An Analysis of Short-Term Price Forecasting of Power Market By Using ANN

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***Abstract*—In deregulated power markets, forecasting electricity parameters are most essential tasks & basis for any decision making. Price forecasting in competitive electricity markets is critical for consumers and producers in planning their operations and managing their price risk, and it also plays a key role in the economic optimization of the electric energy industry. Accurate, short-term price forecasting is an essential instrument which 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 price forecasting that is, the day-ahead hourly forecast of the electricity market price. A new artificial neural network (ANN) has been used to compute the forecasted price in ISO New England market using MATLAB R13. 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 simulation results have shown highly accurate day-ahead forecasts with very small error in price forecasting.**

***Index Terms*--- Day ahead electricity price forecast, locational marginal price (LMP), mean absolute error (MAE), mean absolute percentage error (MAPE), neural network (NN), power system, short-term price forecasting.**

I. INTRODUCTION

Restructuring of power market causes many challenging issues. In electricity market, price and load forecasting are the two major planning tools for generation, transmission and distribution systems. 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 [1]-[2].

However, the principal challenge associated with electricity prices in planning and operation of a competitive market is to perform an accurate forecasting of electricity prices as these prices are highly volatile in nature. The volatile electricity price adds more uncertainties and complexities to power system operation, and consequently affecting the behavior of generation, transmission and demand side in electricity market. Hence, a reliable, highly efficient and an accurate price forecasting tool is important as it can help to develop well-functioning of power systems operations and markets. The market operators can take advantage of forecasted prices in order to compute various indexes and measurements for market monitoring [3]-[5].

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 [6]-[8].

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. 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.

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 [9]-[11]. 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 [12].

In this paper, a new artificial neural network has been used to compute the forecasted price in ISO New England market using MATLAB R13. 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. Hourly natural gas data has been also considered as an input for forecast. The neural network models are trained on hourly data from 2007 to 2011 and tested on out-of-sample

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data from 2012. The simulation results obtained have shown that artificial neural network (ANN) is able to make very accurate short-term price forecast. Box plots [13] of the error distribution of forecasted 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 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. A neural network can be trained to perform a particular function by adjusting the values of the connections (weights) between elements. In load & price 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. 1 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 [14]-[17].

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

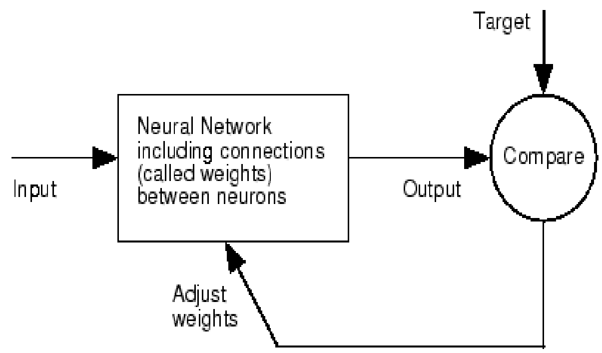

Fig. 1. Working model of an ANN by adjusting it weights.

III. DATA INPUTS AND ANN MODEL

The models are trained on hourly data of 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 power demand and average temperature for ISO New England is shown in Fig. 2, where a close relationship between load and temperature can be observed. Relationship between LMP and system load for ISO New England market 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.

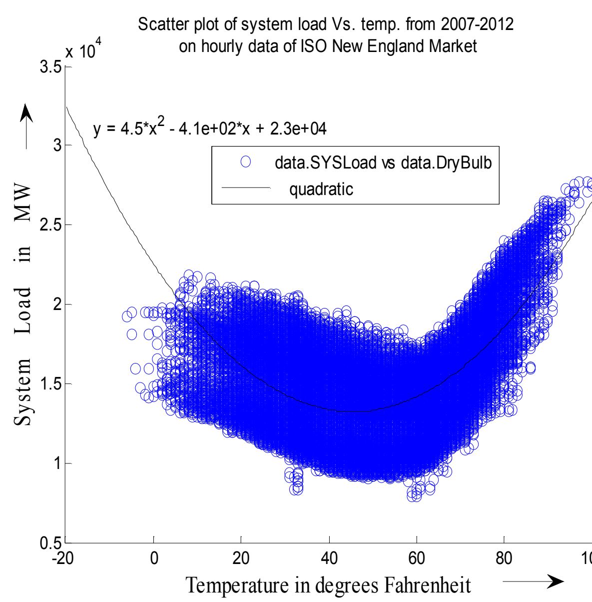

Fig. 2. Scatter plot of system load vs. temperature with quadratic fitting equation.

