Day Ahead Hourly Load and Price Forecast in ISO New England Market using ANN

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***Abstract*—In restructured daily power markets, forecasting electricity price and load are most essential tasks and basis for any decision making. Short-term load forecasting is an essential instrument in power system planning, operation, and control. Also, the accurate day ahead electricity price forecasting provides crucial information for power producers and consumers to develop accurate bidding strategies in order to maximize their profit. In this paper artificial intelligence (AI) has been applied in short-term load and price forecasting that is, the day-ahead hourly forecast of the electricity market parameters (load and price) over a week. Neural network fitting tool of MATLAB Software has been used to compute the forecasted load and price in ISO New England market. The data used in the forecasting are hourly historical data of the temperature, electricity load and natural gas price of ISO New England market. The ANN was trained on hourly data from the 2007 to 2011 and tested on out-of-sample data from 2012. The simulation results have shown highly accurate day-ahead forecasts with very small error in load and price forecasting.**

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 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, neural Network fitting tool of MATLAB 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 NEPOOL region (ISO New England), 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 has been plotted as a

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function of hour of the day, day of the week and month of the year.

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 and activation function for limiting the amplitude of the output of a neuron [12]. Artificial neural network is inspired by biological nervous systems. The Fig. 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.

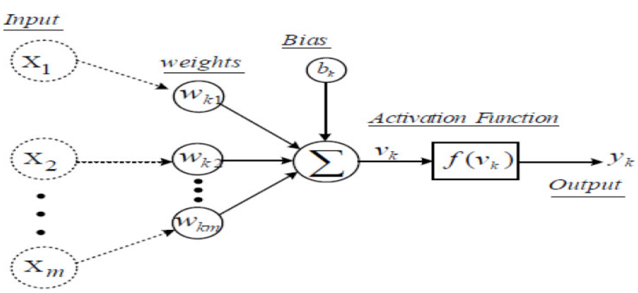

Fig. 1. Model of an artificial neural network (ANN).

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 [13].

III. DATA INPUTS AND ANN MODEL

The models are trained on hourly data from the NEPOOL region (ISO New England) 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. 2, where a close relationship between load and temperature can be observed. Hourly temperature data for location in high demand area of NEPOOL region has been considered in this paper. Relationship between LMP and system load for NEPOOL region in year 2012 is shown by Fig. 3. It shows that as the system load increases with LMP and both are highly correlated. Fig. 4 shows the effect of natural gas price on LMP for ISO New England market and both are interdependent.

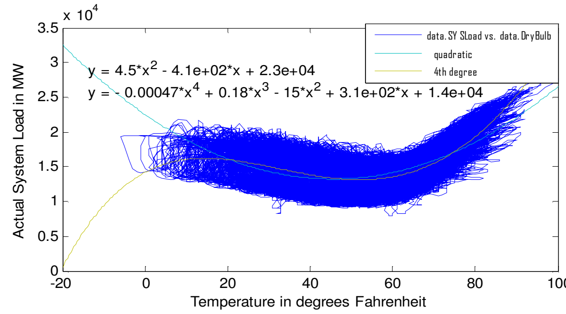

Fig. 2. Scatter plot of system load vs. temperature (degrees Fahrenheit) for NEPOOL region (ISO New England) for year 2007 to 2012 with fitting equation of quadratic and 4th degree.

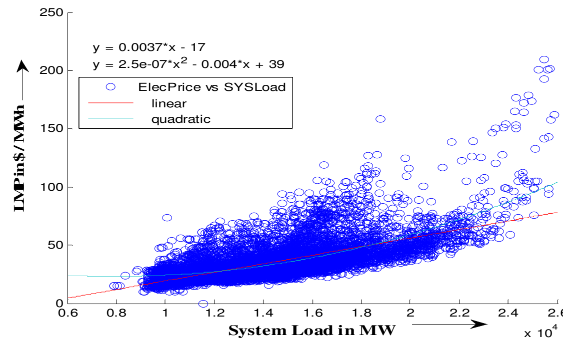

Fig. 3. Relationship between LMP and load in NEPOOL region for the year 2012 with linear and quadratic fitting equation.

