Day Ahead Hourly Load Forecast of PJM Electricity Market and ISO New England Market by Using Artificial Neural Network

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***Abstract*—Short-term load forecasting is an essential instrument in power system planning, operation, and control. Many operating decisions are based on load forecasts, such as dispatch scheduling of generating capacity, reliability analysis, and maintenance planning for the generators. This paper discusses significant role of artificial intelligence (AI) in short-term load forecasting (STLF), that is, the day-ahead hourly forecast of the power system load over two weeks. Neural network fitting tool is used to compute the forecasted load. The data to be used in the model are hourly historical data of the temperature and electricity load. The models are trained on hourly data from the ISO New England market and PJM Electricity Market from 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 forecasting.**

***Index Terms*--Mean absolute percentage error (MAPE), neural network (NN), power system, short-term load forecasting.**

I. Introduction

With an introduction of deregulation in power industry, many challenges have been faced by the participants of the electricity market. Forecasting electricity parameters such as load and energy price have become a major issue in power systems [1]. The fundamental objective of electric power industry deregulation is to maximize efficient generation and consumption of electricity, and reduction in energy prices. To achieve these goals, accurate and efficient electricity load forecasting is becoming more and more important [2]-[3].

Load forecasting is categorized as short-term, medium-term, and long-term forecasts, depending on the time scale. 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 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 earlier hourly loads but also on many important exogenous variables that must be considered, especially weather related variables. Effective integration of various factors into the forecasting model may provide accurate load forecasts for modern power industries.

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 to the load forecasting problem as AI tools have performed better than conventional methods in short-term load forecasting. 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 [5]-[8]. 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 [9].

This paper discusses significant role of artificial intelligence in short-term load forecasting (STLF), that is, the hourly forecast of the power system load over two weeks. In this paper, neural Network fitting tool of MATLAB has been used to compute the short-term load forecast in ISO New England market and PJM electricity 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. The neural network models are trained on hourly data from the NEPOOL region (ISO New England), PJM electricity market (RTO region) from 2007 to 2011 and tested on out-of-sample data from 2012. The simulation results obtained have shown that artificial neural network (ANN) has able to make very accurate short-term load forecast with average errors around 1-2% in NEPOOL region and 2-4.89% in PJM electricity market (RTO region).

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 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 which is fundamental to the operation of an artificial neural network. A set of weights, an adder for summing the input parameters and activation function for limiting the amplitude of the output of a neuron are the three main elements of the neuron network model [10]. 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.

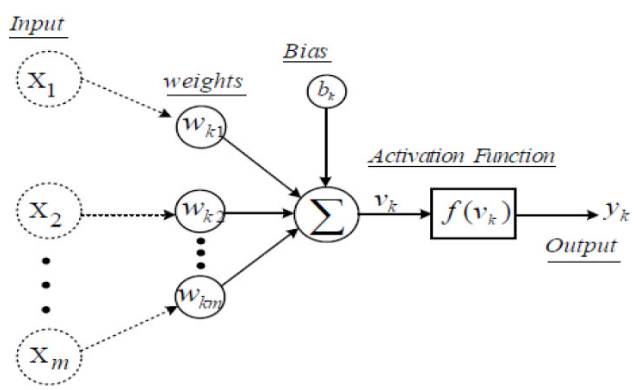

Fig. 1. Model of an artificial neural network (ANN).

In fitting problems, neural network is mapped between data set of numeric inputs and a set of numeric targets. The neural network fitting tool have 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 [11].

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 [12]. If training performance is worse, then increase the number of neurons [13]. Mean squared error which is the average squared difference between outputs and targets indicates the accuracy of forecasting.

III. DATA INPUTS AND ANN MODEL

The models are trained on hourly data from the NEPOOL region (ISO New England), PJM electricity market (RTO region) from 2007 to 2011 and tested on out-of-sample data from 2012. The data used in the ANN model are both the temperature and electricity load hourly historical data. The temperature variable is included because temperature has a close relationship with electricity load. The relationship between demand and average temperature is shown in Fig. 2, where a nonlinear relationship between load and temperature can be observed. In PJM electricity market dry bulb and dew point temperature data have not been considered for forecast but hourly temperature data for location in high demand area of NEPOOL region has been considered in this paper.