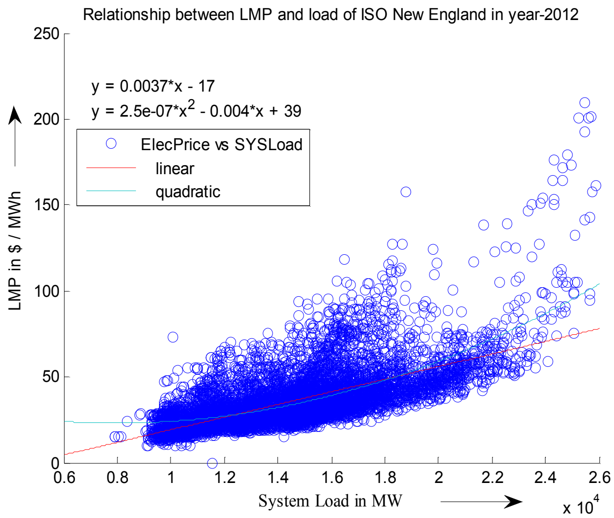

Fig. 3. Scatter plot between LMP and load with linear and quadratic fitting equation.

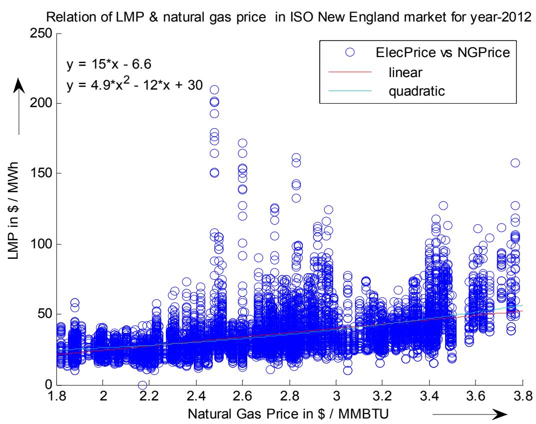

Fig. 4. Scatter plot between LMP and natural gas price with fitting equations.

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 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)
- 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 price forecasting has been done for sample of each day & month of data of year 2012 using neural network tool box of MATLAB R13. 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), is defined in eq. 1 below.

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

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. 2 below-

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left|P_i^{\mathrm{true}} - P_i^{\mathrm{forecast}}\right| \quad (2)$$

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

MAPE & MAE 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.

Various plots comparing the day ahead hourly actual and forecasted price for each day for the year 2012 are also generated. Simulation results are discussed below.

The ANN model used in the forecasting is shown below in Fig. 5. It has input, output and one hidden layer. Hidden layer has 28 neurons. Inputs to the input layer are as listed above for price forecast. After simulation the average MAPE obtained is 9.14% for price forecasting in the testing year 2012.Multiple series plots between actual & forecasted price & also plots of its MAPE for testing year-2012 have been shown in Fig. 6.

Multiple series plots between actual & forecasted price on 13 January, 2012 & 07 February, 2012 and also plots of its MAPE have been shown in Fig. 7 and Fig. 8. The simulation results show that the highest & least error occurred with MAPE of 41.3% & 3.18% for day-ahead price forecast of 20 June & 20 September, 2012 respectively.

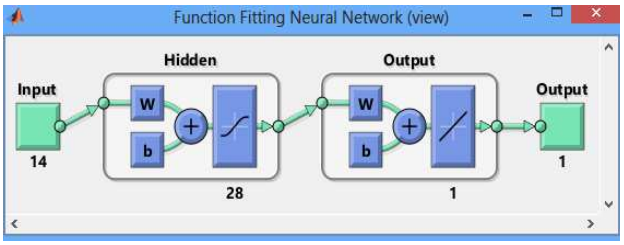

Fig. 5. Showing fourteen different input data for one target data with 28 neurons in hidden layer.

