Short-Term Load & Price Forecast of ISO New England Market with new ANN in presence of volatility

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***Abstract*— *In today's power system which has been restructured and converted into full-fledged market, forecasting of electricity load and price are of paramount importance. They also form the basis for any decision making in the Electricity market. Planning of power system, its operation and control depends upon short-term forecasting of power. Also accurate day ahead electricity price forecasting is crucial to power producers and consumers both so as they can develop accurate bidding strategies in order to maximize their profit. In this paper Neural network has been applied in short-term load and price day-ahead hourly forecasting of electricity market. Also, the forecast of load & price for each day in testing year 2012 is being computed in ISO New England market. The historical data used in the forecasting are hourly temperature, load and natural gas price data. The hourly data from the 2007 to 2011 has been used to train the ANN and tested was done on out-of-sample data from 2012. The results obtained from simulation have shown highly accurate day-ahead forecasts with very small error in load and price forecasting. However load forecast of ISO New England market is far better than price forecast of ISO New England market. This is because price curves of any electricity market is highly volatile & depends on also many other factors which must also be taken care off.*

***Keywords*— Day ahead electricity price forecast, locational marginal price (LMP), mean absolute percentage error, neural network, power system, short-term load forecasting.**

I. INTRODUCTION

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 startup 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 ISO New England market is co-ordinated by an independent system operator (ISO). In the ISO New England market, it is observed that daily power demand curves having similar pattern, but the daily price curves are volatile. Therefore, forecasting of LMPs become more important as it helps market participants not only to determine the bidding strategies of their generators, but also in risk management [5].

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

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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].

In this paper, artificial neural network designed using MATLAB R12 has been used to compute the short-term load and price forecast in ISO New England market. 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 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 [11] of the error distribution of forecasted load and price have been plotted as a function of hour of the day, day of the week.

The paper has been organized in five sections. Section II presents the overview of neural network used**.** Section III discusses the selection of various data and model of ANN for day-ahead load and price forecasting. Results of simulation are presented in Section IV. Section V discusses the conclusion and future work.

II. ARTIFICIAL NEURAL NETWORK FOR LOAD AND PRICE FORECASTING

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 functions 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 and 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 [12]-[13].

III. DATA INPUTS AND ANN MODEL

The models are trained on hourly data from the ISO New England 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 is shown in Fig. 1, where a close relationship between load and temperature can be observed. Hourly temperature data for location in high demand area has been considered in this paper.

Relationship between LMP and system load in year 2012 is shown by Fig. 2. It shows that as the system load increases with LMP and both are highly correlated. Fig. 3 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 (1-24)

- Day of the week (1-7)
- 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 (1-24)
- Day of the week (1-7)
- Holiday/weekend indicator (0 or 1)
- Load on System
- 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

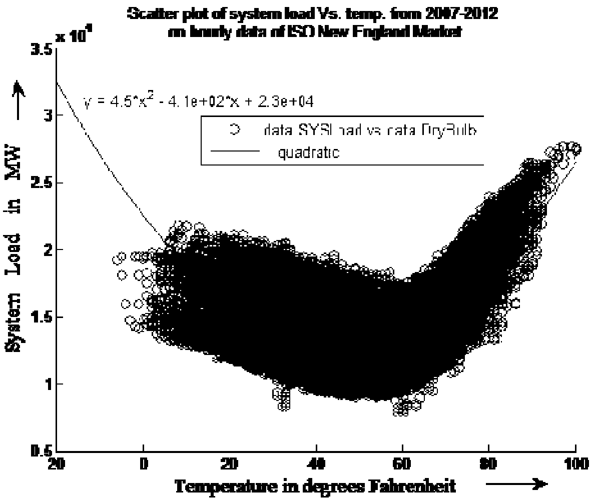

Fig. 1. Scatter plot of system load vs. temperature with quadratic fitting equation.

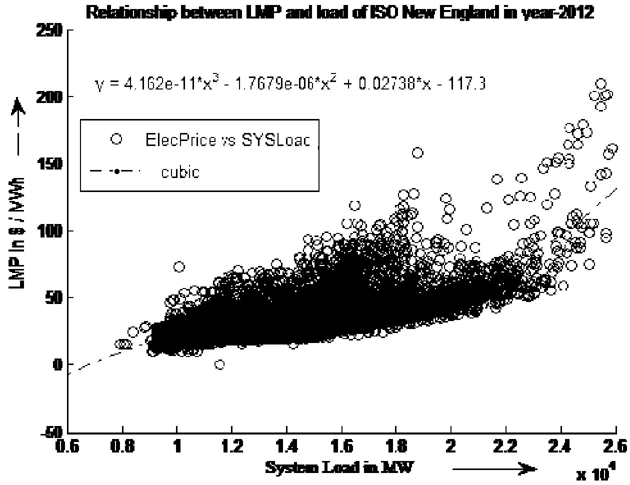

Fig. 2. Relationship between LMP and load in ISO New England market for the year 2012 with cubic fitting equation.

