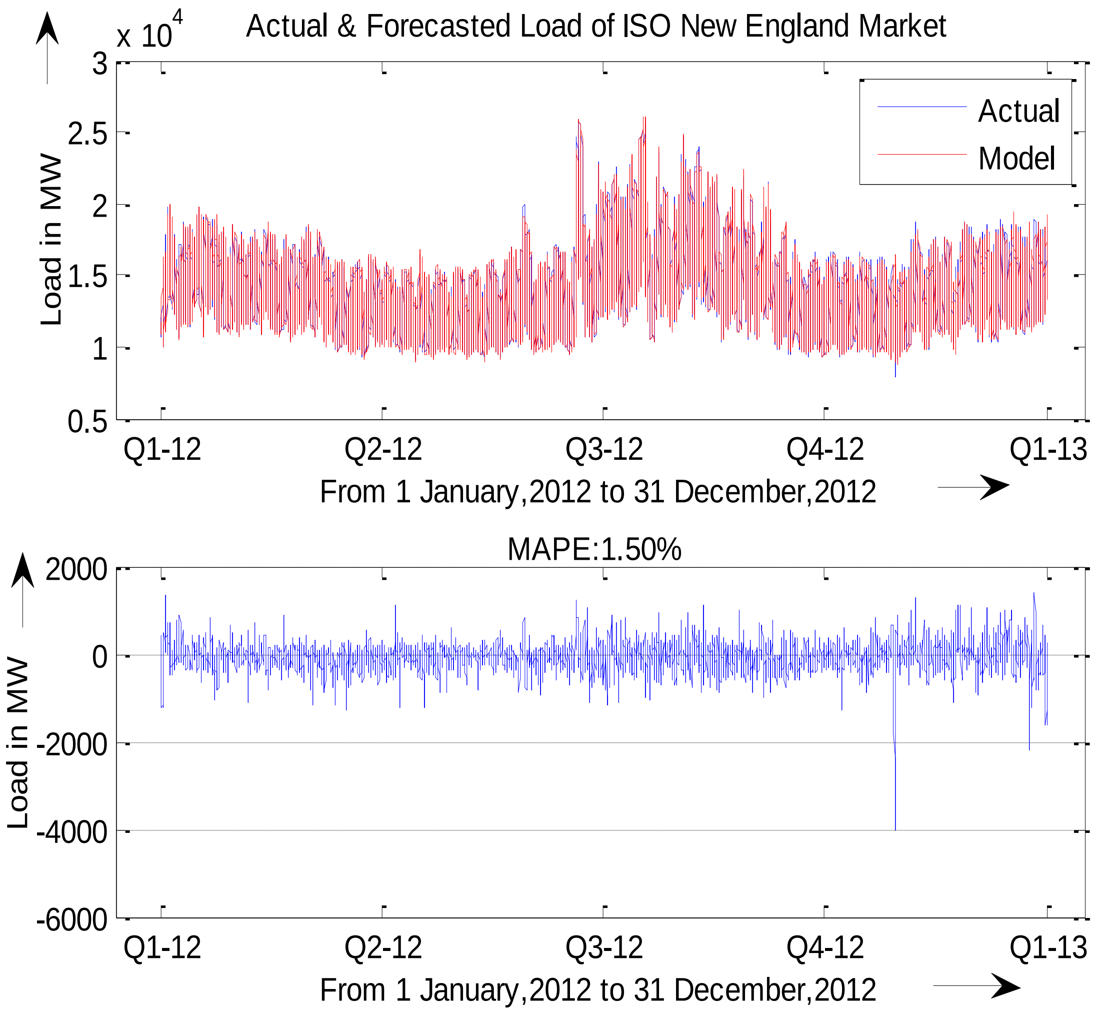

Fig. 5.6.7. Multiple series plot between actual load & forecasted load by improved ANN in year 2012.

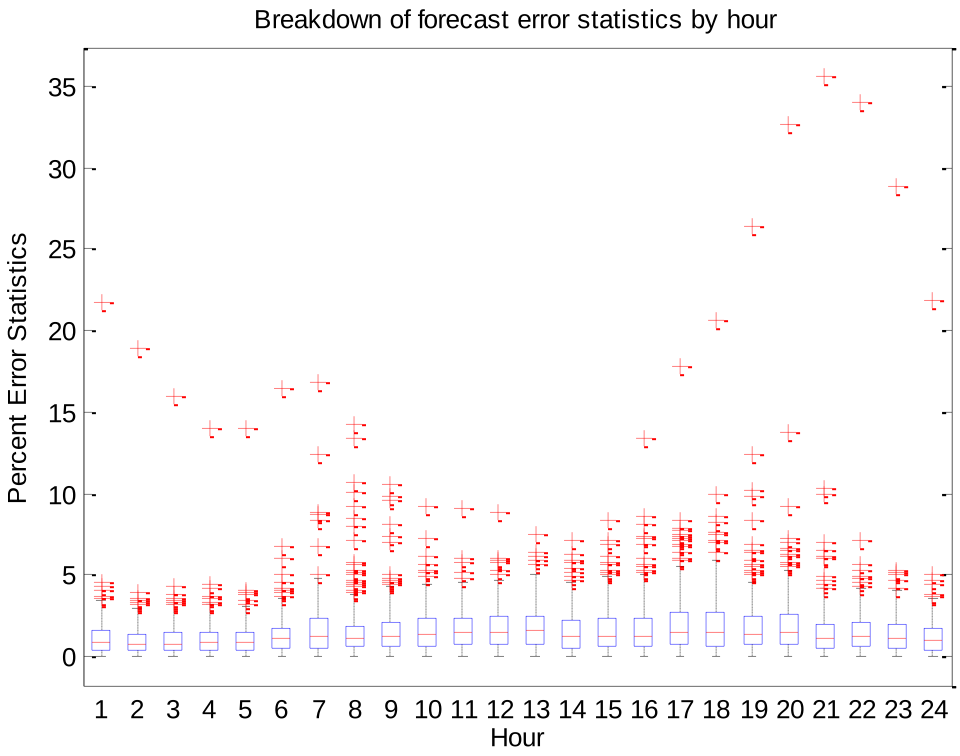

Fig. 5.6.8. Error distribution of forecasted load as a function of hour of the day in year 2012 for ISO New England market by improved ANN.

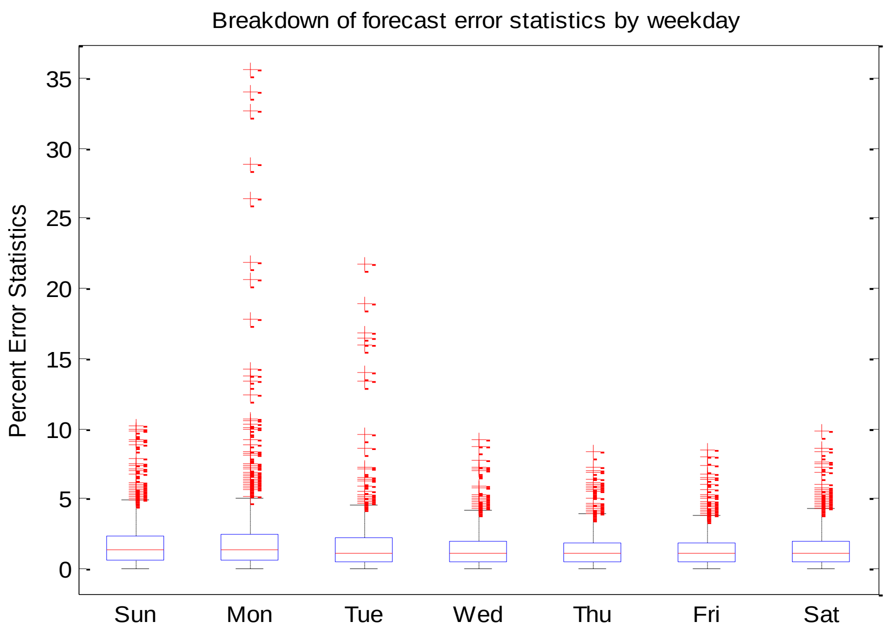

Fig. 5.6.9. Error distribution for the forecasted load as a function of day of the week in the year 2012 for ISO New England market by improved ANN.

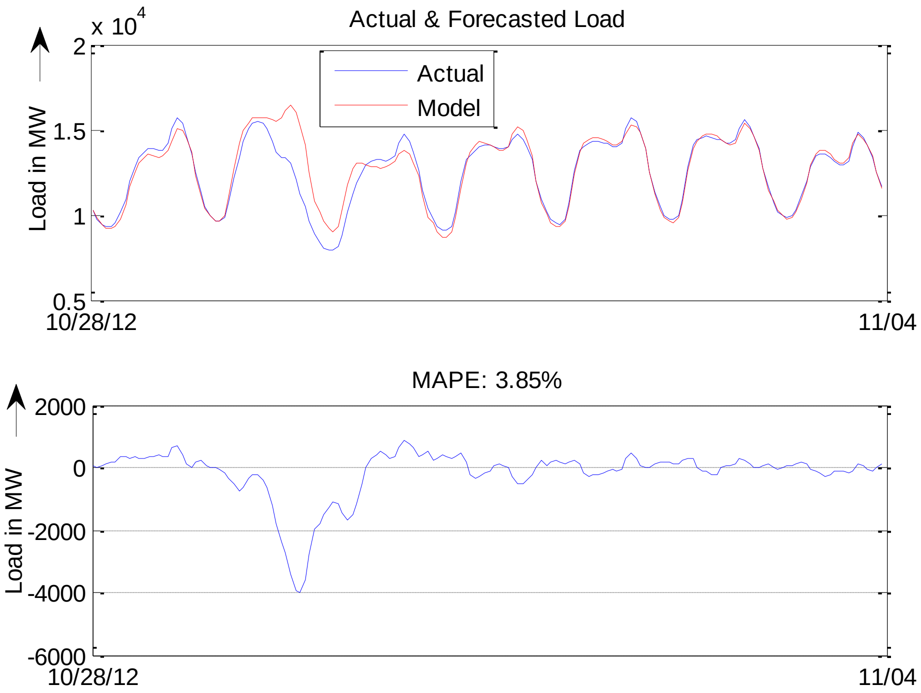

Fig. 5.6.10. Maximum MAPE is 3.85% for the load forecast of 28 October, 2012 to 03 November, 2012 for day ahead hourly weekly forecast for year 2012.

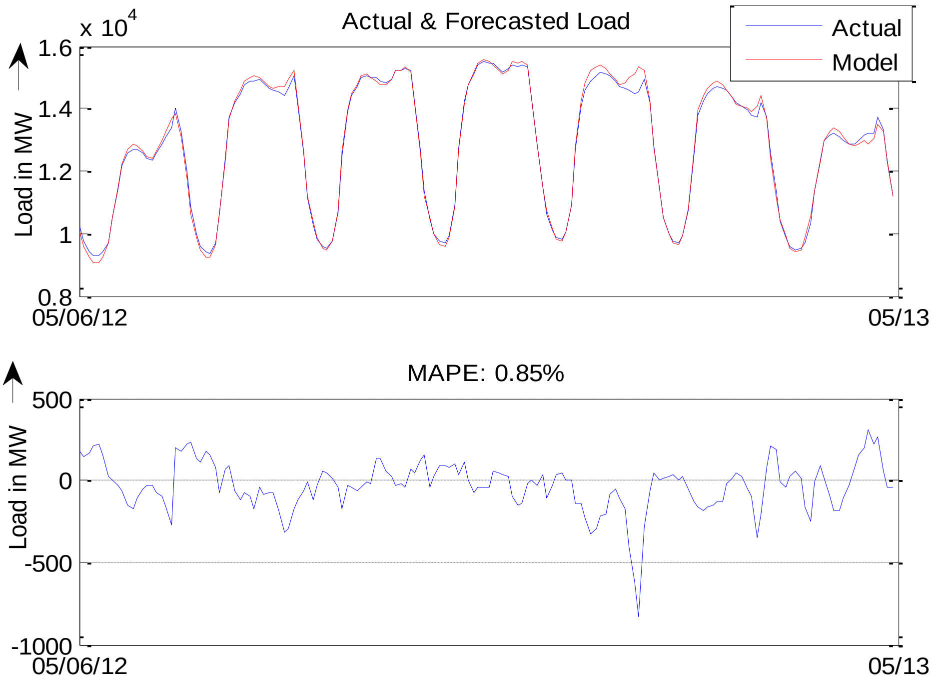

Fig. 5.6.11. Minimum MAPE is 0.85% for the load forecast of 06-12 May, 2012 for day ahead hourly weekly forecast for the year 2012.