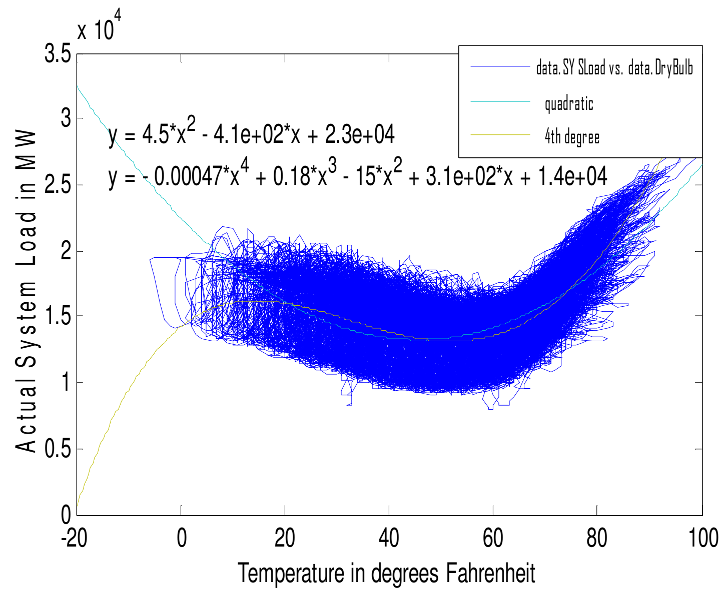

Fig. 2. Scatter plot of system load vs. temperature (degrees Fahrenheit) for ISO New England market for year 2007 to 2012 with fitting equation of quadratic and 4th degree.

The ANN model includes creating a matrix of input parameters from the historical data, selecting and calibrating the chosen model and then running the model as shown in Fig. 3 below.

For the load forecast, the input parameters 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

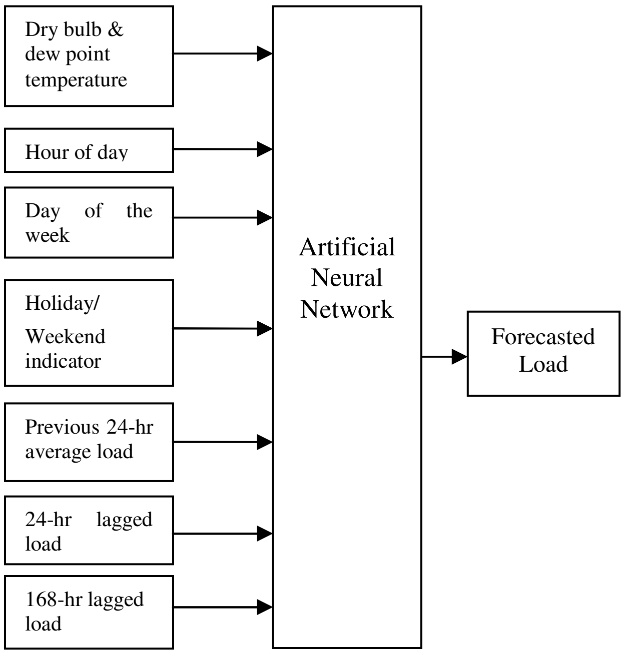

Fig. 3. Shows historical data, selecting and calibrating.

IV. SIMULATION AND RESULTS

The models are trained on data from 2007 to 2011 and tested on completely out-of-sample data from 2012 using neural network tool box of MATLAB R12a. In this paper hourly day-ahead forecasting has been done for sample of every two weeks of data of year 2012 by newly developed forecasting software. 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.

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

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

Various chart comparing the day ahead hourly actual load and forecasted load for every two weeks for the year 2012 are generated. Simulation results of PJM electricity market and new ISO England market are discussed below.

A. *For PJM Electricity Market (RTO Region)*

The ANN model used in the forecasting is shown below in Fig. 4. It has input, output and one hidden layers. Hidden layer has 42 neurons. Inputs to the input layer are 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.

Multiple series plots between actual load & forecasted load from 1 January, 2012 to 14 January, 2012 & from 7 October, 2012 to 20 October, 2012 for PJM electricity market and also plots of MAPE with maximum error (4.89%) and minimum error (2.01%) have been shown in Fig. 5 and Fig. 6

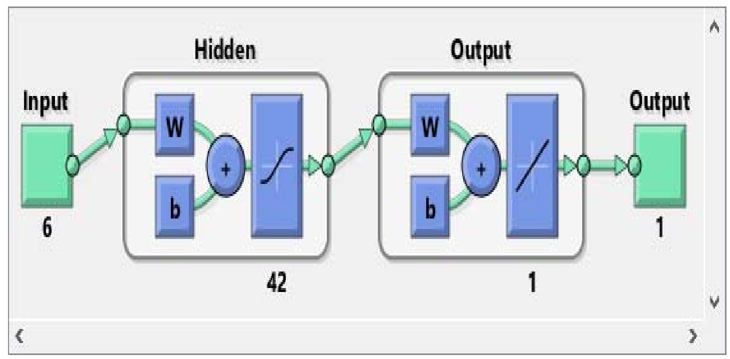

Fig. 4. Showing six different input data for one target data with 42 neurons.