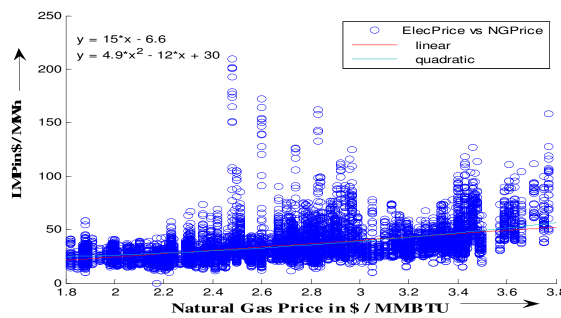

Fig. 4. Relationship between LMP and natural gas price by scatter plot for ISO New England market in year 2012 with fitting equations.

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

IV. SIMULATION AND RESULTS

In this paper hourly day-ahead load and price forecasting has been done for sample of each week 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 and month of the year are generated. Also, the various plots comparing the day ahead hourly actual and forecasted load and price for every weeks for the year 2012 are also generated. Simulation results of new ISO England market is discussed below.

A. Load Forecasting of New England Pool region (ISO New England)

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. 1 below

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

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 48 neurons. Inputs to the neurons are listed above. After simulation the MAPE obtained is 1.59% for load forecasting for the year 2012, as shown in Fig. 5.

The box-plot of the error distribution of forecasted load as a function of hour of the day is presented in Fig. 6. 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. 7 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. The box-plot of the error distribution of forecasted load as a function of month of the year 2012 is evaluated in Fig. 8. The figure indicates that the maximum error is for the October 2012 and minimum error is for May 2012.

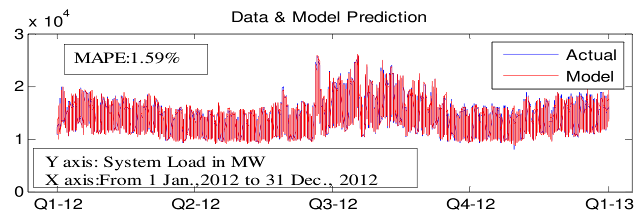

Fig. 5. Multiple series plot between actual load & forecasted load by using ANN in NEPOOL region (ISO New England) for year 2012.

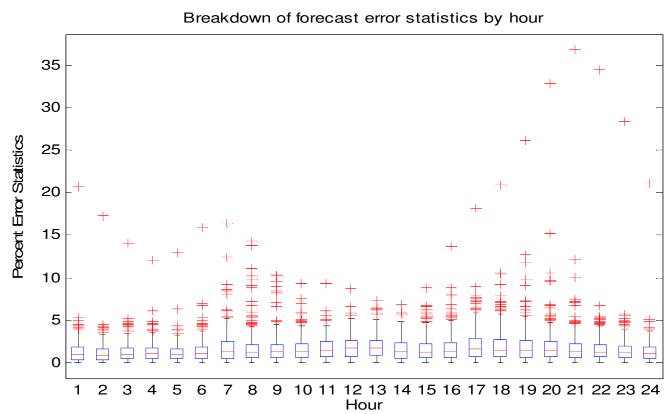

Fig. 6. Box-plot of the error distribution of forecasted load as a function of hour of the day for year 2012.

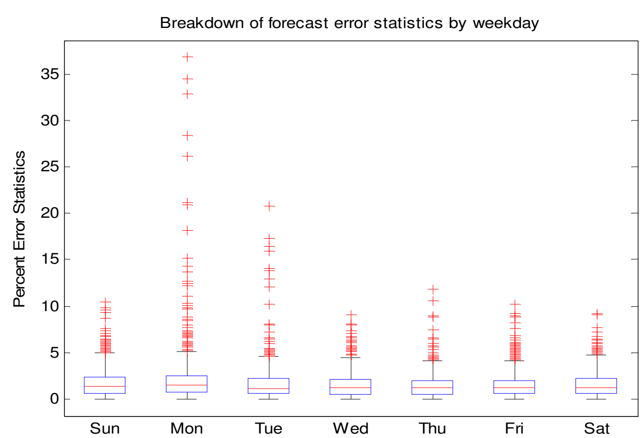

Fig. 7. Box-plot of the error distribution for the forecasted load as a function of day of the week in the year 2012.