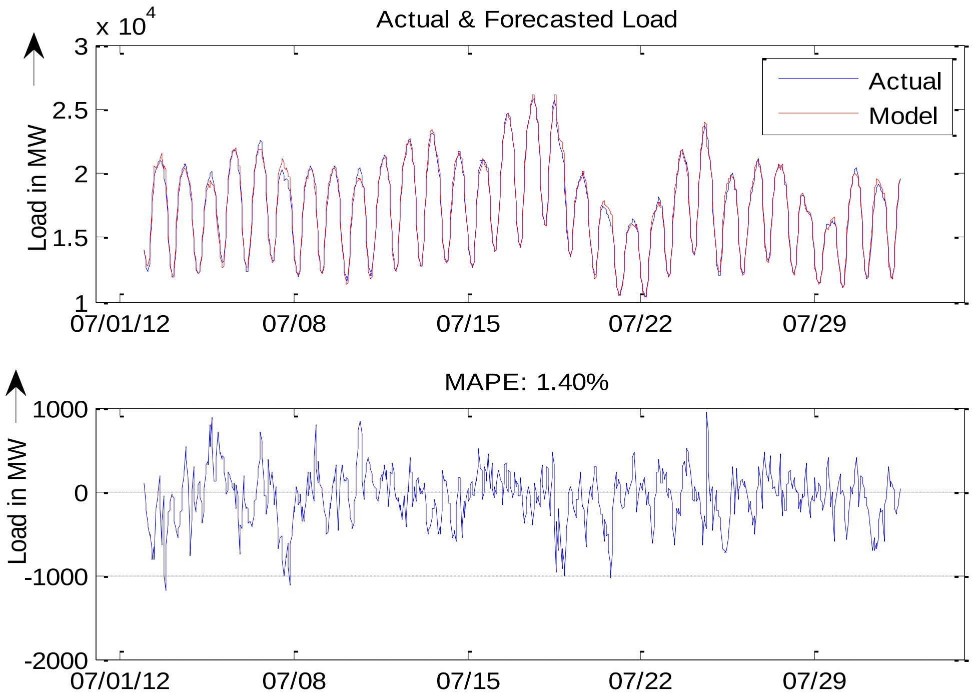

Fig. 5.6.12. MAPE is least (1.40%) for day ahead hourly-monthly forecast of July, 2012 of ISO New England market in year 2012.

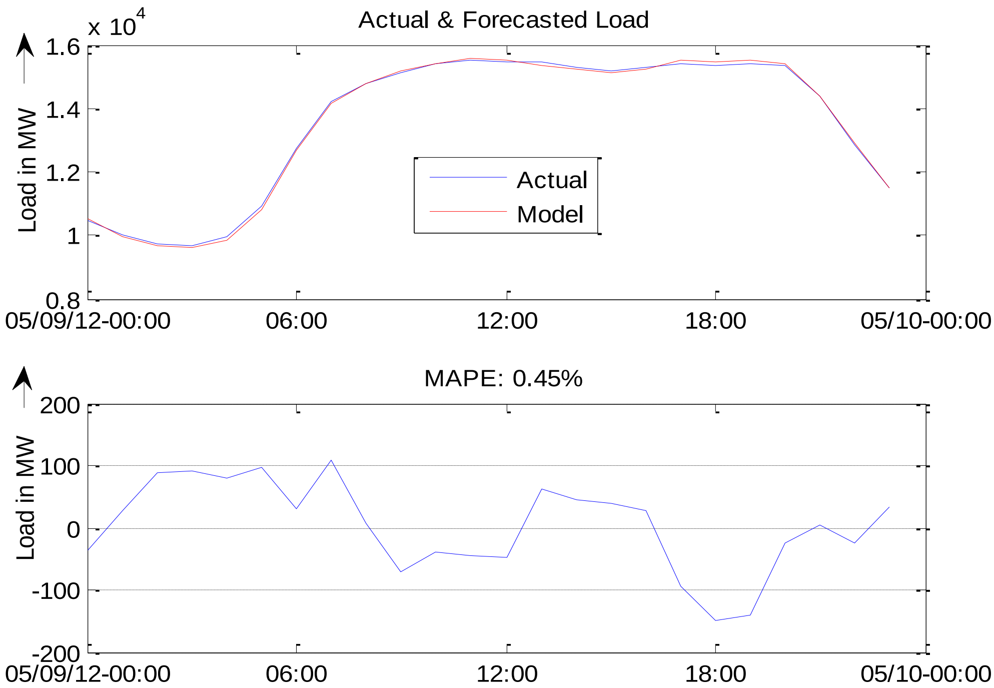

Fig. 5.6.13. MAPE is least (0.45%) for day ahead hourly forecast on 09 May, 2012 for ISO New England market in year 2012.

TABLE 5.8

RESULTS FOR OUT-OF-SAMPLE DAILY TEST FROM JANUARY-JUNE, 2012 BY IMPROVED ANN

Day	MAPE (%) for Each Day of the Month of Year 2012 During Day-Ahead Load Forecast											
	Ontario Electrcity Market Without Temp. Data						ISO New England Market With Temp. Data					
	Jan.	Feb.	Mar.	April	May	Jun.	Jan.	Feb.	March	April	May	Jun.
1	2.29	1.66	1.68	3.56	2.99	2.17	4.51	0.83	1.18	1.73	1.13	1.57
2	4.9	1.71	2.83	3.2	1.54	2.27	2.5	0.71	2.08	1.25	1.44	0.71
3	7.46	1.07	2.15	1.52	1.23	1.09	2.43	0.89	2.39	1.62	1.33	0.94
4	2.96	1.8	2.4	3.13	1.49	1.72	1.44	0.48	0.79	1.15	0.87	1.28
5	4.07	1.39	4.61	2.69	2.28	2.69	1.35	1.64	1.73	0.78	1.85	1.85
6	2.2	2.32	2.67	2.13	1.39	2.59	0.97	1.68	1.3	2.63	1.16	1.27
7	3.09	2.93	6.08	2.51	1.49	3.1	1.11	0.55	2.36	1.14	0.93	1.16
8	2.95	3.69	2.68	2.97	1.16	2.64	1.93	1.06	2.61	2.5	0.49	0.82
9	2.32	3.05	2.31	1.82	1.36	2.07	1.2	1.54	0.81	1.5	**0.45**	0.87
10	3.36	2.53	3.27	2.34	3.06	6.54	0.87	1.13	1.06	1.02	1.3	1.29
11	1.93	3.84	5.04	2.19	1.16	2.85	1.2	0.84	2.07	0.68	0.77	1.01
12	1.46	3.44	2.12	2.68	1.97	4.83	1	0.98	3.2	0.8	0.88	0.72
13	2.78	4.13	5.31	2	1.94	5.01	1.28	1.98	2.28	1.13	0.89	0.82
14	3.06	2.69	1.37	2.11	3.03	2.73	1.13	1.17	0.8	1	0.62	0.83
15	3.07	2.92	1.51	2.91	2.32	5.78	0.73	0.89	1.03	1.07	0.66	0.89
16	4.32	1.74	1.67	2.42	3.58	2.32	1.43	0.63	1.38	1.5	0.65	0.87
17	3.41	2.59	2.56	1.94	2.11	2.21	1.86	0.99	2.37	2.14	1.29	1.11
18	2.8	1.39	2.04	2.02	2.27	3.4	1.41	0.94	2.2	3.54	1.02	1.39
19	3.42	2.11	3.66	1.77	2.21	5.75	1.29	1.55	1.91	1.05	1.36	1.15
20	1.77	5.24	2.4	1.59	1.97	4.75	1.17	2.07	1.28	1.09	0.93	3.23
21	1.26	2.73	3.34	3.96	4.16	2.68	1.7	0.93	0.96	1.15	0.96	1.37
22	2.63	2.57	2.14	2.13	1.75	4.78	3.32	1.95	1.78	1.69	0.77	1.03
23	2.71	1.97	2.88	2.34	1.84	2.9	2.54	1.05	1.93	1.91	0.72	2
24	1.63	3.77	1.8	2.47	5.07	1.6	2.34	1.02	1.47	2	0.8	1.79
25	2.14	2.51	2.56	4.1	3.56	4.55	0.68	1.02	1.53	1.19	1.05	2.71
26	1.45	2.89	2.95	2.6	2.36	4.09	1.17	1.35	1.04	0.59	1.35	1.64
27	2.21	2.96	2.46	1.74	2.39	2.06	1.15	1.6	1.77	1.4	2.24	1.46
28	1.4	2.11	1.5	2.06	6.81	4.8	1.37	1.47	1.05	0.9	1.03	1.86
29	3.56	3.86	2.5	3.03	5.27	3.5	1.15	0.77	0.68	1.46	2.84	1.1
30	3.16	----	2.08	2.11	4.92	3.05	0.97	-----	2.01	1.23	2.11	1.36
31	3.61	-----	2.61	-----	3.83	----	1	------	0.91	-----	1.44	-----

TABLE 5.9

RESULTS FOR OUT-OF-SAMPLE DAILY TEST FROM JULY-DECEMBER, 2012 BY IMPROVED ANN

Day	MAPE (%) for Each Day of the Month of Year 2012 During Day-Ahead Load Forecast											
	Ontario Electricity Market Without Temp. Data						ISO New England Market With Temp. Data					
	July	Aug.	Sep.	Oct.	Nov.	Dec.	July	Aug.	Sep.	Oct.	Nov.	Dec.
1	2.16	3.89	2.9	2.42	2.74	3.57	0.96	0.93	1.27	1.35	1.32	1.12
2	4.81	3.92	3.62	2.44	1.45	1.52	2.55	1.1	1.49	0.87	1.13	2.76
3	3.96	2.89	4.94	2.13	2.34	3.12	1.73	1.08	1.52	1.04	0.85	2.51
4	6.58	2.64	2.97	1.52	1.23	1.71	1.69	1.05	1.41	1.3	2.73	1.18
5	1.44	5.28	3.16	1.6	2.91	3.24	1.47	1.51	1.78	1.33	1.59	1.79
6	3.48	**9.14**	2.01	1.52	2.38	2.7	1.45	1.02	1.6	1.78	1.13	1.97
7	4.39	4.27	3.95	2.13	2.9	2.35	2.75	2.08	1.29	2.27	2.95	1.18
8	4.6	2.54	3.95	4.47	1.93	2.38	1.11	1.48	1.72	2.58	0.84	1.15
9	2.63	5.72	5.19	3.49	1.6	3.44	1.27	1.15	1.92	1.12	1.7	1.46
10	2.58	2.65	2.44	2.36	1.81	3.77	1.77	1.47	2.39	0.87	1.87	1.42
11	3.09	2.83	3.83	1.52	2.04	2.78	1.1	1.98	2.04	1.31	2.2	2.03
12	4.01	1.58	4.49	2.2	1.95	2.46	0.97	1.26	1.52	0.86	2.66	1.93
13	3.03	2.84	3.42	4.21	1.99	2.97	1.27	1.53	1.34	1.09	0.95	1.67
14	2.89	2.91	3.77	2.14	1.72	1.9	1.38	1.28	1.83	1.8	1.39	1.96
15	2.09	3.2	5.25	4.37	2.33	1.73	0.9	1.06	2.35	2.21	1.28	1.87
16	4.21	3.26	2.46	1.74	1.4	1.84	0.67	1.02	2.19	1.69	1.13	2.5
17	3.47	3.15	2.4	1.34	1.93	3.9	0.72	1.61	0.99	0.58	1.66	1.37
18	3.89	4.01	2	1.55	1.39	2.52	1.91	2.71	1.2	1.22	1.96	1.67
19	6.6	1.26	2.39	2.02	1.7	2.91	1.12	1.48	2.23	1.22	1.55	1.53
20	5.27	2.11	1.98	1.51	1.72	1.92	2.2	1.45	2.47	2.3	1.04	1.69
21	4.36	2.34	1.85	2.71	2.56	2.31	1.04	1.27	0.89	1.96	1.18	1.42
22	6.85	2.91	1.97	1.44	1.19	2.77	1.21	1.17	1.1	1.45	2.91	2.28
23	4.76	3.9	2.72	1.1	2.67	2.62	1.37	1.24	1.31	0.85	3.54	1.43
24	5.34	3.32	1.78	2.08	3.88	6.73	1.21	1.18	1.64	0.79	2.09	6.26
25	6.06	3.3	3.5	1.79	1.96	2.1	2.18	0.96	1.73	0.76	2.2	2.71
26	**1.01**	2.81	1.86	2.1	2.34	4.2	1.1	1.69	0.96	1.59	1.3	3.02
27	2.52	2.63	2.4	1.87	2.29	3.65	1	1.2	1.18	1.3	0.6	1.4
28	1.79	3.72	1.6	2.88	2.08	2.31	0.79	1.53	0.56	2.07	0.8	1.67
29	2.49	5.07	2.14	3	2.74	2.62	1.01	1.64	1.27	**11.35**	1.25	1.2
30	3.63	4.54	1.64	2.28	3.48	2.2	1.18	1.44	0.96	8.08	1.16	1.28
31	3.44	4.06	-----	1.07	-----	5.26	2.09	1.65	-----	2.15	------	4.62

5.6.3. Load Forecast of Toronto City, Canada of Ontario Electricity Market

The ANN model used in the forecasting has input, output and one hidden layers. Hidden layer has 56 neurons. Inputs to the input layer as listed above for load forecast. Here hourly temperature & load data of Toronto of Ontario electricity market has been considered. After simulation the MAPE obtained is 1.80% for load forecasting for the year 2012. Multiple series plot between actual load & forecasted load & also the plot of MAPE in testing year-2012 using ANN is shown in Fig. 5.6.14.