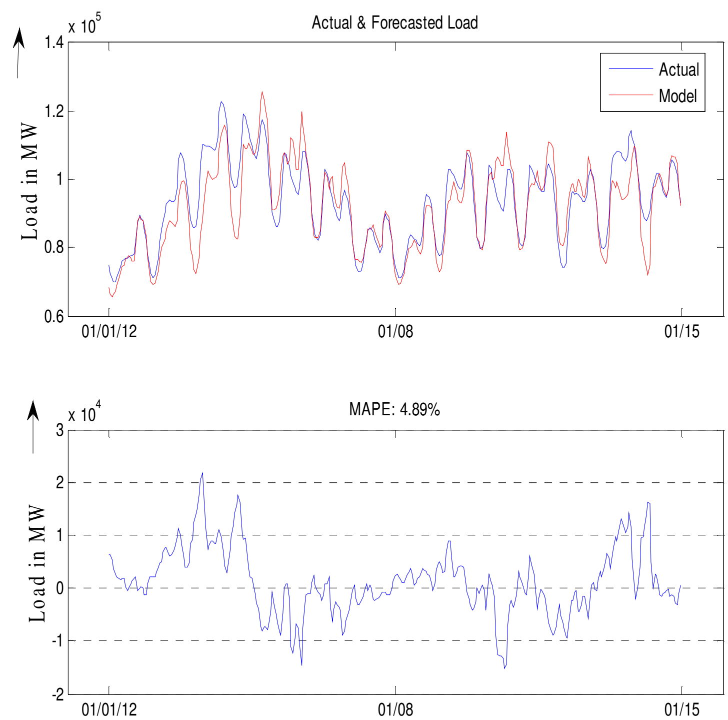

Fig. 5. Maximum MAPE is 4.89% for the forecast of 1 January, 2012 to 14 January, 2012 in PJM electricity market (RTO region).

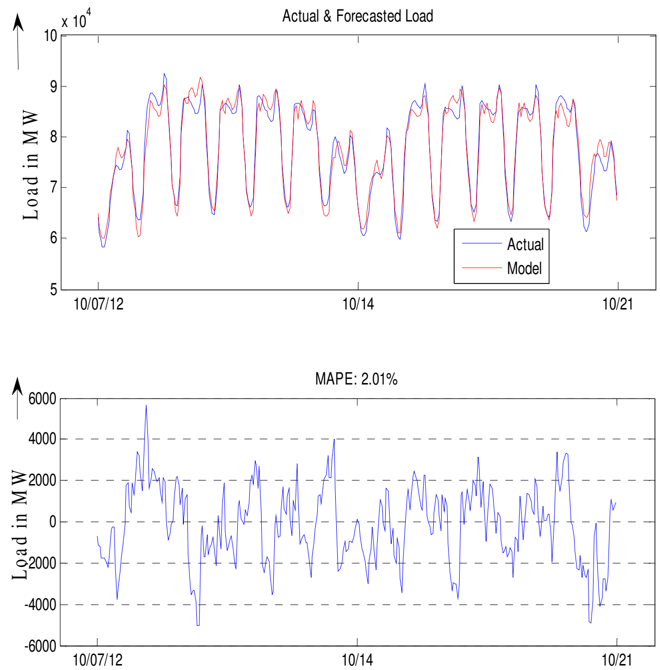

Fig. 6. Minimum MAPE is 2.01% for the forecast of 7 October, 2012 to 20 October, 2012 in PJM electricity market (RTO region).

B. *ISO New England Market*

The ANN model used in the forecasting is shown below in Fig. 7. It has input, output and one hidden layers. Hidden layer has 48 neurons. Inputs to the input layer are 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.

Multiple series plots between actual load & forecasted load from 6 May, 2012 to 19 May, 2012 & from 16 December, 2012 to 29 December, 2012 for NEPOOL region (ISO New England) and also plots of MAPE with maximum error (2.21%) and minimum error (0.97%) have been shown in Fig. 8 and Fig. 9.

The Mean Absolute Percentage Error (MAPE) between the forecasted and actual loads for every 14 days has been calculated and presented in the Table I. From the results in Table I it is observed that MAPE for NEPOOL region (ISO New England) 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 (RTO region) but it is considered for input in NEPOOL region (ISO New England). This indicates that temperature data is a very important parameter for load forecasting using ANN.

Also, we were able to obtain an MAPE 3.14% for PJM electricity market (RTO region) and MAPE 1.59% for NEPOOL region (ISO New England) in the year 2012.

