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Short-Term Load Forecasting of UPPCL using ANN

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***Abstract*—Power sector reforms have been introduced in Uttar Pradesh, India in as early as 1999. Restructuring and unbundling of UP state electricity board was done by segregating power generation, transmission and distribution functions into autonomous and separately accountable entities. Uttar Pradesh power corporation India ltd. (UPPCL) was formed. An independent Regulatory Body was formed. Private sector participation was encouraged and tariff reform was introduced with the objective to rationalize tariff for full cost recovery and minimize cross subsidy. Power is procured through long-term PPA or energy exchange based on forecasting of day-ahead load demand. The present load forecasting method is based on previous year load and uses very crude method with large errors. This paper discusses role of ANN in day-ahead hourly forecast of the power system load in UPPCL so as to minimize the error in demand forecasting. A new artificial neural network (ANN) has been designed to compute the forecasted load of UPPCL. The data used in the modeling of ANN are hourly historical data electricity load. The ANN model is trained on hourly data from UPPCL from April, 2014 to June, 2014 and tested on out-of-sample data of two weeks. Simulation results obtained have shown that day-ahead hourly forecasts of load using proposed ANN is very accurate with very less error.**

***Index Terms*----Mean absolute error (MAE), mean absolute percentage error (MAPE), neural network (NN), power system, short-term load forecasting, Uttar Pradesh Power Corporation India Ltd. (UPPCL).**

I. Introduction

With an introduction of deregulation in power industry, worldwide the traditional power Industry has been changed to a market. The fundamental objective of electric power industry deregulation is to maximize efficient generation and consumption of electricity, and reduction in energy prices. The Government of Uttar Pradesh announced its new power sector reform policy statement in January, 1999. The objective of this policy is to restore the credit worthiness of the power sector and to create an environment which attracts private investments, promote competition and efficiency and facilitate sustainable development of power sector.

UP state electricity board was renamed as U.P. Power Corporation limited, India (UPPCL). UPPCL has five distribution companies (discoms) namely Purvanchal vidyut vitaran nigam limited (PuVVNL) headquarter at Varanasi, Paschimanchal vidyut vitaran ningam limited (PVVNL) headquarter at Meerut, Dakshinanchal vidyut vitaran nigam limited (DVVNL) headquarter at Agra, Madhyanchal vidyut vitaran nigam limited (MVVNL) headquarter at Lucknow and Kanpur electric supply company (KESCO) headquarter at Kanpur. All these discoms are end user of the power purchased by U.P. Power Corporation Limited having its command office at Shakti Bhavan, Lucknow. The Power purchase agreement unit (PPA) of UPPCL is the body which manages the power requirements of all discoms. Following are the sources which give power to UPPCL.

1. Central sector generation utilities such as NTPC, NHPC, GAIL
2. State sector generation utilities at Anpara, Obra, Panki, Parichha, Haiderganj, Pipri(Sonbhadra) and Matatila (Jhansi)
3. Private sector generation utilities situated in Uttar Pradesh like Lanco, Bajaj etc.
4. Solar power at Barabanki and Allahabad

Other than these sugar mills during their off season supply power to U.P. Grid. During winter season hydro unit situated in Uttarakhand, Himachal Pradesh give power to U.P. Grid with the condition that during the summer season U.P.P.C.L. will give the equivalent power to them. The Power required for short duration purchased from Independent Power Producers (IPPs). Generally Swiss challenge methodology is applied to purchase the power for short duration.

UPPCL procures power through bidding process through long term Power purchase agreement or energy exchange. In former case, the tender is floated to purchase the power form Independent Power Producers for the long term which may vary from 10 year to 25 years. In later case, Day-ahead power requirement is forecasted on the basis of last year demand, last year temp & humidity on the day for which power is required. In addition to it, present trend of temp, humidity and demand is also put in the consideration to calculation the demand.

Forecasting electricity demand has become a major issue in deregulated power systems [1]. Load forecasting is categorized as short-term, medium-term and long-term forecasts [2]-[3]. The forecasting of hourly-integrated load carried out for one day to week ahead is usually referred to as short-term load forecasting. Short-term load forecasting plays an important role in power systems since the improvement of

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forecasting accuracy results in the reduction of operating costs and the reliable power system operations [4]. The load at a given hour is dependent not only on previous loads but also on much important weather related variables. Various techniques have been developed for electricity demand forecasting during the past few years. Several research works have been carried out on the application of artificial intelligence (AI) techniques such as fuzzy inference, fuzzy-neural models, artificial neural network (ANN) to the load forecasting problem as AI tools have performed better than conventional methods in short-term load forecasting [5]-[12].