The box-plot of the error distribution of forecasted load as a function of hour of the day is presented in Fig. 5.6.15. It shows the percentage error statistics of hour of the day in year 2012. It is also evident that the maximum error is for the 7^{th} hour of the day and minimum error for 14^{th} hour of the day in year 2012. The box-plot of the error distribution of forecasted load as a function of day of the week is evaluated in Fig. 5.6.16 which shows the percentage error statistics of day of the week in year 2012. The maximum error is for the Monday and minimum error for Friday in year 2012.

Multiple series plots between actual load & forecasted load from 1-7 July, 2012 & from 12-18 February, 2012 and also plots of MAPE with maximum error (3.85%) and minimum error (1.07%) for day ahead hourly weekly forecast in testing year 2012 have been shown in Fig. 5.6.17 and Fig. 5.6.18 respectively. Also, the day ahead load forecast for each day in testing year-2012 is calculated & presented in Table 5.10. It shows that maximum error during forecasting is occurred on 06 August with MAPE (9.43%) & minimum on 26 January with MAPE (0.52%) as shown in Fig. 5.6.19. Plot between actual load & forecasted load & also the plot of MAPE on 02 January, 2012 is shown in Fig. 5.6.20.

The Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE) between the forecasted and actual loads for each week & month has been calculated and presented from Table 5.11-5.13 for the year 2012. From the results obtained from Table 5.13, it is clear that maximum MAPE (2.35%) is for July, 2012 and minimum MAPE (1.43%) is for February, 2012 as shown in Fig. 5.6.21 & 5.6.22.

From the results obtained in Table 5.8-5.13, it is observed that MAPE in load forecasting for Ontario Electricity Market with temperature data is much better than MAPE without considering it. This is due to the fact that temperature and weather data are having high degree of correlation with load of that particular region. This indicates that temperature data is a very important parameter for load forecasting using ANN.

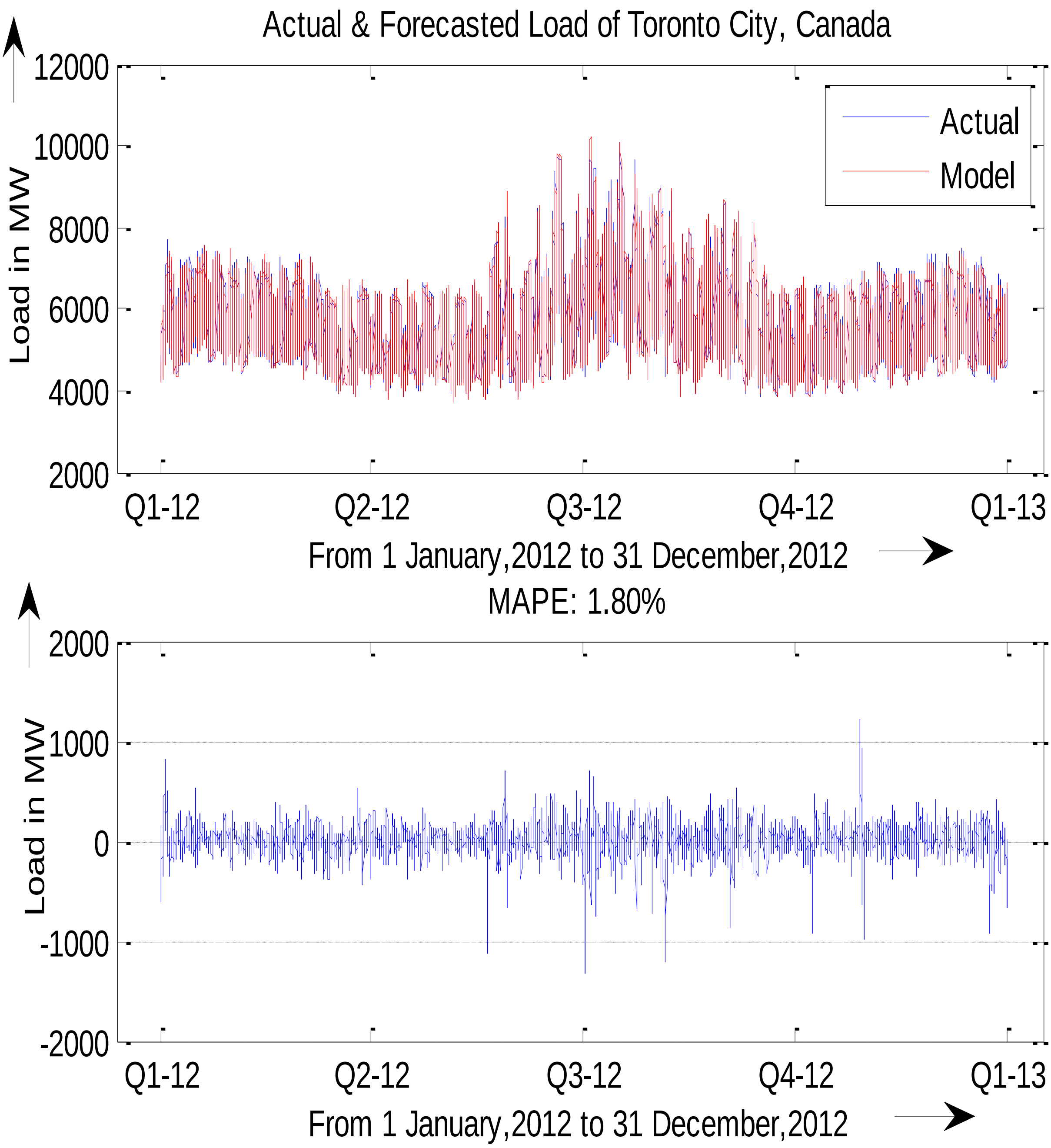

Fig. 5.6.14. Multiple series plot between actual load & forecasted load in year 2012.

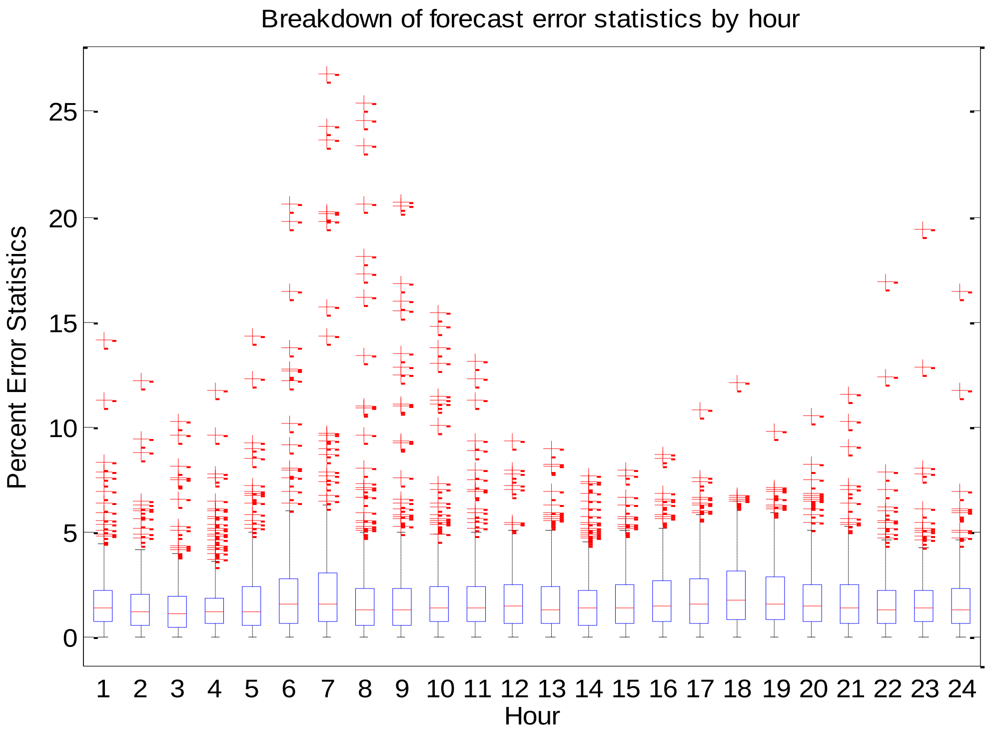

Fig. 5.6.15. Error distribution of forecasted load as a function of hour of the day in year 2012 for Toronto, Canada.

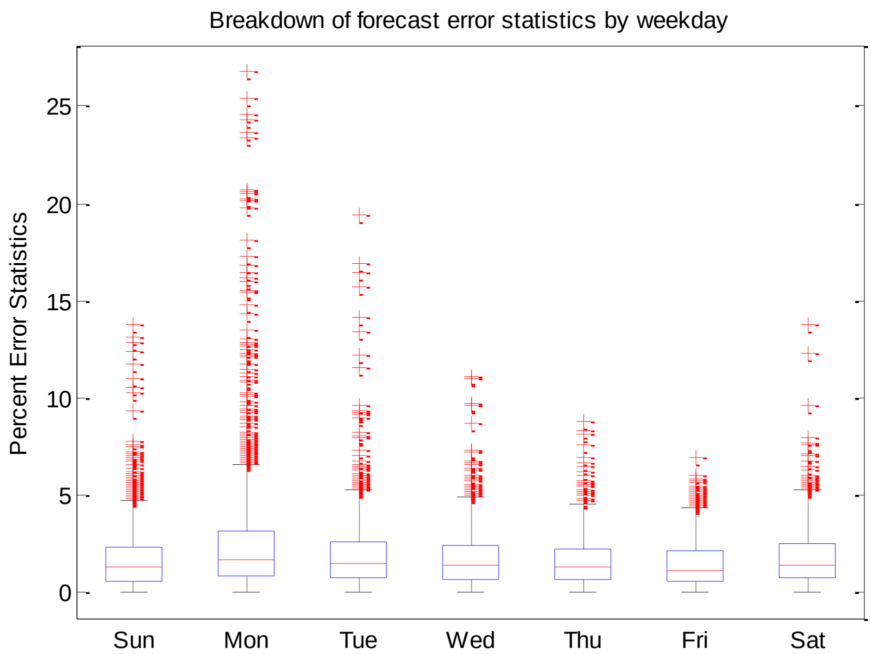

Fig. 5.6.16. Error distribution for the forecasted load as a function of day of the week in the year 2012 for Toronto, Canada.