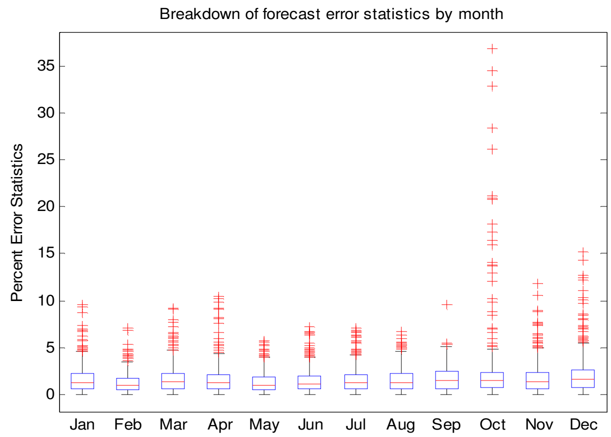

Fig. 8. Box-plot of the error distribution of forecasted load as a function of month of the year for the year 2012.

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 NEPOOL region (ISO New England) and also plots of MAPE with maximum error (3.87%) and minimum error (0.90%) have been shown in Fig. 9 and Fig. 10.

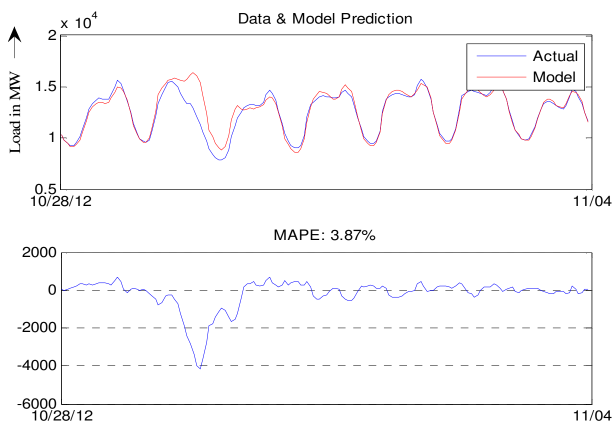

Fig. 9. Maximum MAPE is 3.87% for the load forecast of 28 October, 2012 to 03 November, 2012 NEPOOL region (ISO New England).

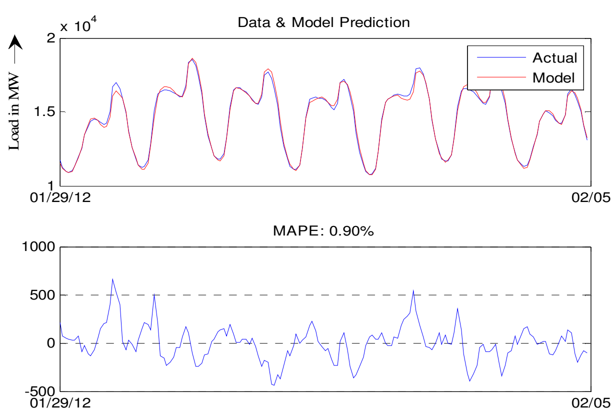

Fig. 10. Minimum MAPE is 0.90% for the load forecast of 29 January, 2012 to 04 Febuary, 2012 NEPOOL region (ISO New England).

B. Price Forecasting of New England Pool region (ISO New England)

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

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

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. 11.

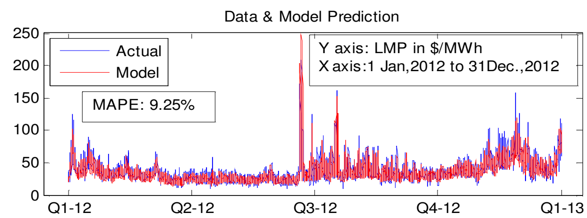

Fig. 11. Multiple series plot between actual & forecasted price by using ANN in NEPOOL region (ISO New England) for year 2012.

The box-plot of the error distribution of forecasted price as a function of hour of the day is evaluated in Fig. 12. It shows the percentage error statistics of hour of the day in year 2012. It is clear that the maximum error is for the 8th hour of the day and minimum error for 1st 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. 13. It shows the percentage error statistics of day of the week in year 2012. The maximum error is for the Saturday and minimum error for Monday in year 2012. The box-plot of the error distribution of forecasted price as a function of month of the year is evaluated in Fig. 14 which shows the percentage error statistics of month of the year in year 2012. The maximum error is for the June month and minimum error for February.