This paper discusses significant role of ANN in day-ahead load forecasting of UPPCL, that is, the hourly forecast of the power system load over a day. In this paper, a new artificial neural network has been designed using MATLAB R13b to compute the day-ahead hourly load forecast in UPPCL. The neural network models are trained on hourly data of UPPCL from April, 2014 to June, 2014 and tested on out-of-sample data of two weeks. The simulation results obtained have shown that artificial neural network (ANN) is able to make very accurate short-term load forecast with average errors around 3.05% for UPPCL.

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 forecast. Results of simulation are presented and discussed 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 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. 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]-[16].

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.

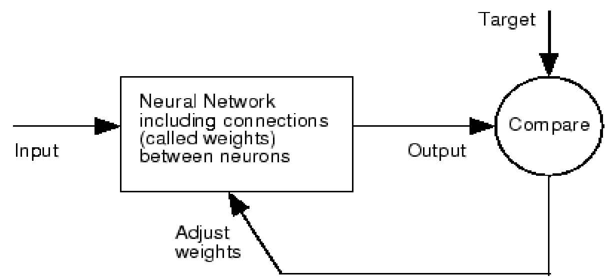

Fig. 1. Working model of an ANN by adjusting its weights.

III. DATA INPUTS AND ANN MODEL

The models are trained on hourly data of UPPCL from April, 2014 to June, 2014 and tested on out-of-sample data of two weeks. For the load forecast, the input parameters include-

- Hour of day (1 to 24)
- Day of the week (1 to 7)
- Holiday/weekend indicator (0 or 1)
- Previous 24-hr average load
- 24-hr lagged load
- 168-hr (previous week) lagged load

IV. SIMULATION AND RESULTS

In this paper hourly day-ahead load forecasting has been done for sample of each day using neural network tool box of MATLAB R13b. The ANNs are trained with data from April, 2014 to June, 2014 and tested on out-of-sample data of two weeks. 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.

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

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

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

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

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.

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 load for every day are also generated. Simulation results of UPPCL are discussed below.

The ANN model used in the forecasting is shown below in Fig. 2. It has input, output and one hidden layers. Hidden layer has 6 neurons. Inputs to the input layer are as listed above for load forecast. After simulation the MAPE obtained is 3.05% for load forecasting during testing as shown in Fig. 3.

The box-plot of the error distribution of forecasted load as a function of hour of the day is presented in Fig. 4. It shows the percentage error statistics of hour of the day. It is also evident that the maximum error is for the 8th hour of the day and minimum error for 17th hour of the day. The box-plot of the error distribution of forecasted load as a function of day of the week is evaluated in Fig. 5 which shows the percentage error statistics of day of the week. The maximum error is for the Monday and minimum error for Saturday.

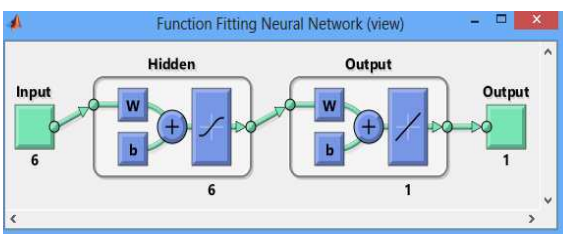

Fig. 2. Showing six different input data for one target data with 6 neurons.

Multiple series plots between actual load & day-ahead hourly forecasted load for each day during testing and also plots of its MAPE have been shown from Fig. 6-Fig. 19. The simulation results show that the highest & least error occurred with MAPE of 6.8% & 1.63% for day-ahead forecast of 30 June & 26 June, 2014 respectively.

The Mean Absolute Percentage Error (MAPE) & Mean Absolute Error (MAE) between the forecasted and actual loads for each day during testing has been calculated and presented in the Table I.

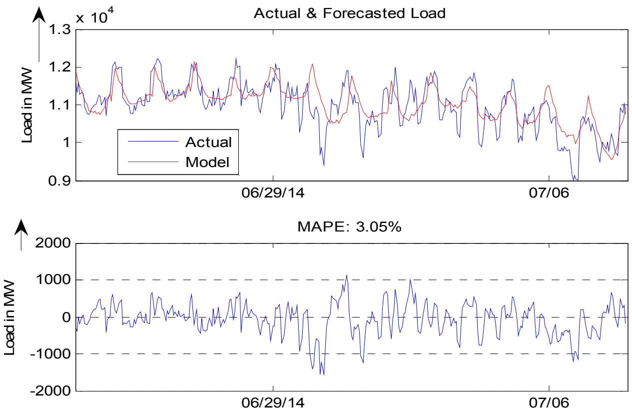

Fig. 3. Multiple series plot between actual load & forecasted load by ANN for testing data sample of two weeks.