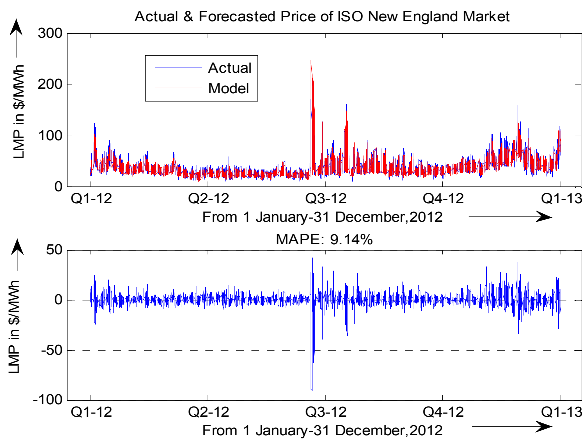

Fig. 6. Multiple series plot between actual & forecasted price by using ANN in the year 2012.

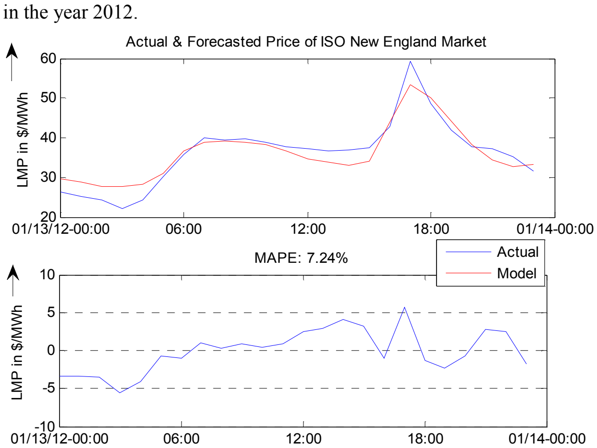

Fig. 7. Day-ahead hourly price forecast of 13 January, 2012.

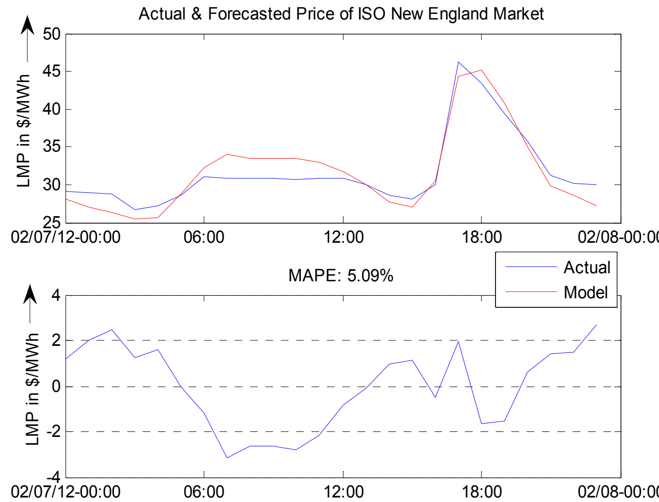

Fig. 8. Day-ahead hourly price forecast of 07 February, 2012.

The box-plot of the error distribution of forecasted price as a function of hour of the day is presented in Fig. 9. 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 8th hour of the day and minimum error for 10th 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 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 Monday in year 2012. Fig. 11 shows the plot of regression obtained from simulation.

The Mean Absolute Percentage Error (MAPE) & Mean Absolute Error (MAE) between the forecasted and actual price for each day & month has been calculated and presented in the Table I-IV respectively for the year 2012.From the results obtained from Table IV, it is clear that maximum MAPE (11.66%) is for June and minimum MAPE (6.92%) is for February, 2012