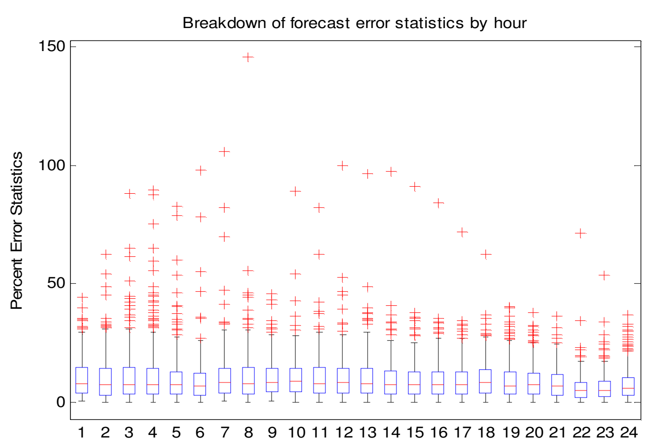

Fig. 12. Box-plot of the error distribution of forecasted price as a function of hour of the day for year 2012.

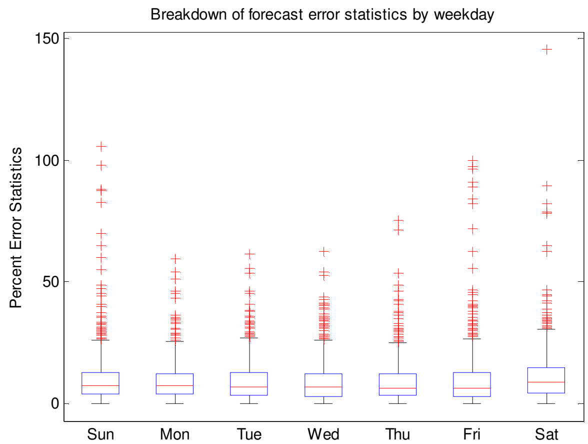

Fig. 13. Box-plot of the error distribution for the forecasted price as a function of day of the week in the year 2012.

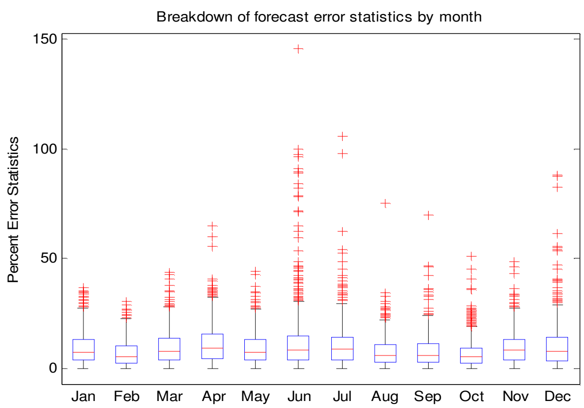

Fig. 14. Box-plot of the error distribution of forecasted price as a function of month of the year for the year 2012.

Multiple series plots between actual price & forecasted price from 17 June, 2012 to 23 June, 2012 & from 07 October, 2012 to 13 October, 2012 and also plots of MAPE with maximum error (19.87%) and minimum error (5.60%) have been shown in Fig. 15 and Fig. 16.

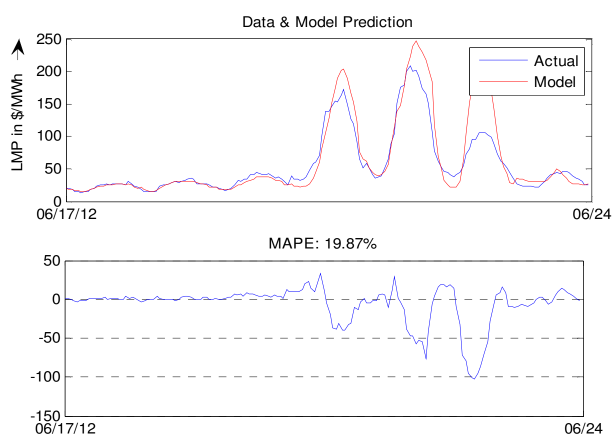

Fig. 15. Maximum MAPE is 19.87% for the price forecast of 17 June, 2012 to 23 June, 2012 in NEPOOL region (ISO New England).