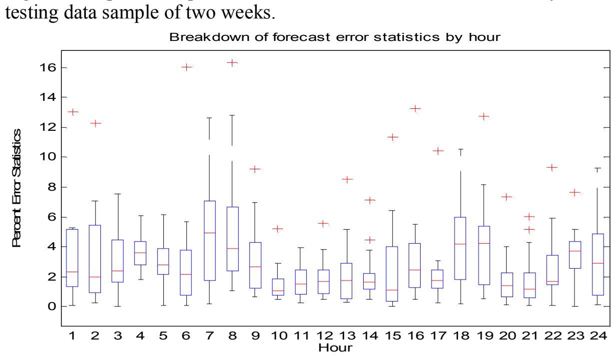

Fig. 4. Error distribution of forecasted load as a function of hour of the day.

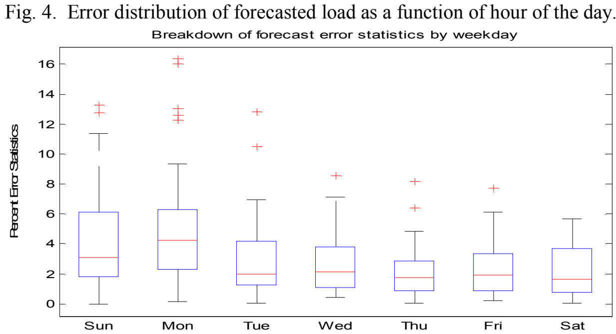

Fig. 5. Error distribution for forecasted load as a function of day of the week.

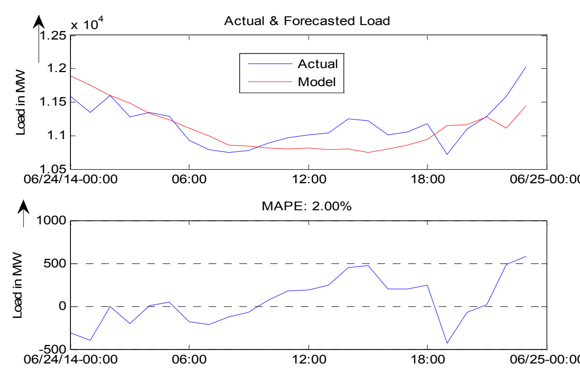

Fig. 6. Actual & day-ahead hourly load forecast of 24 June, 2014

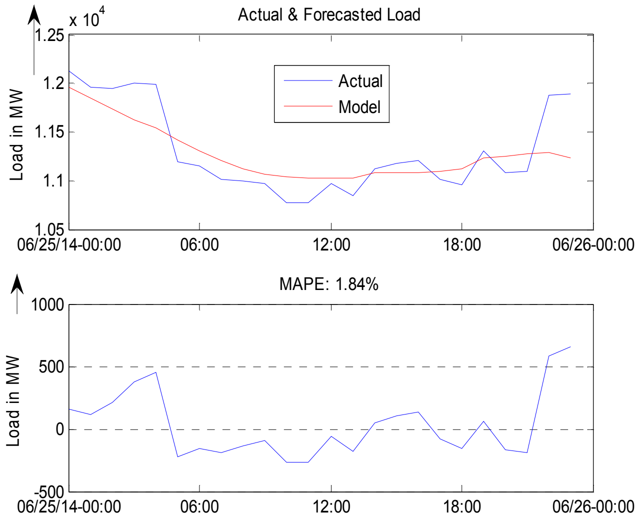

Fig. 7. Actual & day-ahead hourly load forecast of 25 June, 2014.

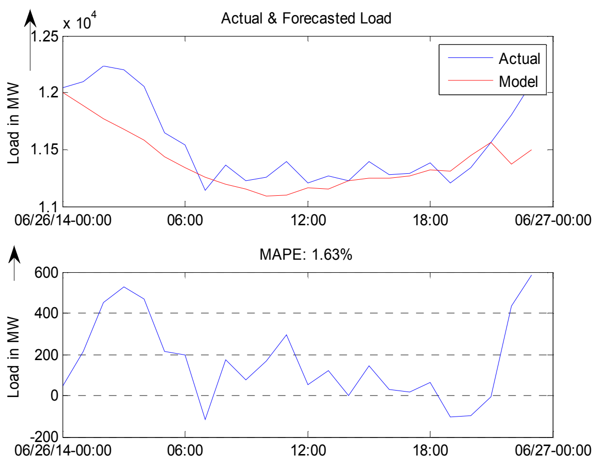

Fig. 8. Actual & day-ahead hourly load forecast of 26 June, 2014.