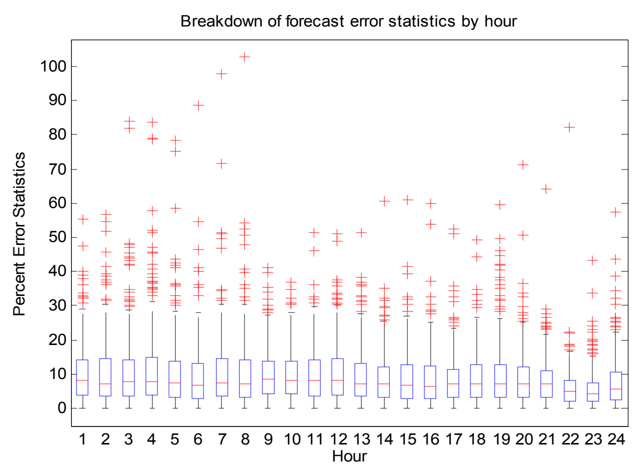

Fig. 9. Box-plot of the error distribution of forecasted price as a function of hour of the day for year 2012.

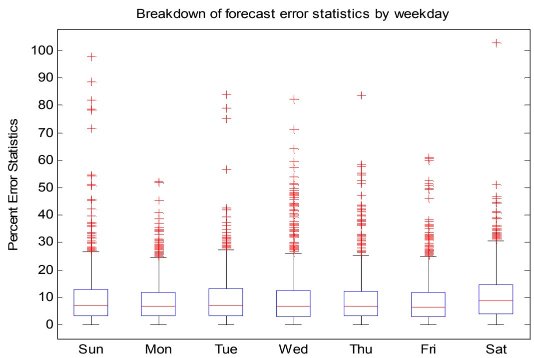

Fig. 10. Box-plot of the error distribution for the forecasted price as a function of day of the week in the year 2012.

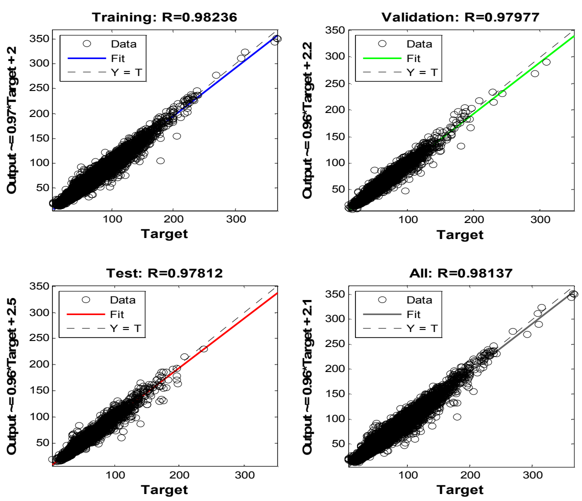

Fig. 11. Regression plot during training, testing & validation.

TABLE I
RESULTS FOR OUT-OF-SAMPLE DAILY TEST FROM JANUARY TO APRIL IN YEAR 2012

Day	MAPE & MAE for Each Day of the Month of Year 2012 During Day-Ahead Price Forecast of ISO New England Market							
	MAPE (%)				MAE ($/MWh)			
	Jan.	Feb.	Mar.	April	Jan.	Feb.	March	April
1	17.54	7.11	6.99	11.94	6.79	1.94	2.09	2.95
2	9.86	5.92	6.95	7.94	4.49	1.63	2.22	2.39
3	10.71	6.81	9.55	5.57	7.86	1.99	3.11	1.41
4	19.63	4.82	8.36	9.69	11.56	1.45	2.69	2.6
5	17.1	5.75	10.57	8.33	7.31	1.77	4.52	1.9
6	8.28	7.52	5.13	10.37	3	2.68	2.13	2.14
7	6.64	5.09	15.61	11.89	2.13	1.59	4.11	3.16
8	7.44	5.44	5.49	9.14	2.44	1.98	1.5	1.9
9	6.36	4.53	8.8	13.44	2.43	1.57	1.84	3.94
10	12.01	4.02	6.08	7.05	4.23	1.22	1.61	1.97
11	9.63	11.64	8.41	13.29	3.96	4.67	2.12	4.29
12	6.99	9.38	5.85	13.21	2.66	3.4	1.58	3.07
13	7.24	7.49	12.31	9.47	2.34	3.71	2.78	2.29
14	15.22	12.85	6.77	18.45	8.1	4.12	1.58	4.43
15	7.41	3.85	4.95	18.93	4.06	1.19	1.2	4.6
16	10.56	5.03	7.03	12	5.32	1.49	1.49	4.18
17	9.29	4.82	8.39	12.61	4.77	1.37	1.88	3.23
18	18.72	5.84	11	8.95	6.73	1.71	2.11	2.41
19	7.65	7.53	10.29	10.49	3.8	2.03	2.79	1.99
20	4.66	6.87	7.14	5.19	1.87	2.18	1.58	1.23
21	6.86	5.92	12.92	16.14	2.66	1.87	2.31	4.97
22	4.76	4.25	14.76	8.26	1.92	1.28	3.43	2.23
23	8.35	5.12	10.06	14.17	3.29	1.42	2.08	3.69
24	13.7	6.53	12.39	6.25	4.11	1.75	2.29	1.52
25	4.11	11.89	9.7	12.15	1.39	2.85	1.66	3.87
26	6.92	11.85	10.03	15.65	1.98	3.03	2.33	4.43
27	5.15	7.38	11.31	15.98	1.49	2.21	3	3.34
28	5.15	9.11	13.3	11.61	1.6	2.59	3.84	3.28
29	6.58	7.33	14.51	6.53	2.08	2.08	3.07	1.43
30	6.54	------	16.29	9.97	2.51	----	4.75	2.93
31	5.99	------	13.84	-----	1.9	----	4.57	----