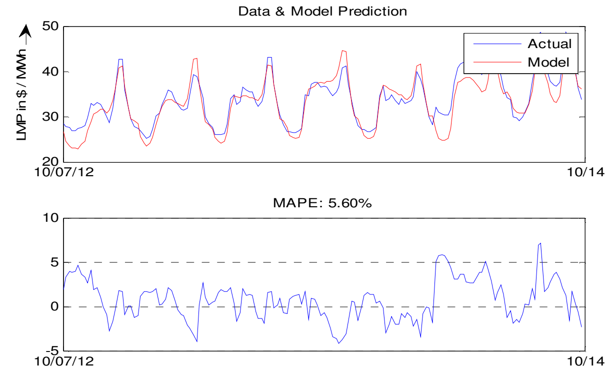

Fig. 16. Minimum MAPE is 5.60% for the price forecast of 7 October , 2012 to 13 October, 2012 in NEPOOL region (ISO New England).

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 I for the year 2012. 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.

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

TABLE I
RESULTS FOR OUT-OF-SAMPLE TEST FOR YEAR 2012

S. N.	Duration mm/dd/yy -mm/dd/yy	MAPE (%)	
		Load	Price
1	01/01/12-01/07/12	2.03	11.23
2	01/08/12-01/14/12	1.24	8.72
3	01/15/12-01/21/12	1.39	10.61
4	01/22/12-01/28/12	1.79	6.46
5	01/29/12-02/04/12	**0.90 (min)**	7.25
6	02/05/12-02/11/12	1.22	6.57
7	02/12/12-02/18/12	1.13	6.88
8	02/19/12-02/25/12	1.36	6.49
9	02/26/12-03/03/12	1.49	9.13
10	03/04/12-03/10/12	1.59	8.19
11	03/11/12-03/17/12	1.96	7.71
12	03/18/12-03/24/12	1.73	9.64
13	03/25/12-03/31/12	1.32	11.64
14	04/01/12-04/07/12	1.61	8.70
15	04/08/12-04/14/12	1.34	11.37
16	04/15/12-04/21/12	1.80	12.58
17	04/22/12-04/28/12	1.53	12.15
18	04/29/12-05/05/12	1.45	9.79
19	05/06/12-05/12/12	0.93	8.78
20	05/13/12-05/19/12	1.01	7.68
21	05/20/12-05/26/12	1.15	9.08
22	05/27/12-06/02/12	1.76	8.92

23	06/03/12-06/09/12	1.29	7.61
24	06/10/12-06/16/12	0.94	8.39
25	06/17/12-06/23/12	1.58	**19.87 (max)**
26	06/24/12-06/30/12	1.68	14.73
27	07/01/12-07/07/12	1.78	11.59
28	07/08/12-07/14/12	1.43	9.64
29	07/15/12-07/21/12	1.43	10.44
30	07/22/12-07/28/12	1.47	12.07
31	07/29/12-08/04/12	1.23	7.40
32	08/05/12-08/11/12	1.70	5.98
33	08/12/12-08/18/12	1.60	6.59
34	08/19/12-08/25/12	1.25	8.79
35	08/26/12-09/01/12	1.64	10.73
36	09/02/12-09/08/12	1.53	9.70
37	09/09/12-09/15/12	2.08	7.87
38	09/16/12-09/22/12	1.70	6.99
39	09/23/12-09/29/12	1.28	6.49
40	09/30/12-10/06/12	1.37	6.63
41	10/07/12-10/13/12	1.56	**5.60 (min)**
42	10/14/12-10/20/12	1.80	7.08
43	10/21/12-10/27/12	1.35	6.37
44	10/28/12-11/03/12	**3.87 (max)**	11.01
45	11/04/12-11/10/12	1.86	11.41
46	11/11/12-11/17/12	1.59	7.31
47	11/18/12-11/24/12	2.27	8.81
48	11/25/12-12/01/12	1.28	11.11
49	12/02/12-12/08/12	1.74	13.72
50	12/09/12-12/15/12	1.76	8.47
51	12/16/12-12/22/12	1.84	6.16
52	12/23/12-12/29/12	2.57	10.95

TABLE II
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	**ANN Used in this Paper**	**3.87**	**0.90**	**1.59**

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 NEPOOL region (ISO New England). 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 every week of the year 2012 and results indicates that it has performed well in every week 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 0.9% to 3.87% and it varies from 5.6% to 19.87% in the case of price forecasting. The average MAPE obtained is 1.59% 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. 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 ANN model will also be worked out to take care of some high error weeks and refine the forecasting.

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