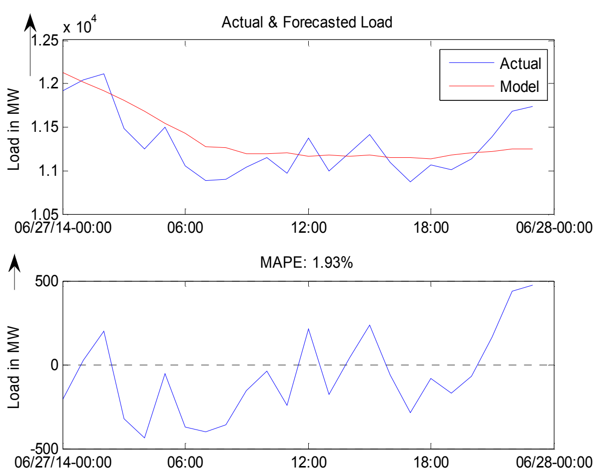

Fig. 9. Actual & day-ahead hourly load forecast of 27 June, 2014.

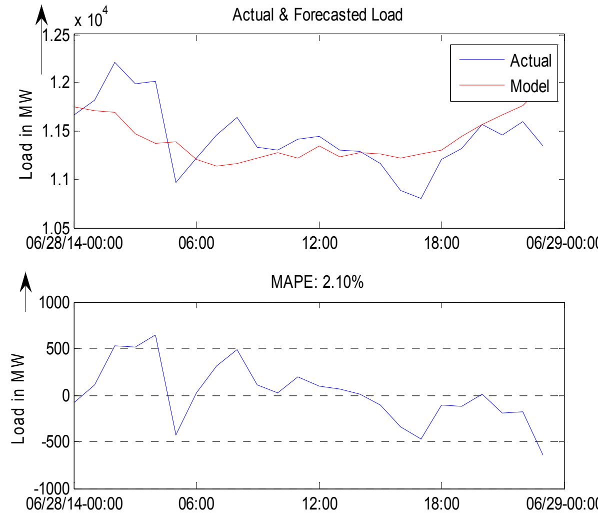

Fig. 10. Actual & day-ahead hourly load forecast of 28 June, 2014.

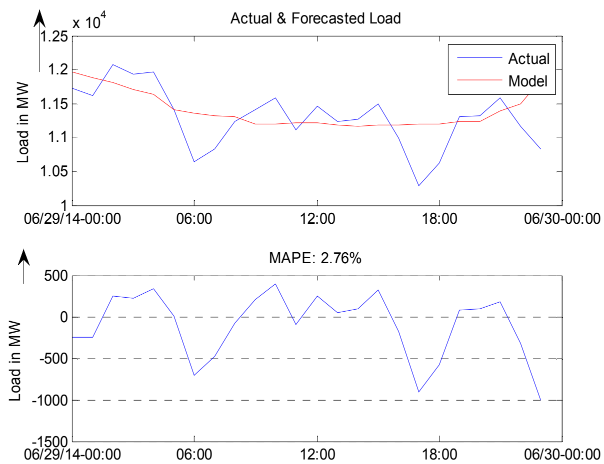

Fig. 11. Actual & day-ahead hourly load forecast of 29 June, 2014.

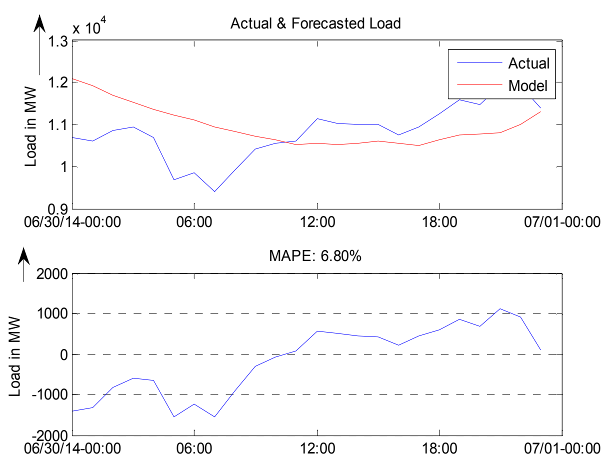

Fig. 12. Actual & day-ahead hourly load forecast of 30 June, 2014.