TABLE II
RESULTS FOR OUT-OF-SAMPLE DAILY TEST FROM MAY TO AUGUST IN YEAR 2012

Day	MAPE & MAE for Each Day of the Month of Year 2012 During Day-Ahead Price Forecast of ISO New England Market							
	MAPE (%)				MAE ($/MWh)			
	May	Jun.	July	Aug.	May	Jun.	July	Aug.
1	9.54	7.74	7.61	6.44	2.84	1.76	3.08	2.45
2	12.55	7.43	11.98	8.8	2.77	1.63	4.04	4.19
3	12.14	6.89	9.56	7.13	4.16	1.59	4.72	3.91
4	9.51	10	10.86	11.17	2.52	2.6	3.21	4.24
5	3.92	6.53	8.28	6.84	**0.95**	1.48	4.24	2.64
6	9.47	9	6.14	5.54	2.06	1.71	3.03	2.41
7	6.7	8.41	15	4.8	1.58	1.8	8.91	2.31
8	8.56	6.36	13.62	5.02	1.83	1.44	5.66	2.17
9	12.58	10.96	7.56	7.36	2.75	2.57	2.91	3.23
10	7.7	8.21	5.21	5.11	1.97	1.69	2.02	2.06
11	13.19	12.77	6.14	9.17	2.75	3.19	2.46	3.35
12	10.47	5.24	6.24	5.03	2.44	1.37	2.13	1.95
13	9.87	5.84	9.59	5.12	1.96	1.35	3.39	2.24
14	9.3	10.29	8.59	6.98	1.87	2.35	3.58	3.37
15	6.39	6.41	6.79	4.87	1.52	1.52	2.7	2.15
16	4.93	8.26	6.39	4.53	1.16	1.85	3.62	1.95
17	12.23	4.28	15.89	7.83	2.68	0.96	11.06	3.48
18	4.26	5.5	15.15	8.64	1.05	1.31	9.47	2.49
19	7.35	10.92	4.41	6.21	1.61	3.68	1.75	1.55
20	7.75	**41.3**	8.46	9.77	1.51	**38.84**	2.38	3.02
21	8.78	25	5.72	10.7	2.48	19.21	1.62	3.33
22	5.49	29.31	13.76	4.41	1.32	23.03	2.39	1.56
23	9.47	20.59	7.53	9.13	2.42	5.64	3.54	3.06
24	7.99	8.62	19.8	4.35	2.49	2.31	9.41	1.66
25	9.04	4.06	6.51	12.58	3.03	1.18	2.75	3.95
26	14.02	12.92	11.97	12.41	4.23	4.35	6.72	5.18
27	10.57	7.49	6.97	6.32	2.63	2.8	2.52	2.33
28	4.68	16.47	12.68	5.07	1.33	4.55	4.53	2.06
29	7.94	17.77	9.69	6.25	2.71	12.38	3.46	1.96
30	9.31	17.73	6.88	15.72	3.39	5.07	2.69	6.25
31	11.66	----	8.11	8.35	2.85	----	2.68	3.74