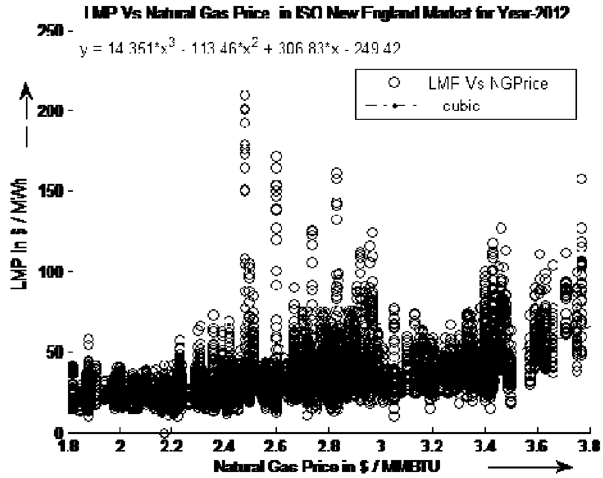

Fig. 3. Relationship between LMP and natural gas price by scatter plot for ISO New England market in year 2012 with cubic fitting equation.

IV. SIMULATION AND RESULTS

In this paper hourly day-ahead load and price forecasting has been done for sample of each day of data of year 2012 using neural network tool box of MATLAB R12a. The ANNs are trained with data from 2007 to 2011 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 for the year 2012 are also generated.

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. Simulation results of ISO New England market is discussed below.

A. Load Forecasting of ISO New England Market

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. 1 below

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

where L_A is the actual load, L_F is the forecasted load, N is the number of data points.

The ANN model used in the forecasting has input, output and one hidden layers. Hidden layer has 52 neurons. Inputs to the neurons are as listed above. After simulation the MAPE obtained is 1.55% for load forecasting for the year 2012, as shown in Fig. 4.

The box-plot of the error distribution of forecasted load as a function of hour of the day is presented in Fig. 5. It shows the percentage error statistics of hour of the day in year 2012. It is also evident that the highest error is for the 21st hour of the day and least 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. 6 which shows the percentage error statistics of day of the week in year 2012. The highest error is for the Monday and least error for Saturday in year 2012.

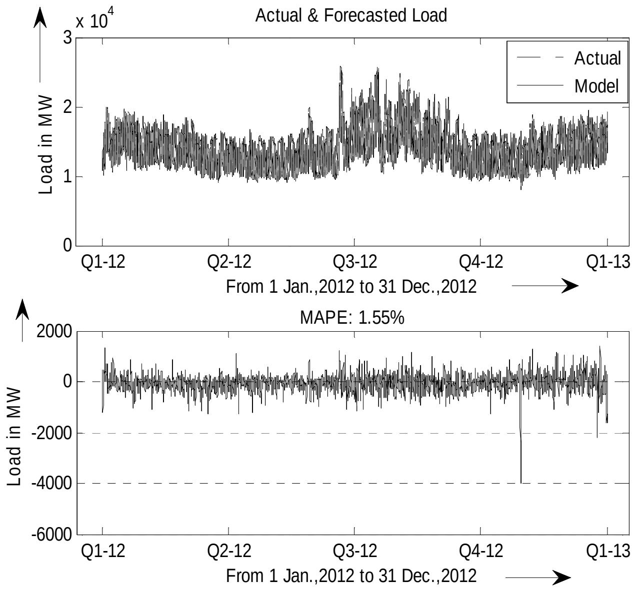

Fig. 4. Multiple series plot between actual load & forecasted load by using ANN for year 2012 with MAPE 1.59%.

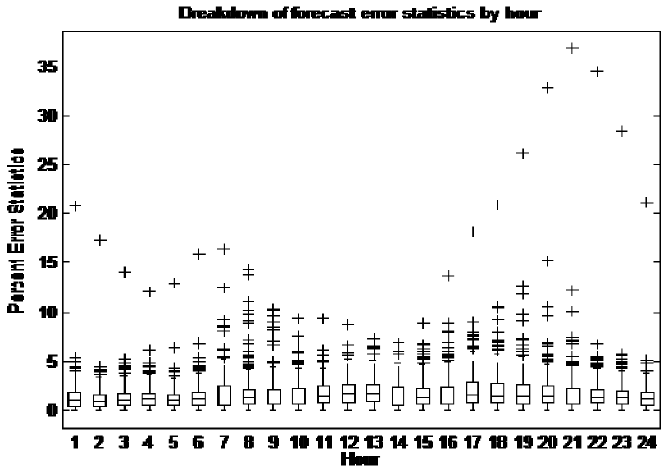

Fig. 5. Box-plot of the error distribution of forecasted load as a function of hour of the day for year 2012.