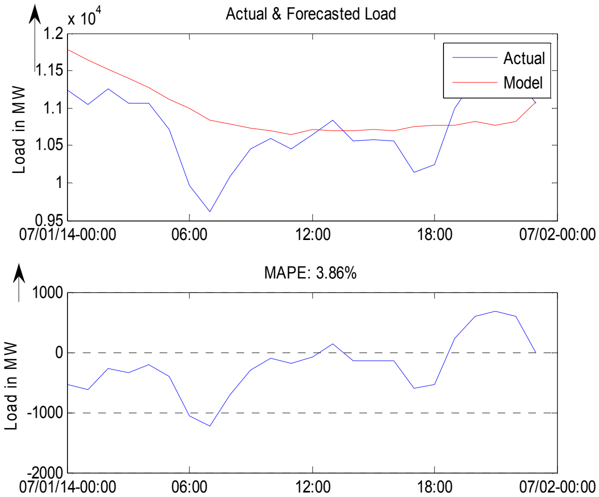

Fig. 13. Actual & day-ahead hourly load forecast of 01 July, 2014.

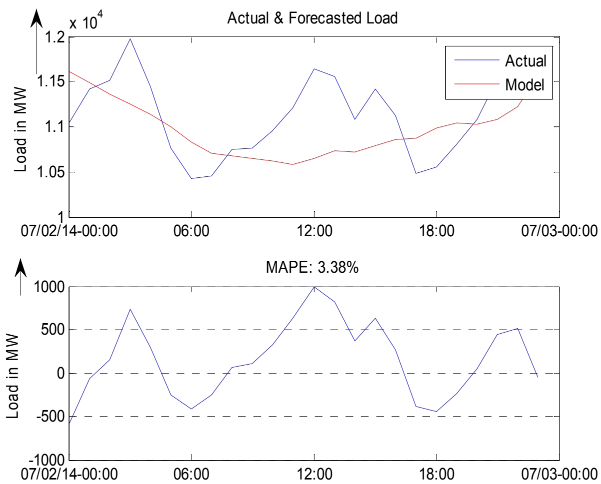

Fig. 14. Actual & day-ahead hourly load forecast of 02 July, 2014.

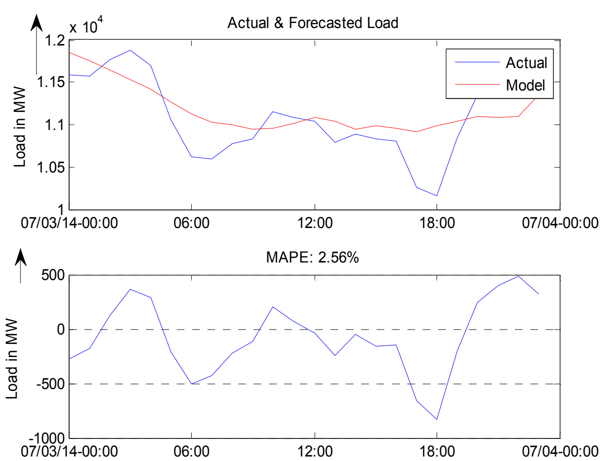

Fig. 15. Actual & day-ahead hourly load forecast of 03 July, 2014.

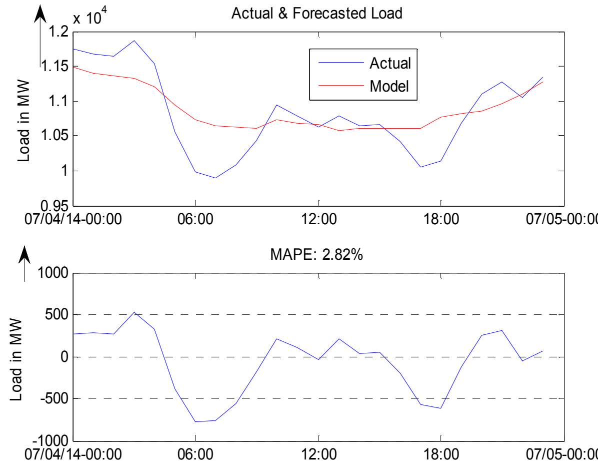

Fig. 16. Actual & day-ahead hourly load forecast of 04 July, 2014.