TABLE III
RESULTS FOR OUT-OF-SAMPLE DAILY TEST FROM SEPTEMBER TO DECEMBER IN YEAR 2012

Day	MAPE & MAE for Each Day of the Month of Year 2012 During Day-Ahead Price Forecast of ISO New England Market							
	MAPE (%)				MAE ($/MWh)			
	Sep.	Oct.	Nov.	Dec.	Sep.	Oct.	Nov.	Dec.
1	15.05	9.74	9.3	15.79	4.11	2.31	3.76	9.61
2	6.44	8.4	5.96	18.56	1.67	2.5	2.11	7.91
3	9.62	6.55	14.8	6.06	2.53	2.51	7.14	2.99
4	7.48	4.82	8.41	15.09	2.81	1.69	4.17	6.2
5	10.28	5.05	11.62	12.91	3.74	1.56	4.69	4.28

6	8.45	5.94	15.29	14.9	4.1	1.88	8.35	9.93
7	9.72	8.98	12.6	23.2	4.2	2.61	8.78	10.45
8	12.43	5.04	8.4	13.14	5.15	1.64	5.18	4.78
9	5.42	3.33	7.94	7.8	1.68	1.03	3.9	2.74
10	7.32	3.73	12.16	10.32	2.29	1.26	4.51	3.01
11	4.31	4.9	6.53	6.13	1.23	1.64	2.67	2.59
12	11.16	9.74	8.17	13.47	4.56	3.56	3.43	5.23
13	8.99	5.71	5.24	5.07	2.94	2.12	2.29	2.27
14	6.14	3.76	9.34	9.3	1.89	1.28	5.77	3.6
15	10.8	6.42	6.3	5.88	2.85	2.79	3.75	2.42
16	10.82	9.27	5.56	6.99	2.88	3.77	3.15	2.79
17	6.77	7.2	8.91	6.89	1.87	2.7	5.42	2.94
18	12.57	6.28	13.34	6.27	4.33	2.15	6.56	2.28
19	7.55	3.72	10.8	6.1	2.42	1.46	5.98	2.29
20	**3.18**	11.67	7.04	6.56	1.01	5.23	4.03	2.47
21	4.67	14.84	5.06	7.29	1.52	4.93	3.16	2.1
22	7.21	8.29	5.15	5.2	2.25	3.44	2.63	2.02
23	11.6	4.07	8.42	7.55	2.68	1.6	5.27	2.49
24	5.98	4.22	11.35	3.34	1.91	1.56	6.61	1.23
25	9.94	4.54	7.96	20.34	2.42	1.73	4.73	6.33
26	3.49	3.76	11.63	6.08	1.1	1.43	6.07	3.01
27	4.62	5.68	10.19	6.76	1.45	1.89	9.99	2.94
28	3.54	7.26	9.94	17.56	1.09	2.45	7.81	10.28
29	6.01	13.86	10.22	10.79	1.7	4.49	7.6	8.44
30	8.36	16.98	8.8	22.01	2.23	4.21	6.74	10.42
31	----	6.35	----	9.9	-----	1.86	-----	6.78

TABLE IV

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

S.N.	Month	MAPE & MAE for Each Month of Year 2012 During Day-Ahead Price Forecast	
		MAPE (%)	MAE ($/MWh)
1	January	9.34	3.94
2	**February**	**6.92**	2.15
3	March	10	2.55
4	April	11.04	2.92
5	May	8.92	2.26
6	**June**	**11.66**	5.16
7	July	9.46	4.08
8	August	7.5	2.93
9	September	8.07	2.55
10	October	7.01	2.43
11	November	9.29	5.27
12	December	10.5	4.67

V. CONCLUSION AND FUTURE WORK

This paper presented day-ahead short-term electricity 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 price for each day 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 electricity price values. The average MAPE obtained for price forecasting is 9.14% during the testing. 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 price forecasting may be worked out. A hybrid ANN model will also be worked out to take care of some high error days and refine the forecasting.

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