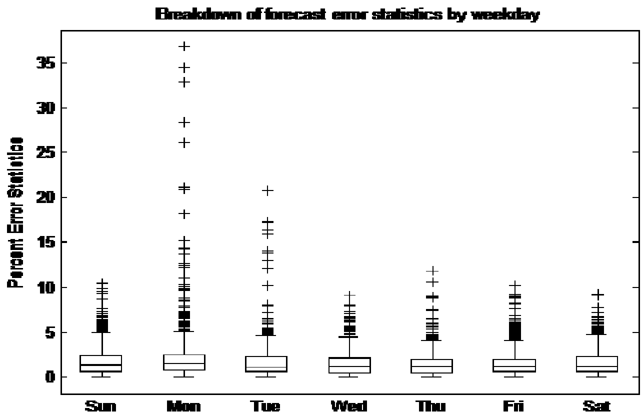

Fig. 6. Box-plot of the error distribution for the forecasted load as a function of day of the week in the year 2012.

B. Price Forecasting of ISO New England Market

For price forecasting the accuracy of forecast is accomplished by MAPE, this is computed as in eq. 2 below

$$MAPE\ [\%] = \frac{1}{N}\sum_{i=1}^{N}\frac{|P_A^i - P_F^i|}{P_A^i} \times 100 \qquad (2)$$

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.

The ANN model used in the forecasting 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. 8.

The box-plot of the error distribution of forecasted price as a function of hour of the day is evaluated in Fig. 9. 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. 10. 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. The Mean Absolute Percentage Error (MAPE) between the forecasted and actual loads and prices for each day of month from September to December, 2012 has been calculated and presented in the Table I.

The MAPE between the forecasted & actual load, price for each month has been calculated and presented in the Table II for the year 2012. From the results obtained from Table II, it is clear that highest MAPE (2.10%) is for October month and least MAPE (1.18%) is for the month of February for day ahead hourly load forecast from the testing samples of each month in year-2012.Also from Table II, it is clear that highest MAPE (12.27%) is for June month and least MAPE (6.90%) is for October month for day ahead hourly price forecast from the testing samples of each month in year-2012.

From the simulation results it is clear that MAPE obtained during forecast on 24 December, 2012 is equal to 6.23 % between actual load & forecasted load & similarly different MAPE for load & price of each day is discussed in Table I. Also there is least error for day-ahead hourly load forecast on 28 Sep., 2012 from the testing sample of each day in the year 2012 with MAPE (0.48%) for ISO New England market as shown in Fig. 13 & Table I.

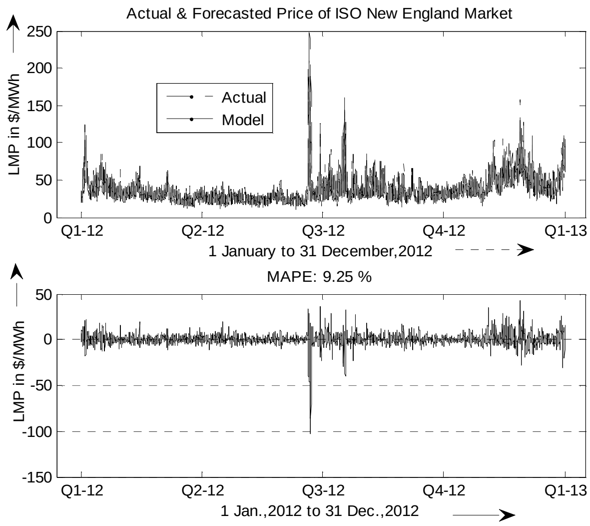

Fig. 8. Multiple series plot between actual & forecasted price by using ANN in the year 2012.

A plot between actual & forecasted price also the plot it's MAPE on 15 Feb., 2012 for day-ahead hourly price forecast from testing sample of each day in the year 2012 with MAPE (3.14%) is shown in Fig. 14.

The MAPE for load forecasting varies from 0.90% to 3.87% and it varies from 5.6% to 19.87% in the case of price forecasting for weekly testing sample sets.