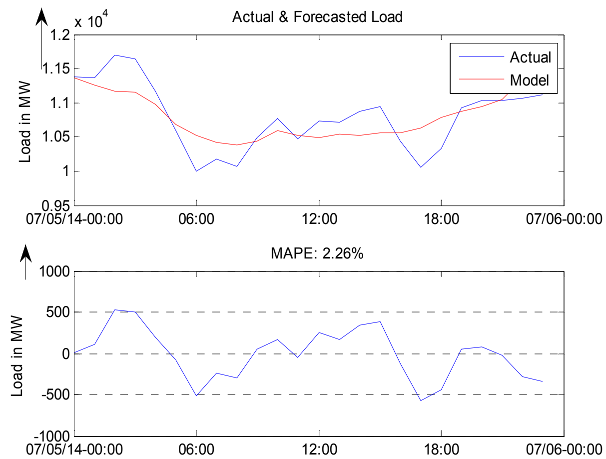

Fig. 17. Actual & day-ahead hourly load forecast of 05 July, 2014.

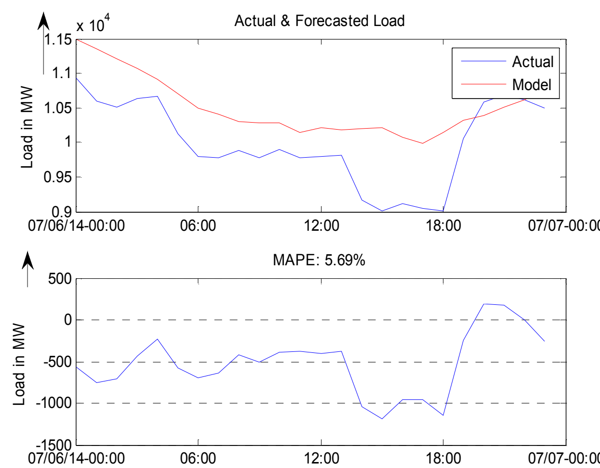

Fig. 18. Actual & day-ahead hourly load forecast of 06 July, 2014.

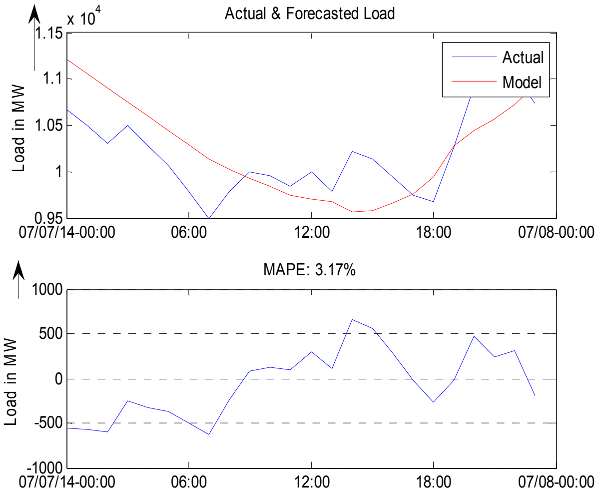

Fig. 19. Actual & day-ahead hourly load forecast of 07 July, 2014.

TABLE I
RESULTS FOR OUT-OF-SAMPLE TEST SETS

S. N.	Date mm/dd/yyyy	UPPCL	
		MAPE (%)	MAE (MW)
1	6/24/2014	2	224.41
2	6/25/2014	1.84	210.92
3	6/26/2014	**1.63 (mim.)**	**191.99**
4	6/27/2014	1.93	217.68
5	6/28/2014	2.1	241.74
6	6/29/2014	2.76	305.79
7	6/30/2014	**6.8 (max.)**	**722.86**
8	7/1/2014	3.86	407
9	7/2/2014	3.38	379.09
10	7/3/2014	2.56	280.73
11	7/4/2014	2.82	298.84
12	7/5/2014	2.26	242.59
13	7/6/2014	5.69	551.47
14	7/7/2014	3.17	323.83
15	**Average**	**3.05**	**328.49**

V. CONCLUSION AND FUTURE WORK

This paper presents an ANN model for day-ahead short-term electricity loads forecasting in UPPCL. Its forecasting reliabilities were evaluated by computing the MAPE between the exact and predicted electricity load values. We were able to obtain an MAPE 3.05% during testing. The results suggest that ANN model with the developed structure can perform well in day ahead load forecasting of UPPCL with least possible error. In future effect of weather parameters like temperature, humidity, precipitation, and wind velocity on short-term load forecasting may be worked out.

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