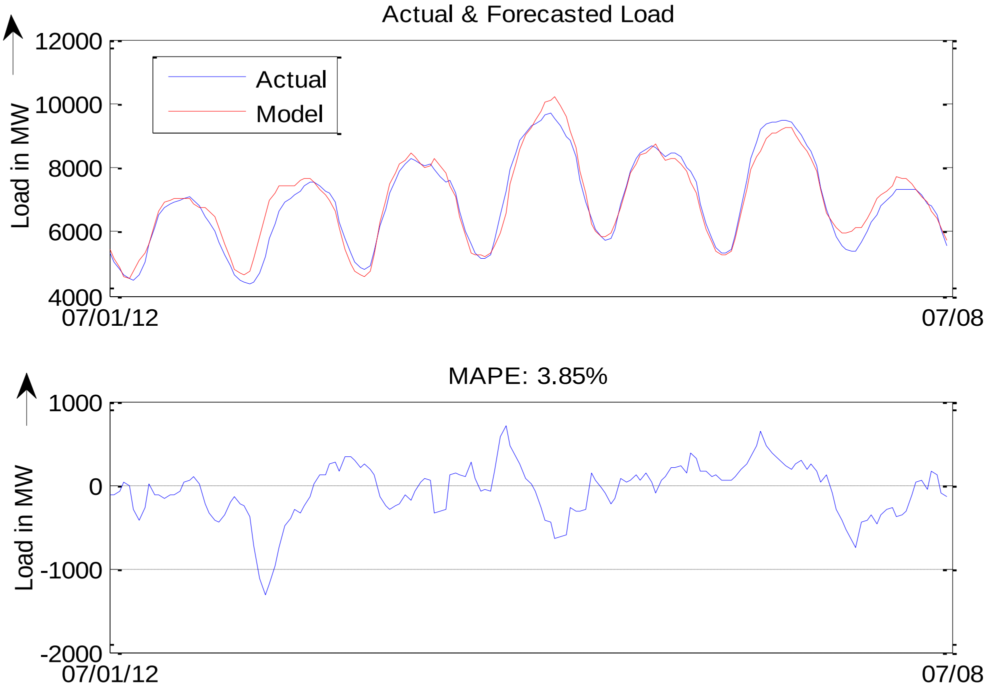

Fig. 5.6.17. MAPE is maximum (3.85%) for the load forecast sample of 01-07 July, 2012 for day ahead hourly weekly forecast for year 2012.

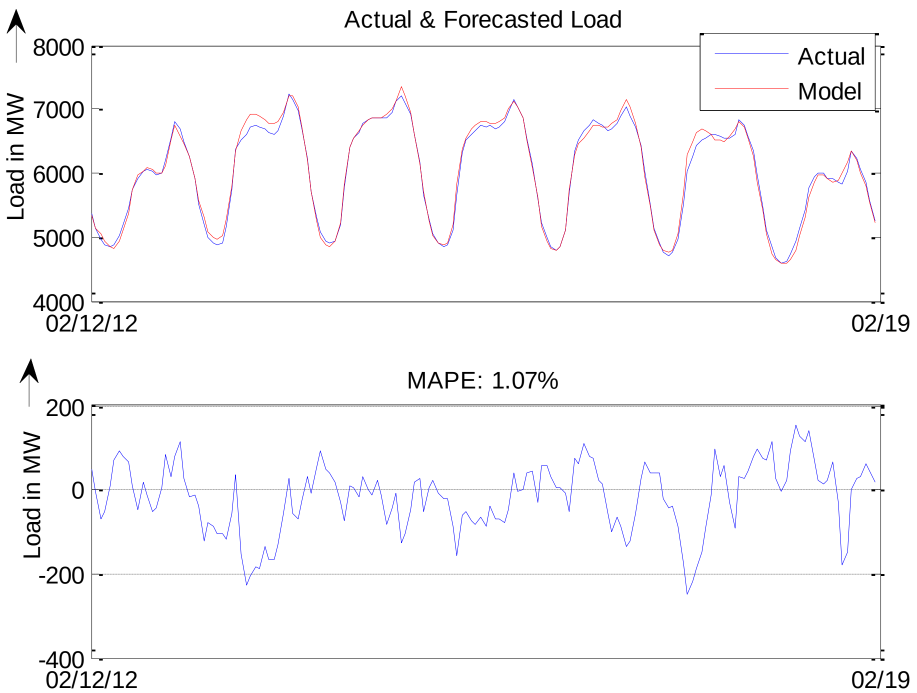

Fig. 5.6.18. MAPE is minimum (1.07%) for the load forecast sample of 12-18 February, 2012 for day ahead hourly weekly forecast.

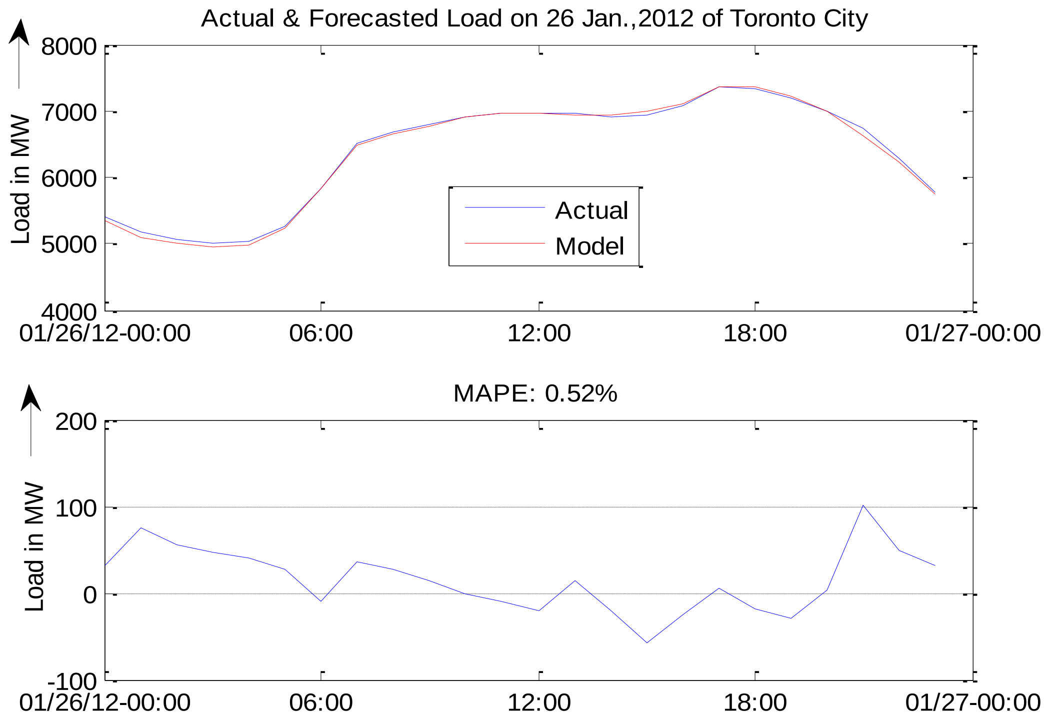

Fig. 5.6.19. MAPE is least (0.52%) for day ahead load hourly forecast on 26 January.

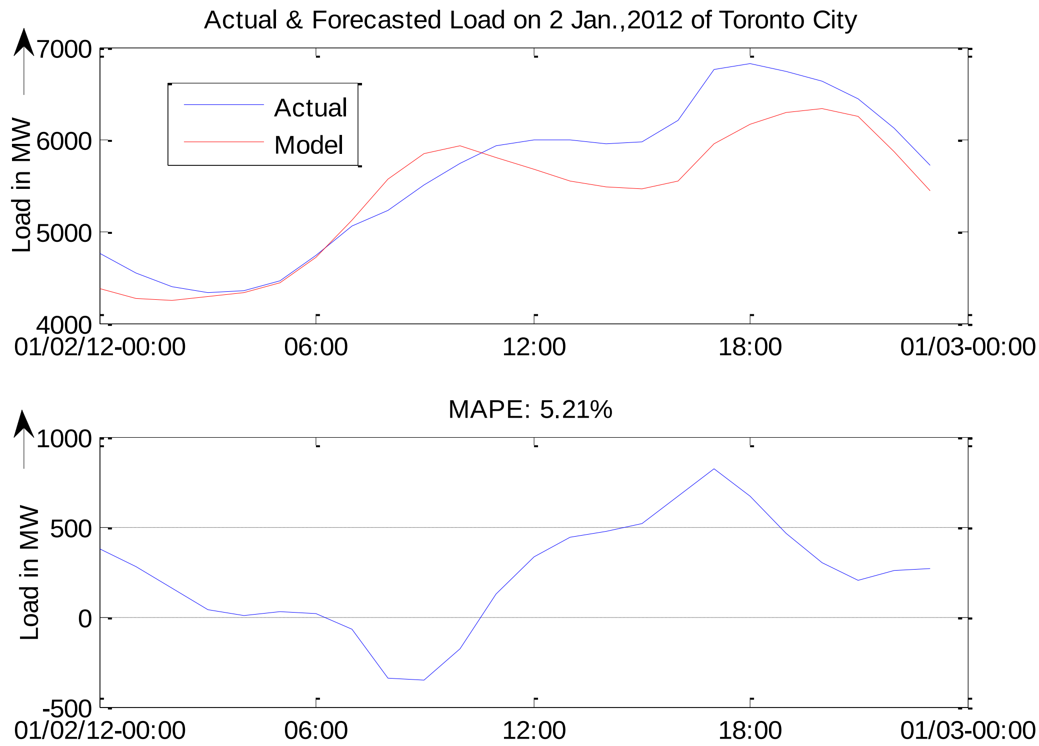

Fig. 5.6.20. Day ahead hourly load forecast on 02 January, 2012 of Toronto City.

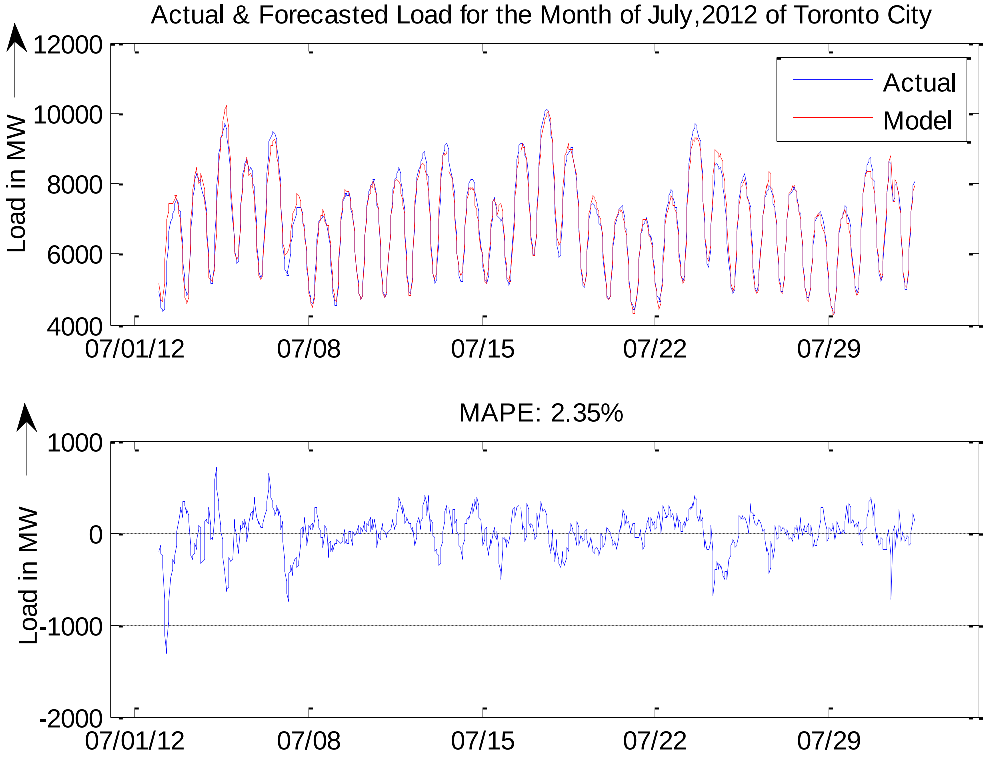

Fig. 5.6.21. MAPE is maximum (2.35%) for July from the monthly forecasting set.