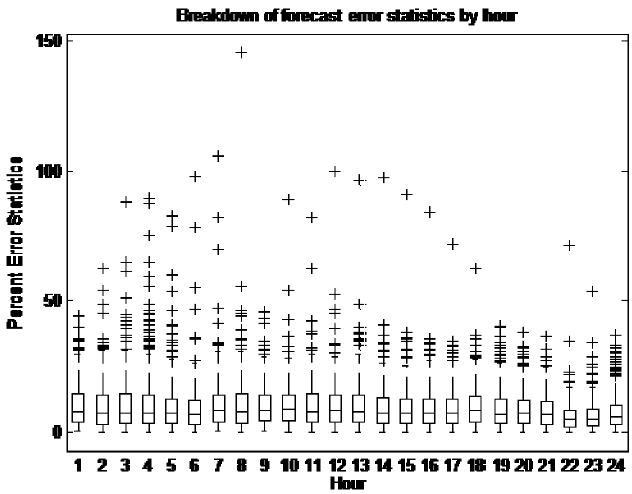

Fig. 9. Box-plot of the error distribution of forecasted price as a function of hour of the day for year 2012.

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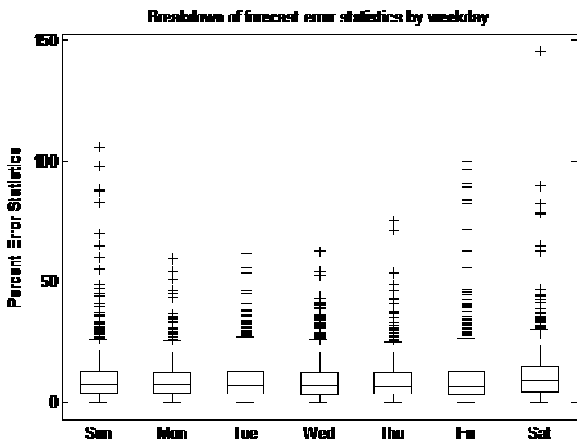

Fig. 10. Box-plot of the error distribution for the forecasted price as a function of day of the week in the year 2012.

TABLE I
RESULTS FOR OUT-OF-SAMPLE DAILY TEST FROM SEPTEMBER-DECEMBER, 2012

Day	MAPE (%) for Each Day of the Month of Year 2012 During Day-Ahead Load & Price Forecast of ISO New England Market							
	Price				Load			
	Sep.	Oct.	Nov.	Dec.	Sep.	Oct.	Nov.	Dec.
1	16.85	10.28	9.53	14.26	1.5	1.34	1.58	1.25
2	11.62	7.21	6.3	17.89	1.54	0.91	1.44	2.16
3	7.84	6.14	15.84	5.27	1.5	1.29	0.79	2.39
4	9.25	4.18	8.34	15	1.35	1.64	2.67	1.23
5	7.91	5.72	13.64	10.01	1.7	1.36	1.34	1.89
6	10.2	5.16	17.09	12.86	1.58	1.94	1.38	2.08
7	8.58	7.31	14.62	21.87	1.33	2.23	3.19	1.24
8	12.45	4.49	7.89	13.09	1.74	2.74	0.88	1.18
9	7.26	3.78	8.3	7.92	2.44	1.18	1.55	1.46
10	7.98	4.65	9.93	11.61	2.32	1.14	2.03	1.34
11	4.01	3.96	4.95	7.2	2.16	1.37	2.33	1.95
12	11.19	9.63	6.57	13.01	1.64	0.97	2.54	1.89
13	10.28	5.36	6.11	4.43	1.43	1.27	0.93	1.78
14	4.72	3.65	10	7.21	2.09	2.21	1.32	1.96
15	9.6	7.62	5.62	7.91	2.49	2.22	1.31	1.98
16	8.77	9.6	6.34	5.46	1.96	1.62	1.12	2.85
17	7.91	8.23	11.55	6.12	1.01	0.75	1.57	1.21
18	13.16	6.4	10.85	5.46	1.45	1.35	1.9	1.8
19	4.14	3.82	12.79	6.59	2.61	1.75	1.62	1.52
20	4.36	10.22	7.88	4.91	2.42	2.67	0.99	1.83
21	4.31	13.27	5.49	6.58	1.04	1.85	1.25	1.46
22	6.21	6.72	6.08	7.96	1.44	1.54	4.03	2.23
23	9.17	3.15	7.15	7.76	1.33	0.96	3.96	1.47
24	6.95	4.3	11.42	6.6	1.61	0.9	2.18	6.23
25	11.13	5.25	9.27	19.62	1.8	0.89	2.05	2.71
26	2.51	3.75	9.99	7.34	1.07	1.82	1.48	3.12
27	3.99	8.15	13.72	7.16	1.34	1.49	0.63	1.36
28	4.02	7.83	8.04	19.87	0.48	2.04	0.74	1.71
29	7.64	12.92	9.13	8.3	1.35	11.45	1.48	1.41
30	7.71	18.3	13.29	23.45	1.1	7.23	1.34	1.37
31	-----	6.32	-----	9.82	-----	2.59	------	4.72