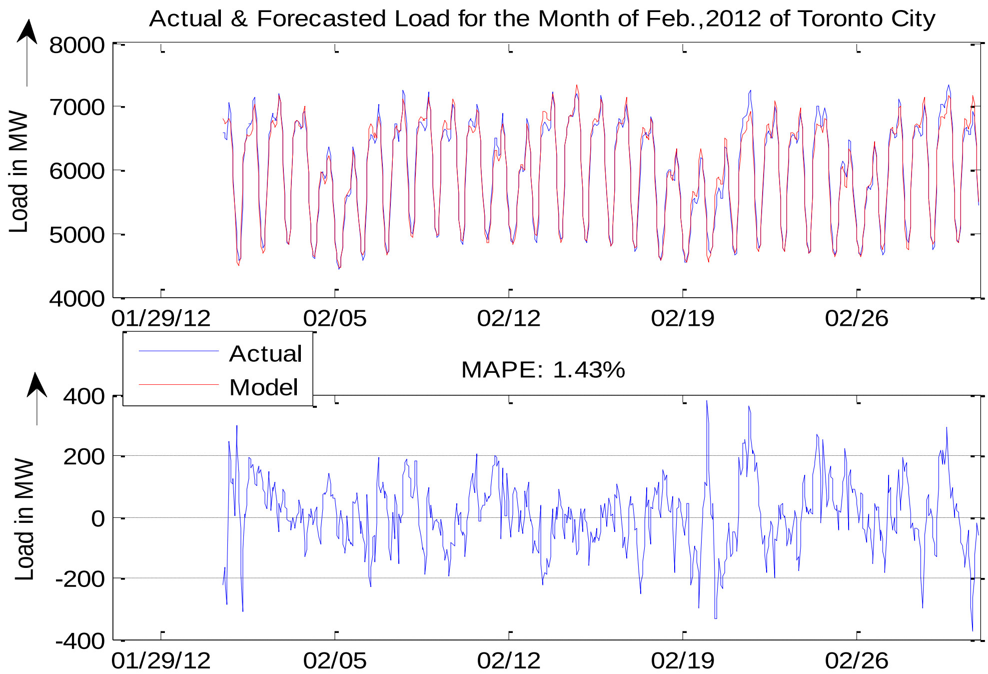

Fig. 5.6.22. MAPE is minimum (1.43%) for February from the monthly forecasting sample.

TABLE 5.10

RESULTS FOR OUT-OF-SAMPLE DAILY TEST FROM JANUARY-DECEMBER IN YEAR 2012

Day	MAPE (%) for Each Day of the Month of Year 2012 During Day-Ahead Forecast (With Hourly Temp. Data of Toronto as Input to ANN Model for Forecasting)											
	Toronto,Canada of Ontario Electricty Market											
	Jan.	Feb.	Mar.	April	May	Jun.	July	Aug.	Sep.	Oct.	Nov.	Dec.
1	4.03	2.34	1.72	2.12	1.65	1.09	3.04	1.47	2.44	1.3	1.31	0.87
2	5.21	1.28	2.24	1.78	1.02	0.74	7.76	1.94	1.49	1.24	1.15	1.32
3	4.25	0.53	2.89	0.8	1.1	1.23	2.87	1.52	6.29	1.03	1.32	2.07
4	1.62	0.98	1.77	0.94	1.51	2.43	3.87	3.28	3.17	1.8	1.45	2.06
5	2.03	1.07	0.98	1.33	0.82	1.14	1.87	6.17	2.09	1.6	1.48	1.94
6	1.37	1.7	0.99	1.76	0.91	1.26	2.75	**9.43**	1.62	1.45	1.31	1.2
7	1.95	1.29	2.72	2.48	0.87	1.42	4.85	2.14	1.38	1.58	1.64	1.15
8	1.53	1.42	2.42	2.18	1.07	0.88	1.9	1.25	2.17	5.95	1.04	1.92
9	1.4	1.08	1.61	1.25	1.18	2.29	1.37	2.33	1.05	2.52	1.54	1.83
10	1.06	1.06	1.28	1.68	1.15	2.71	0.94	1.05	1.39	2.23	1.5	1.74
11	1	1.68	3.11	1.6	0.9	1.06	1.77	1.52	1.23	1.39	2.5	1.48
12	1.58	0.79	1.92	1.1	1.55	1.7	2.13	2.05	1.89	0.98	3.38	1.2
13	2.13	1.72	2.78	0.81	1.31	2.48	2.43	0.97	2.17	2.78	1.26	1.38
14	0.96	0.67	1.72	1.61	1.42	1.48	2.73	1.48	3.13	2.26	1.68	1.52
15	1.29	0.81	1.28	1.12	1.32	1.78	2.14	1.37	1.4	1.97	0.83	2.81
16	2.51	0.93	1.4	2.12	1.25	1.65	2.08	1.1	1.62	1.72	1.59	1.16
17	1.26	1.4	2.34	0.94	0.94	1.86	1.81	2.03	1.41	1.11	1.12	2.16
18	1.45	1.23	1.28	1.59	0.85	2.44	2.49	1.1	2.77	1.89	1.5	1.7
19	1.1	1.86	2.1	1.74	1.59	2.96	1.84	1.01	1.79	1.49	1.67	1.36
20	0.55	3.04	1.33	0.93	1.26	1.19	1.5	1.04	1.43	0.67	1.82	2.25
21	0.96	2.66	1.48	1.81	6.15	1.53	1.4	1.1	1.2	1.36	1.5	2.41
22	0.96	1.32	2.05	1.2	1.63	1.76	2.4	1.41	1.27	1.76	2.82	1.72
23	1.39	1.01	1.21	1.94	1.96	2.08	2.16	1.29	0.92	1.57	2.14	1.58
24	1.51	1.74	1.68	1.91	1.2	1.34	4.54	2.08	1.62	1.26	2.1	7.66
25	0.79	1.49	1.06	1.68	1.82	1.27	2.18	2.4	2	2.14	0.85	2.14
26	**0.52**	0.87	3.4	0.89	1.85	0.89	2.09	2.28	1.43	1.16	1.48	3.68
27	0.98	1.48	1.44	0.88	1.51	2.72	0.74	1.98	0.82	2.05	1.32	2.9
28	2	1.52	2.15	0.94	4.19	1.99	1.46	1.15	0.83	2.31	0.91	1.8
29	1.01	1.85	1.63	1.05	3.51	1.16	1.53	1.69	1.29	6.54	1	1.45
30	1.05	-----	1.43	1.19	2.15	2.73	1.79	1.44	1.31	8.12	2.22	1.36
31	2.25	-----	2.34	-----	1.51	-----	1.75	1.24	-----	1.12	-----	5.65

TABLE 5.11

RESULTS FOR OUT-OF-SAMPLE TEST FOR YEAR 2012

S. N.	Duration (Year 2012) mm/dd -mm/dd	MAPE (%) Between Actual & Forecasted Load						
		ISO New England Market				Ontario Electricity Market		
		With Temp. data		Without Temp. data		Without Temp. data		With Temp. data (Toronto)
		ANN	Imp. ANN	ANN	Imp. ANN	ANN	Imp. ANN	Imp. ANN
1	01/01-01/07	2.16	2.04	4.03	3.9	3.9	3.85	2.92
2	01/08-01/14	1.32	1.23	2.57	2.45	2.59	2.55	1.37
3	01/15-01/21	1.47	1.37	4.13	4.05	2.99	2.86	1.3
4	01/22-01/28	1.86	1.8	3.11	3.05	2.07	2.02	1.16
5	01/29-02/04	**0.9**	0.86	2.21	2.02	2.33	2.37	1.34
6	02/05-02/11	1.28	1.21	2.62	2.51	2.82	2.82	1.32
7	02/12-02/18	1.12	1.08	2.41	2.27	2.77	2.7	**1.07**
8	02/19-02/25	1.47	1.37	2.75	2.58	2.92	2.98	1.87
9	02/26-03/03	1.66	1.55	2.85	2.71	2.69	2.64	1.79
10	03/04-03/10	1.51	1.52	2.86	2.71	3.43	3.43	1.68
11	03/11-03/17	1.94	1.87	2.78	2.76	2.84	2.8	2.07
12	03/18-03/24	1.68	1.65	1.57	1.61	2.64	2.61	1.59
13	03/25-03/31	1.49	1.28	2.95	2.97	2.43	2.38	1.92
14	04/01-04/07	1.58	1.47	2.53	2.44	2.74	2.68	1.6
15	04/08-04/14	1.22	1.23	1.99	1.87	2.25	2.3	1.45
16	04/15-04/21	1.63	1.65	2.29	2.11	2.4	2.37	1.46
17	04/22-04/28	1.32	1.38	2.26	2.12	2.48	2.49	1.34
18	04/29-05/05	1.35	1.33	1.55	1.45	2.16	2.1	1.19
19	05/06-05/12	0.92	**0.85**	**1.23**	**1.19**	**1.68**	**1.66**	1.09
20	05/13-05/19	0.99	0.93	1.61	1.59	2.52	2.5	1.23
21	05/20-05/26	0.91	0.94	2.06	2.01	2.96	2.96	2.26
22	05/27-06/02	1.72	1.71	3.75	3.68	4	3.95	2.1
23	06/03-06/09	1.14	1.17	1.96	1.82	2.42	2.27	1.51
24	06/10-06/16	0.97	0.92	1.93	1.88	4.21	4.29	1.83
25	06/17-06/23	1.84	1.61	**5.13**	**5.38**	3.83	3.78	1.97
26	06/24-06/30	1.86	1.7	3.96	3.81	3.49	3.38	1.73
27	07/01-07/07	2.07	1.8	4.12	4.07	4.34	3.83	**3.85**
28	07/08-07/14	1.26	1.27	3.29	3.51	3.37	3.26	1.89
29	07/15-07/21	1.25	1.22	4.46	3.95	4.31	4.27	1.89
30	07/22-07/28	1.34	1.27	4.1	3.65	4	4.05	2.22
31	07/29-08/04	1.34	1.21	3.11	3.15	3.24	3.27	1.89
32	08/05-08/11	1.53	1.53	3.7	3.89	**4.6**	**4.63**	3.41
33	08/12-08/18	1.54	1.5	3.48	3.17	3.01	2.99	1.44

34	08/19-08/25	1.37	1.25	2.61	2.73	2.8	2.74	1.47
35	08/26-09/01	1.46	1.49	4.27	4.14	3.71	3.68	1.74
36	09/02-09/08	1.71	1.54	3.55	3.57	3.61	3.52	2.6
37	09/09-09/15	1.78	1.91	3.84	3.83	4.1	4.06	1.74
38	09/16-09/22	1.59	1.58	2.83	2.79	2.25	2.15	1.64
39	09/23-09/29	1.26	1.23	1.52	1.48	2.25	2.29	1.27
40	09/30-10/06	1.18	1.23	1.42	1.25	1.93	1.89	1.38
41	10/07-10/13	1.41	1.44	2.03	2.05	2.95	2.91	2.49
42	10/14-10/20	1.5	1.58	1.98	1.89	2.16	2.09	1.59
43	10/21-10/27	1.24	1.24	1.32	1.42	1.88	1.87	1.61
44	10/28-11/03	**3.89**	**3.85**	4.08	4.65	2.23	2.25	3.12
45	11/04-11/10	1.96	1.83	3.82	3.86	2.11	2.11	1.42
46	11/11-11/17	1.7	1.61	2.57	2.39	1.94	1.91	1.76
47	11/18-11/24	1.92	2.04	3.14	2.6	2.17	2.16	1.93
48	11/25-12/01	1.19	1.2	3.11	3.07	2.61	2.64	1.23
49	12/02-12/08	1.93	1.79	3.58	3.42	2.45	2.43	1.66
50	12/09-12/15	1.81	1.76	3.01	2.68	2.74	2.72	1.7
51	12/16-12/22	1.77	1.78	2.27	2.24	2.54	2.6	1.81
52	12/23-12/29	2.58	2.53	3.89	3.75	3.45	3.46	3.03
53	**Average**	**1.55**	**1.50**	**2.90**	**2.81**	**2.90**	**2.85**	**1.80**