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

S.N.	Month	MAPE (%)	
		Price	Load
1	January	9.21	1.56
2	February	6.92	**1.18 (min)**
3	March	9.57	1.69
4	April	10.78	1.53
5	May	9.00	1.26
6	June	**12.27 (max)**	1.36

7	July	10.52	1.51
8	August	7.60	1.51
9	September	8.17	1.62
10	October	**6.90 (min)**	**2.10 (max)**
11	November	9.63	1.71
12	December	10.39	2.04

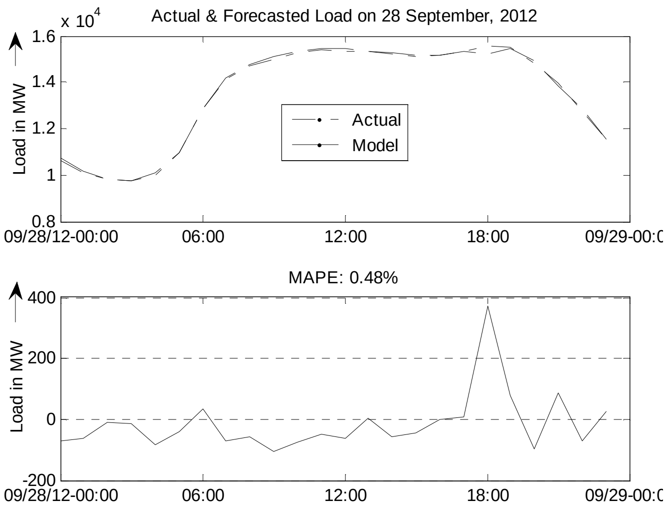

Fig. 13. MAPE is least (0.48%) for day ahead hourly load forecast on 28 September from the testing samples of each day in year-2012.

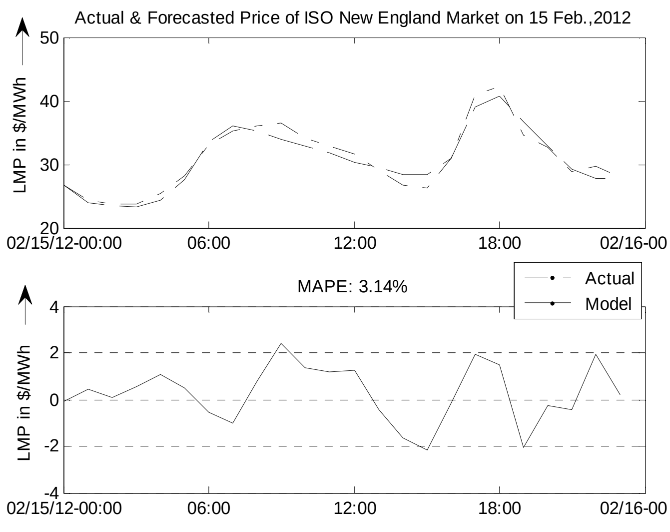

Fig. 14. MAPE is 3.14% for day ahead hourly price forecast on 15 February from the testing sample of each day in year 2012.

MAPE for day ahead hourly load & price forecast of ISO New England market in year-2012 has been calculated. From these simulation results it is clear that highest & least error occurred during the load forecast is on 29 October & 28 September with MAPE equal to 11.45% & 0.48% respectively. Also the highest & least error occurred during the price forecast is on 22 June & 26 September with MAPE equal to 50.55% & 2.51% respectively. 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.

V. CONCLUSION AND FUTURE WORK

This paper presented day-ahead short-term electricity load and price forecast by using artificial neural network (ANN) approach in ISO New England market. 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 has forecasted load and price for each day of the year 2012 and results indicates that it has performed well in each day 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 electricity load and price values. The MAPE for load forecasting varies from 0.90% to 3.87% and it varies from 5.6% to 19.87% in the case of price forecasting for weekly testing sample sets. The average MAPE obtained is 1.55% for load forecast and average MAPE for price forecast is 9.25% in the year 2012. The results suggest that present ANN model with the developed structure can perform good prediction with least error.

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