TABLE 5.12

RESULTS FOR OUT-OF-SAMPLE TEST FOR YEAR 2012

S. N.	Duration (Year 2012) mm/dd -mm/dd	MAE (MW) Between Actual & Forecasted Load						
		ISO New England Market				Ontario Electricity Market		
		With Temp. data		Without Temp. data		Without Temp. data		With Temp. data (Toronto)
		ANN	Imp. ANN	ANN	Imp. ANN	ANN	Imp. ANN	Imp. ANN
1	01/01-01/07	321.3	303.2	606.4	588.2	719.8	709.3	169.5
2	01/08-01/14	202.2	187	391.5	368.6	486.3	478.9	83.8
3	01/15-01/21	239.6	223.6	649.8	631.7	589.9	564.3	80.73
4	01/22-01/28	287.4	276.9	457.8	452	382.2	373.7	70.68
5	01/29-02/04	134.1	129.4	330.8	299.2	418.8	424.8	81.22
6	02/05-02/11	192.4	182.7	380.2	366.4	532.1	533.4	80.52
7	02/12-02/18	170.4	165.6	357	335.6	510.8	497.7	**64.62**
8	02/19-02/25	218.3	200.5	389.5	364.8	530.6	542.1	111.1
9	02/26-03/03	248.6	231	408.3	389.3	498.2	488.2	107.55
10	03/04-03/10	219.2	222	402.4	378.4	625.4	625.2	99.33

11	03/11-03/17	263.9	255.1	362.5	361.4	467	460.7	111.78
12	03/18-03/24	226.2	221.3	205.6	209	420.3	415.7	88.7
13	03/25-03/31	203.8	174.9	391.5	393.6	415	407.1	109.57
14	04/01-04/07	210.5	197.9	333.7	319.2	470.2	458.7	84.11
15	04/08-04/14	155.1	156.3	255.1	243	382.7	390	77.44
16	04/15-04/21	217.5	218.6	310.9	287.8	400.1	396.4	81.3
17	04/22-04/28	172.6	181.9	290.6	273.1	426.8	427.9	76.27
18	04/29-05/05	181.3	177.9	203.4	188.1	344.6	335.6	65.29
19	05/06-05/12	119.4	110.3	163.5	157.4	272	267.2	57.08
20	05/13-05/19	132.4	123.3	219.6	215	423.1	419.3	65.93
21	05/20-05/26	131.1	135.3	308.9	300.3	525	526.3	125.1
22	05/27-06/02	261.1	257.6	571.8	561.7	713.9	704.6	135.3
23	06/03-06/09	158.5	162.9	271.9	252.2	413.7	391.3	83.85
24	06/10-06/16	139.7	131.2	279.2	270.7	773.6	789.6	115.04
25	06/17-06/23	328.9	279.7	974.1	1008	783.1	774.9	138.06
26	06/24-06/30	295.5	271.9	633.3	605.1	671.1	649.5	111.4
27	07/01-07/07	361.8	315.3	709	692.5	883.5	788.1	**252.43**
28	07/08-07/14	225.7	224.6	559.8	596.9	644.1	625.1	130.96
29	07/15-07/21	227.6	221.6	772.2	680.4	837.2	829.6	132.6
30	07/22-07/28	233.5	217.5	675.3	615.5	786.4	799	156.99
31	07/29-08/04	234.5	211.5	551	562.3	657.4	665.4	132.71
32	08/05-08/11	276	272.6	675.1	721.1	835.8	843.9	202.7
33	08/12-08/18	263.5	254.8	575.7	526.7	551	547.1	85.52
34	08/19-08/25	218.8	198.7	383.6	396.5	536.8	525.4	93.12
35	08/26-09/01	243.7	246.3	676.1	649.8	700.7	695.1	112.72
36	09/02-09/08	273.9	251.3	545.9	554.5	621.4	604	156.89
37	09/09-09/15	255.7	275.2	520.8	524.1	645.4	643.5	103.58
38	09/16-09/22	213.5	213.5	381.6	369	368	352.2	89.74
39	09/23-09/29	167	163.3	201.5	195.7	360.4	365.6	68.13
40	09/30-10/06	164	172.3	194.2	171	312.7	306.5	76.67
41	10/07-10/13	180.8	186.2	263.4	267.4	475.3	469.8	129.27
42	10/14-10/20	202.6	212.6	271.3	258.1	365	353.6	86.96
43	10/21-10/27	164.1	164.7	174.9	188.9	311.4	309.9	89.42
44	10/28-11/03	448.4	444.1	483.1	555.1	384.2	388.1	176.45
45	11/04-11/10	285.3	262.5	537.7	542.2	392.7	392.9	82.18
46	11/11-11/17	239.8	226.3	354.9	327.8	352.3	347.1	98.59
47	11/18-11/24	264.6	279.5	428.6	355.3	387.4	386.5	110.94
48	11/25-12/01	182.7	185.3	458	454.9	493.7	499	76.55
49	12/02-12/08	285.2	266.2	499.6	472.9	446.2	442	97.77
50	12/09-12/15	275.6	269.9	442.9	391.7	515.5	510.2	104.64
51	12/16-12/22	279.2	281.1	352	343.2	472.4	481.9	107.46
52	12/23-12/29	395.5	386.7	576.8	558.8	613.7	617.5	162.55
53	**Average**	**230.6**	**222.7**	**431**	**419.1**	**522**	**516.1**	**113.90**

TABLE 5.13

RESULTS FOR OUT-OF-SAMPLE MONTHLY TEST IN YEAR 2012 BY IMPROVED ANN

S.N.	Month	ISO New England Market			Ontario Electricity Market			
		MAPE (%)		MAE (MW) (With Temp. data)	Without temp. data		With Temp. data	
		Without Temp.	With Temp.		MAPE (%)	MAE (MW)	Toronto City	
							MAPE (%)	MAE (MW)
1	January	3.25	1.56	239.03	2.86	535.93	1.65	98.95
2	February	2.47	1.17	175.06	2.67	494.5	**1.43**	**86.39**
3	March	2.52	1.63	226.27	2.79	475.86	1.87	105.22
4	April	2.11	1.41	186.09	2.47	417.56	1.44	78.6
5	May	**1.91**	1.14	160.19	2.63	455.23	1.63	93.67
6	June	3.17	1.33	207.72	3.34	629.5	1.76	110.87
7	July	**3.84**	**1.4**	243.82	**3.85**	761.38	**2.35**	**161.91**
8	August	3.41	**1.4**	240.33	3.49	660.34	2.02	125.9
9	September	2.86	1.54	221.14	2.95	481.79	1.8	104.19
10	October	2.29	1.98	249.9	2.22	367.85	2.15	118.2
11	November	2.88	1.62	229.91	**2.17**	397.61	1.57	90.64
12	December	3.03	**2.02**	309.32	2.89	527.38	2.13	122

CHAPTER 6

APPLICATION OF DIFFERENT OPTIMIZATION TECHNIQUES IN POWER MARKETS

CHAPTER 6

APPLICATION OF DIFFERENT OPTIMIZATION TECHNIQUES IN POWER MARKET

Optimization is a mathematical technique that concerns the finding of maxima or minima of functions in some feasible region. There is no business or industry which is not involved in solving optimization problems. A variety of optimization techniques compete for the best solution. Economic load dispatch (ELD) problem is a common task in the operational planning of a power system, to schedule the connected generating units of plant outputs so as to fulfill power demands at minimum operating cost while satisfying all operational constraints.

Here, different optimization techniques like genetic algorithm, pattern search, minimax optimization, hybrid of genetic & pattern search algorithm, hybrid of genetic algorithm & fmincon & Particle Swarm Optimization have been successfully applied to solve the ELD problem & day ahead economic load forecast (DAELF) problems using IEEE 30-bus (06 machine) & standard 26-bus (06 thermal units & 46 transmission line) system. All above algorithms have been compared for five trial runs for ELD problems. The best, worst, average fitness and their standard deviation for all the algorithms have been determined for it. The results shows that PSO techniques gives the optimum operating cost. Also, it has been observed that the diversity of GA can been reduced by using hybrid of GA & fmincon optimization.

6.1. Introduction to ELD Problems

Mainly, Economic Load Dispatch (ELD) Problem describes the optimal scheduling of power outputs of all the connected generating units of the plant to minimize the total production cost while fulfilling the total power demand and system equality and inequality constraints of the connected generating units. The ELD contributes to considerable saving in the plant production cost by proper planning of connected unit outputs [44]-[45].

ELD problems have been solved by a number of techniques during past years using conventional as well as intelligent techniques. The examples of conventional techniques to solve ELD problems are Lambda iteration method, Fast lambda method, Base point and Participation factors method and Gradient method. All these conventional techniques have limitation on the nature of cost curves. In addition, these techniques have oscillatory problems due to existence of several local minima in the ELD problems with large number of connected units in the systems. Due to complex algorithm of conventional techniques, it takes high computational time. Modern stochastic techniques such as Linear programming, Quadratic programming, Genetic algorithm, Biogeography based optimization, Chemical reaction optimization, Enhanced Bee swarm optimization, Modified Teacher learning algorithm have been employed successfully to solve the ELD problems. The Hybrid genetic algorithm with ant colony optimization and Hybrid differential evolution with biography based optimization also have been used to solve ELD problems. These intelligent optimization techniques do not suffer from any limitation on the nature of cost curve, due to their ability to find the optimal solution. But, these methods have large number of parameters involved in the algorithm, and takes large number of iterations to settle to the global optimum.

6.2. Different Optimization Techniques

Here, different optimization technique to solve ELD & day ahead economic load forecast (DAELF) problems using IEEE 30-bus (06 machine) & standard 26-bus (06 thermal units & 46 transmission line) system has been consider for the simulation for the power demand. The various methods of Optimization used are as follows –

- Genetic Algorithms (GA)
- Pattern Search Algorithm (PS)

- Minimax Optimization (MM)
- Fmincon -constrained nonlinear minimization (FN)
- Particle Swarm Optimization (PSO)
- Hybrid of GA & fmincon (HGFN)
- Hybrid of GA & Pattern search (HGPS)

6.3. Formulation of ELD Problem

The main objective of ELD is to determine the power generation of each unit of the plant so that total production costs of the plant should be minimum by fulfilling the required power demand under the given equality and inequality constraints.

The production costs of each unit are generally expressed by a quadratic function of the power output from those generating units. The total production costs of the plant are the sum of production cost of each individual units of the plant.

Mathematically,

$$F_i(P_i)=a_iP_i^2+b_iP_i + c_i \qquad (6.1)$$

Where $F_i(P_i)$, P_i, (a_i,b_i,c_i) are the production cost, power generation, cost coefficient of ith unit of the plant respectively. Therefore total production cost of the plant having n units,

$$F_T = \sum_{i=1}^{n}(F_i(P_i))$$

$$= \sum_{i=1}^{n}(a_iP_i^2 + b_iP_i + c_i) \qquad (6.2)$$

For power mismatch, an equality constraint has been introduced i.e the generated power by the plant should be equal to the total power demand plus the total losses. Thus the power balance equation of ELD problems is given by,

$$\sum_{i=1}^{n} P_i - P_D - P_L = 0 \qquad (6.3)$$

Where P_D is total demand and P_L is losses respectively.

The transmission losses can be determined from unit outputs and loss coefficients as,

$$P_L = \sum_{i=1}^{n}\left(\sum_{j=1}^{n}\left(P_i B_{ij} P_j\right)\right) + \sum_{i=1}^{n}\left(B_{i0} P_i\right) + B_{00} \qquad (6.4)$$

Where B_{ij} is the ijth element of the loss coefficient square matrix, B_{i0} is the ith element of the loss coefficient vector, and B_{00} is the loss coefficient constant.

The inequality constraints for each unit of the plant must be also satisfied i.e. the generation power of each unit of the plant should be laid between its maximum and minimum limits of power generation. The inequality (generator) constraint for each unit of the plant is represented by,

$$P_i^{min} < P_i < P_i^{max} \qquad (6.5)$$

Where P_i^{min} is minimum and P_i^{max} is maximum limit of power generation of ith unit of the plant.

The Objective (fitness) function of ELD problems is defined to minimize the sum of the generation cost function given by (6.2) and the penalized demand (equality) constraint given by (6.3) as follows:

Minimize the fuel cost,

$$F = \sum_{i=1}^{n} (a_i P_i^2 + b_i P_i + c_i) + K^* \sum_{i=1}^{n} (P_i - P_D - P_L) \quad (6.6)$$

Subjected to generators constraints. Where K is the lagrangian multiplier.

This ELD concept can also be applied for predicting the ELD on each unit of a particular plant or system for next day by using forecasted load data of particular area. This concept has been named day-ahead economic load forecast (DAELF) in this thesis, where day-ahead forecasted load has been used for predicting power at each unit for ELD operation on next day.

6.4. Simulation & Results

Here, different optimization techniques like genetic algorithm, pattern search, minimax optimization, hybrid of genetic & pattern search algorithm, hybrid of genetic algorithm & fmincon & Particle Swarm Optimization have been successfully applied to solve the ELD of a 26-bus (06 thermal units & 46 transmission line) system for the power demand of 1263 MW with 5 trials each.

Also, day ahead economic load forecast (DAELF) problems using IEEE 30-bus (06 machine) & standard 26-bus (06 thermal units & 46 transmission line) system has been performed using PSO on forecasted demand of ISO New England Market (ME-Region).

6.4.1. ELD Problem of a 26-bus (06 Thermal Units & 46 Transmission Line)

Simulation results of standard 26-bus (06 thermal units & 46 transmission line) system for the power demand (Pd) of 1263 MW with different optimisation techniques in each trial have been presented in Table 6.1. It consist of fuel cost ($/hr.) for each trial with its average, best, worst & standard deviation results.

From the Simulation results for 5 trials it has been observed that GA & HGPS shows high variation in optimum fuel cost & its average is 15454.512 & 15459.254 \$/hr. Whereas minimax optimization & HGFN shows comparatively better as well nearly constant result with an average fuel cost of 15443.075 & 15443.121 \$/hr. respectively. Also, the pattern search gives constant result in each trial with fuel cost of 15464.872 \$/hr.

It has been observed that hybrid GA is performing better than conventional GA with a very less variation in fuel cost by using GA with fmincon. It can clearly observed from the simulation results in Table 6.1.

Lastly the ELD is performed with the help of Particle Swarm Optimization technique which shows the best & constant result in comparisons with any optimization techniques described above with fuel cost of 15442.656 \$/hr. Worst, best & average fuel cost using different optimization techniques is shown in Fig. 6.1, also the load at each unit with different optimization for their best fuel cost is shown in Fig. 6.2.

Table 6.2 shows economic load dispatch by 06 units when different optimization techniques have been applied for best fuel cost in five trial. Where, 'P' is summation of power at each unit & 'PL' is power loss. 'UP' is defined in eq. 6.7 below-

$$UP=P-PL \tag{6.7}$$

TABLE 6.1

RESULTS OF FUEL COST (\$/hr.) FOR TEST OF 26-BUS USING DIFFERENT OPTIMIZATION TECHNIQUES

Trial	GA	PS	MM	PSO	HGFN	HGPS
1	15448.17	15464.87	15443.07	15442.65	15443.10	15455.81
2	15446.40	15464.87	15443.07	15442.65	15443.09	15445.71

3	15455.44	15464.87	15443.07	15442.65	15443.11	15451.00
4	15462.52	15464.87	15443.07	15442.65	15443.21	15488.11
5	15460.01	15464.87	15443.07	15442.65	15443.07	15455.62
Average	15454.51	15464.87	15443.07	15442.65	15443.12	15459.25
Best	15446.40	15464.87	15443.07	15442.65	15443.07	15445.71
Worst	15462.52	15464.87	15443.07	15442.65	15443.21	15488.11
Std.	7.093	0	0	0	0.054	16.651

TABLE 6.2

RESULTS FOR TEST OF 26 BUS 6 UNIT SYSTEM USING DIFFERENT OPTIMIZATION TECHNIQUES

Parameters	GA	PS	MM	PSO	HGFN	HGPS
P1 (MW)	444.887	420	447.418	447.069	447.351	453.933
P2 (MW)	171.695	178	173.277	173.181	173.35	166.175
P3 (MW)	262.534	272	263.418	263.923	263.543	275.636
P4 (MW)	128.214	113	138.916	139.051	138.965	134.245
P5 (MW)	166.353	178	165.39	165.576	165.449	161.493
P6 (MW)	101.959	115.119	87.026	86.616	86.789	84.069
PL (MW)	12.641	13.119	12.446	12.416	12.447	12.55
Pd (MW)	1263	1263	1263	1263	1263	1263
F $/hr	15446.401	15464.872	15443.075	15442.657	15443.075	15445.72
P (MW)	1275.641	1276.119	1275.446	1275.416	1275.446	1275.55
UP (MW)	1263	1263	1263	1263	1263	1263

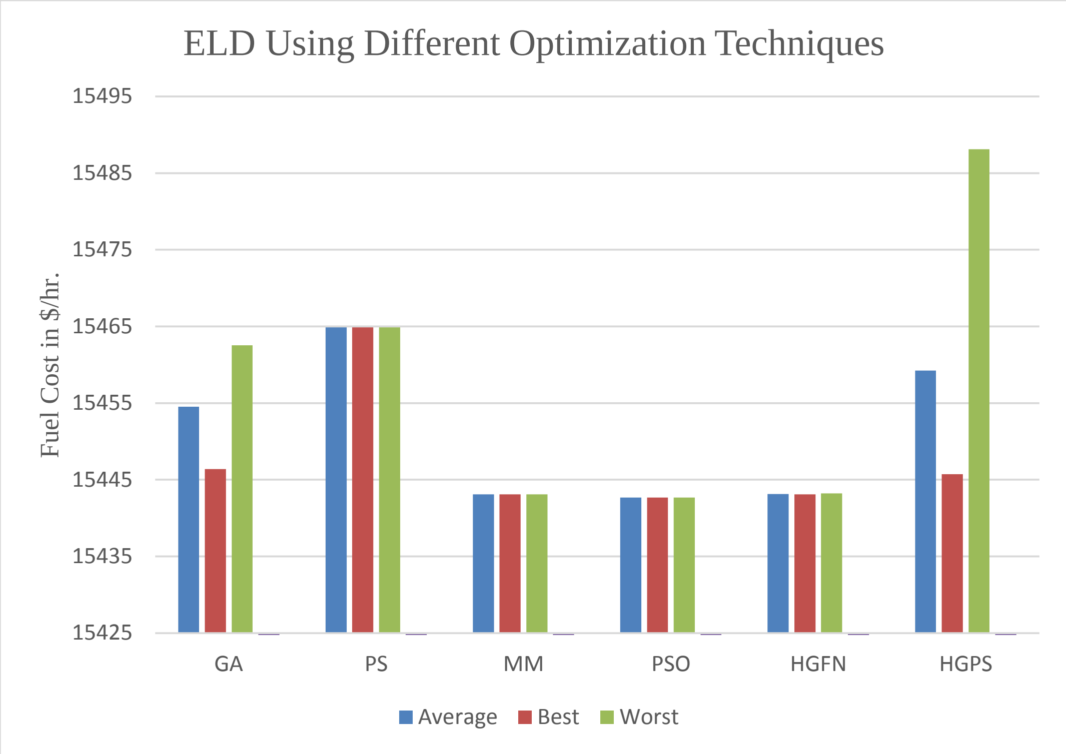

Fig. 6.1. Worst, best & average fuel cost using different optimization techniques.

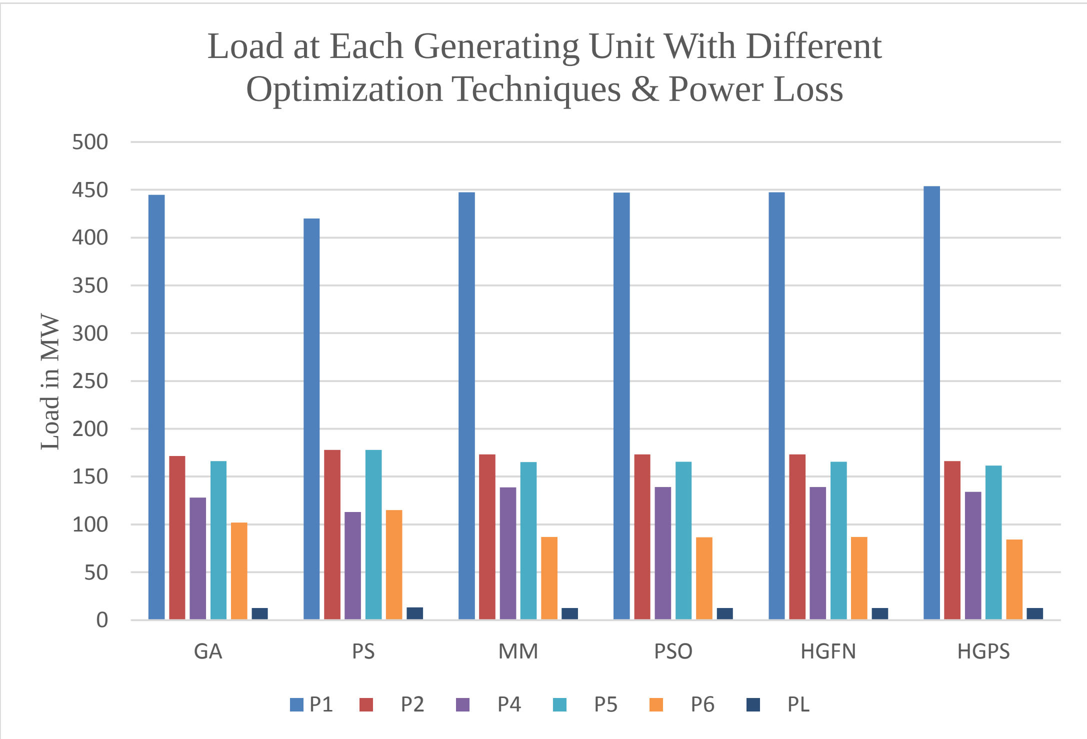

Fig. 6.2. Load at each unit using different optimization techniques.

6.4.2. Day Ahead Economic Load Forecast of ISO New England market

Day ahead economic load forecast (DAELF) problems using IEEE 30-bus (06 machine) & standard 26-bus (06 thermal units & 46 transmission line) system has been performed using PSO on day-ahead forecasted demand of ISO New England Market (ME-Region).The IEEE 30-bus & standard 26-bus system has a standard power demand of 283.4 MW & 1263 MW respectively.

The ANNs are trained with data from 2007 to 2011 and tested on out-of-sample data from 2012 of ISO New England market. The ANN model used in the forecasting has input, output and one hidden layers. Hidden layer has 56 neurons. Inputs to the input layer as listed above for load forecast. After simulation the MAPE obtained is 2.03% for load forecasting for the year 2012. Multiple series plot between actual load & forecasted load & also the plot of MAPE in testing year-2012 using ANN is shown in Fig. 6.3. Table 6.3-6.6 shows hourly DAELF using PSO by using standard 26-bus (06 thermal units & 46 transmission line) on the data of day-ahead hourly forecasted load of ISO New England (ME-Region) on 1 January, 2012.

Table 6.7-6.8 shows hourly DAELF using PSO by using IEEE 30-bus (06 machine) & standard 26-bus (06 thermal units & 46 transmission line) system for hourly forecasted load exceeding 1360 MW on 1 January, 2012. Here both systems are used to ELF at their standard load & then supplying required amount of demand to consumer, whereas the reserve power may be used to satisfy another demand area. It has also been observed that if the demand exceeds from the standard load of the system then it is better to use another system for fulfilling the demand requirement. Otherwise, the fuel cost will be higher for satisfying the same load.

Here P1,P2,P3,P4,P5,P6,Pd,PL,P,UP,RP (reserve power), actual load & forecasted load in MW. Where F, TF & F1 are the fuel cost, total fuel cost & fuel cost when alone 26-bus system is used in $/hr. respectively for fulfilling the forecasted demand.

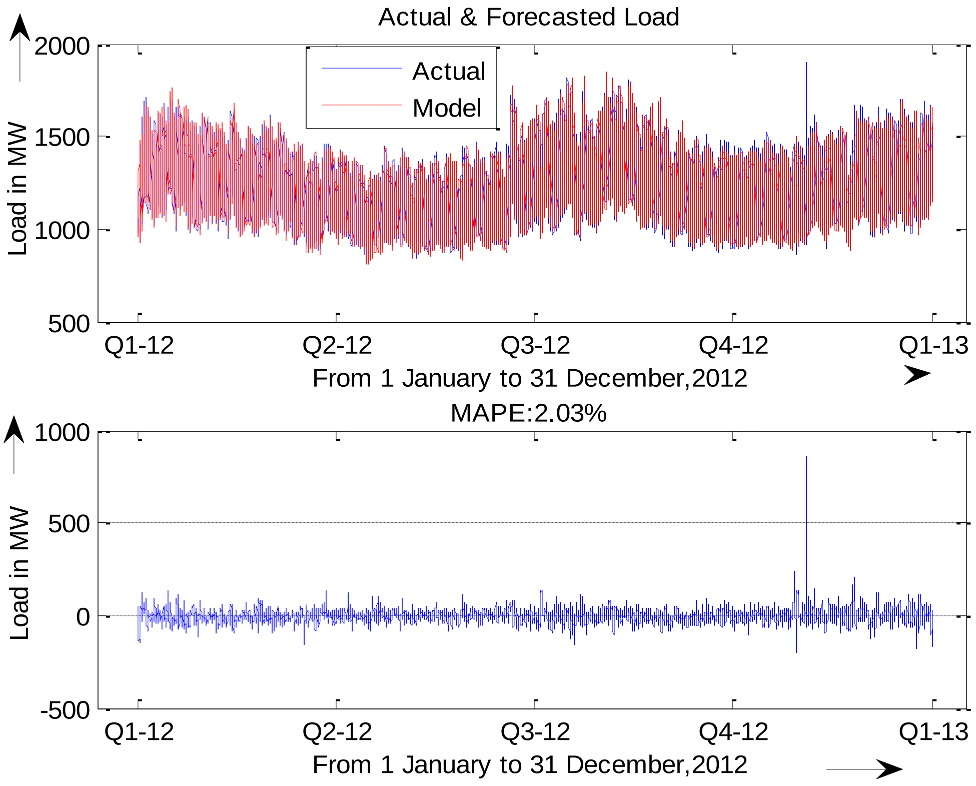

Fig. 6.3. Multiple series plot between actual load & forecasted load in year 2012.

TABLE 6.3

RESULTS FOR TEST OF ELF BY 26 BUS 6 UNIT SYSTEM USING PSO FOR DAY-AHEAD FORECASTED LOAD REQIREMENT

Hour	1	2	3	4	5	6
Date	1/1/2012	1/1/2012	1/1/2012	1/1/2012	1/1/2012	1/1/2012
Actual Load	1064	1016	986	978	979	1000
Forecasted load	1015.22	1017.72	984.22	954.78	971.09	1031.23
P1	394.762	395.38	387.105	379.84	383.864	398.719
P2	134.513	134.971	128.846	123.469	126.448	137.442
P3	223.305	223.782	217.387	211.772	214.882	226.362
P4	96.387	96.886	90.198	84.326	87.578	99.586
P5	124.579	125.065	118.541	112.803	115.982	127.695
P6	50	50	50	50	50	50
PL	8.326	8.364	7.858	7.43	7.665	8.574
Pd	1015.22	1017.72	984.22	954.78	971.09	1031.23
F $/hr.	12182.948	12214.855	11789.222	11418.59	11623.528	12387.679
P	1023.546	1026.084	992.078	962.21	978.755	1039.804
UP	1015.22	1017.72	984.22	954.78	971.09	1031.23

TABLE 6.4

RESULTS FOR TEST OF ELF BY 26 BUS 6 UNIT SYSTEM USING PSO FOR DAY-AHEAD FORECASTED LOAD REQIREMENT

Hour	7	8	9	10	11	12
Date	1/1/2012	1/1/2012	1/1/2012	1/1/2012	1/1/2012	1/1/2012
Actual Load	1048	1101	1176	1227	1233	1233
Forecasted load	1108.47	1214.38	1311.15	1359.5	1376.86	1372.24
P1	415.077	436.986	457.07	468.518	472.888	471.724
P2	149.535	165.728	180.573	189.054	192.294	191.431
P3	239.064	256.088	271.694	280.597	283.997	283.092
P4	112.914	130.807	147.234	150	150	150
P5	140.553	157.707	173.366	182.216	185.581	184.686
P6	61.079	78.595	94.549	103.532	106.942	106.034
PL	9.752	11.53	13.336	14.418	14.841	14.728
Pd	1108.47	1214.38	1311.15	1359.5	1376.86	1372.24
F $/hr.	13387.327	14788.005	16098.227	16764.135	17005.355	16941.048
P	1118.222	1225.91	1324.486	1373.918	1391.701	1386.968
UP	1108.47	1214.38	1311.15	1359.5	1376.86	1372.24

TABLE 6.5

RESULTS FOR TEST OF ELF BY 26 BUS 6 UNIT SYSTEM USING PSO FOR DAY-AHEAD FORECASTED LOAD REQIREMENT

Hour	13	14	15	16	17
Date	1/1/2012	1/1/2012	1/1/2012	1/1/2012	1/1/2012
Actual Load	1233	1226	1227	1229	1391
Forecasted load	1331.44	1309.79	1295.89	1321.12	1431.25
P1	461.464	456.788	453.899	459.143	487.395
P2	183.823	180.364	178.229	182.105	200
P3	275.109	271.474	269.23	273.304	295.27
P4	150	147.002	144.639	148.93	150
P5	176.777	173.146	170.897	174.978	196.653
P6	98.018	94.325	92.036	96.19	118.169
PL	13.75	13.309	13.04	13.532	16.237
Pd	1331.44	1309.79	1295.89	1321.12	1431.25
F $/hr.	16376.649	16079.611	15889.678	16234.873	17768.588
P	1345.19	1323.099	1308.93	1334.652	1447.487
UP	1331.44	1309.79	1295.89	1321.12	1431.25

TABLE 6.6

RESULTS FOR TEST OF ELF BY 26 BUS 6 UNIT SYSTEM USING PSO FOR DAY-AHEAD FORECASTED LOAD REQIREMENT

Hour	20	21	22	23	24
Date	1/1/2012	1/1/2012	1/1/2012	1/1/2012	1/1/2012
Actual Load	1381	1308	1222	1137	1050
Forecasted load	1408.42	1348.88	1252.8	1134.67	1045.88
P1	480.841	465.847	444.952	420.49	402.167
P2	198.193	187.073	171.616	153.536	139.993
P3	290.185	278.519	262.278	243.27	229.03
P4	150	150	137.32	117.332	102.381
P5	191.699	180.158	163.926	144.798	130.408
P6	113.135	101.446	84.935	65.417	50.7
PL	15.632	14.163	12.226	10.173	8.799
Pd	1408.42	1348.88	1252.8	1134.67	1045.88
F $/hr.	17446.813	16617.131	15304.708	13730.598	12575.842
P	1424.052	1363.043	1265.026	1144.843	1054.679

TABLE 6.7

RESULTS FOR TEST OF ELF BY IEEE-30 BUS & 26 BUS 6 UNIT SYSTEM USING PSO FOR DAY-AHEAD FORECASTED LOAD

Hour	11	11	12	12	17	17
Date	1/1/2012	1/1/2012	1/1/2012	1/1/2012	1/1/2012	1/1/2012
Actual Load	1233	1233	1233	1233	1391	1391
Forecasted load	1376.86	1376.86	1372.24	1372.24	1431.25	1431.25
Load	1263	283.4	1263	283.4	1263	283.4
P1	447.069	178.754	447.069	178.754	447.069	178.754
P2	173.181	47.906	173.181	47.906	173.181	47.906
P3	263.923	18.431	263.923	18.431	263.923	18.431
P4	139.051	28.705	139.051	28.705	139.051	28.705
P5	165.576	10	165.576	10	165.576	10
P6	86.616	12	86.616	12	86.616	12
PL	12.416	12.395	12.416	12.395	12.416	12.395
Pd	1263	283.4	1263	283.4	1263	283.4
F $/hr.	15442.657	813.22	15442.657	813.22	15442.657	813.22
P	1275.416	295.795	1275.416	295.795	1275.416	295.795
UP	1263	283.4	1263	283.4	1263	283.4
RP	169.54	169.54	174.16	174.16	115.15	115.15

TF ($/hr.)	16255.877	16255.877	16255.877	16255.877	16255.877	16255.877
F1	17005.355	17005.355	16941.048	16941.048	17768.588	17768.588

TABLE 6.8

RESULTS FOR TEST OF ELF BY IEEE-30 BUS & 26 BUS 6 UNIT SYSTEM USING PSO FOR THE DAY-AHEAD FORECASTED LOAD

Hour	18	18	19	19	20	20
Date	1/1/2012	1/1/2012	1/1/2012	1/1/2012	1/1/2012	1/1/2012
Actual Load	1465	1465	1439	1439	1381	1381
Forecasted Load	1484.77	1484.77	1461.38	1461.38	1408.42	1408.42
Load	1263	283.4	1263	283.4	1263	283.4
P1	447.069	178.754	447.069	178.754	447.069	178.754
P2	173.181	47.906	173.181	47.906	173.181	47.906
P3	263.923	18.431	263.923	18.431	263.923	18.431
P4	139.051	28.705	139.051	28.705	139.051	28.705
P5	165.576	10	165.576	10	165.576	10
P6	86.616	12	86.616	12	86.616	12
PL	12.416	12.395	12.416	12.395	12.416	12.395
Pd	1263	283.4	1263	283.4	1263	283.4
F $/hr.	15442.66	813.22	15442.66	813.22	15442.66	813.22
P	1275.416	295.795	1275.416	295.795	1275.416	295.795
UP	1263	283.4	1263	283.4	1263	283.4
RP	61.63	61.63	85.02	85.02	137.98	137.98
TF	16255.88	16255.88	16255.88	16255.88	16255.88	16255.877
F1	------	-------	-------	-------	17446.81	17446.813

CHAPTER 7

CONCLUSION

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CONCLUSION

This thesis presents an ANN & improved ANN model for day-ahead short-term electricity loads forecasting in ISO New England market, PJM electricity market, Ontario electricity market & Toronto city of Ontario market, Canada. Its forecasting reliabilities were evaluated by computing the MAPE & MAE between the exact and predicted electricity load values. The MAPE for load forecasting varies from 1% to 4% in the case of day-ahead load forecasting for weekly testing samples. The average MAPE for load forecast is 1.50%-1.80% in the year 2012. The results suggest that ANN model with the developed structure can perform well in day ahead load forecasting with least possible error. It has been observed that temperature plays an important role in electricity load forecasting therefore it must be considered as an input in forecasting model.

Also, the day-ahead short-term electricity price forecast by using artificial neural network (ANN) approach in ISO New England market has been presented. In ISO New England market, the main challenging issue is that the daily market price curves are highly volatile. The simulation result produced accurate predictions even in volatility cases. The test results also confirm that the power demand is the most important variable affecting the electricity price. The ANN model used had forecasted load and price for testing samples of each day, week & month of the year 2012 and results indicates that it has performed well even in the case of sudden weather changes. The forecasting reliabilities of the ANN model were evaluated by computing the MAPE between the exact and predicted price values. The MAPE for price forecasting varies from 5.6% to 19.87% in the case of day-ahead price forecasting for weekly testing samples. The average MAPE for price forecast is 9.25% in the year 2012 for ISO New England Market. The results suggest that present ANN model with the developed structure can perform good prediction with least error.

This thesis also present a different optimization techniques like genetic algorithm, pattern search, fmincon, minimax optimization, hybrid of GA & pattern search, hybrid of GA & fmincon & particle swarm optimization, which have been successfully applied on IEEE-30 bus (6 machine) & standard 26-bus (06 thermal units & 46 transmission line) system to solve the ELD & DAELF problem.The results shows that PSO techniques gives the optimum operating cost.

CHAPTER 8

FUTURE SCOPE OF WORK

CHAPTER 8

FUTURE SCOPE OF WORK

In future effect of other weather parameters like humidity, precipitation, and wind velocity on short-term load and price forecasting may be worked out. A hybrid model such as Neural-Fuzzy-Wavelet Hybrid model will also be worked out to take care of some high error weeks and refine the forecasting.

Artificial Intelligence tools and different optimization algorithms would be applied for optimization of bids and formulating better bidding strategy in deregulated electricity market. In addition to that i wish to apply these tools in forecasting of non-conventional energy such as Wind energy.

Also, the multi-objective ELD can be also solved by improved PSO for the minimization of fuel cost, power losses, emission etc.

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