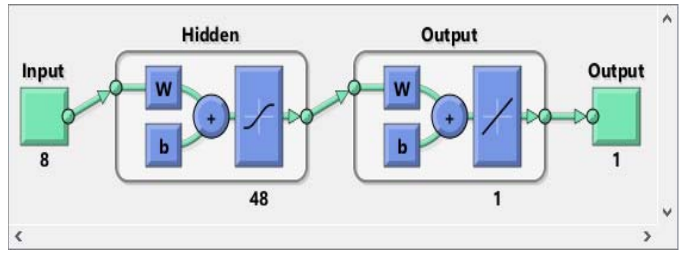

Fig. 7. Showing eight different input data for one target data with 48 neurons.

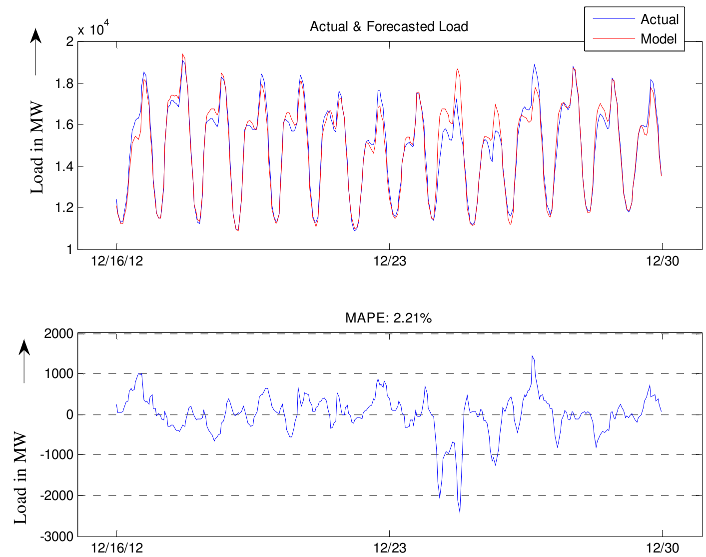

Fig. 8. Maximum MAPE is 2.21% for the forecast of 16 December, 2012 to 29 December, 2012 NEPOOL region (ISO New England).

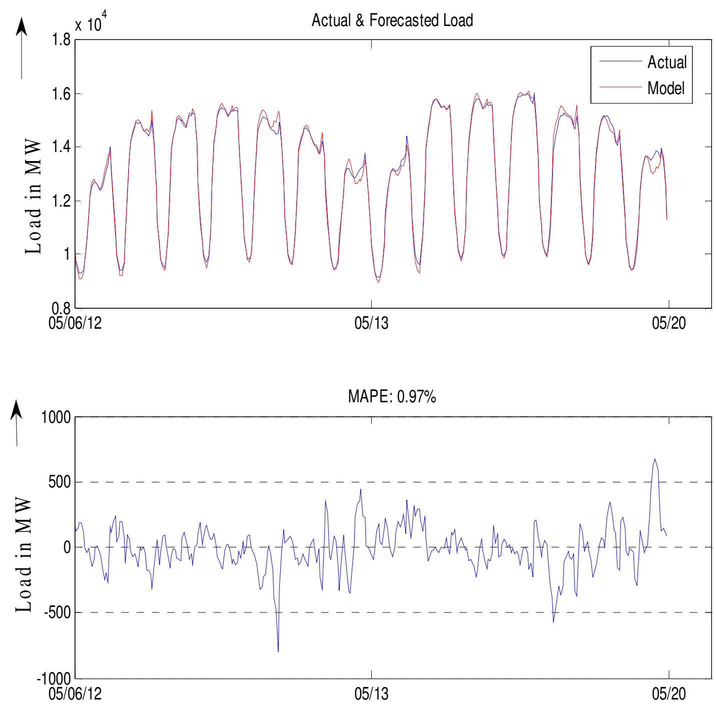

Fig. 9. Minimum MAPE is 0.97% for the forecast of 6 May, 2012 to 19 May, 2012 NEPOOL region (ISO New England).

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

S. No.	Duration mm/dd/yy-mm/dd /yy (Year-2012)	MAPE (%)	
		(PJM)	(ISO New England)
1	01/01/12 -01/14/12	4.89	1.64
2	01/15/12 -01/28/12	3.85	1.59
3	01/29/12 -02/11/12	3.10	1.06
4	02/12/12-02/24/12	3.58	1.25
5	02/26/12-03/10/12	3.43	1.54
6	03/11/12-03/24/12	2.38	1.84
7	03/25/12-04/07/12	2.35	1.46
8	04/08/12-04/21/12	2.80	1.57
9	04/22/12-05/05/12	2.66	1.49
10	05/06/12-05/19/12	2.56	0.97
11	05/20/12-06/02/12	3.55	1.46
12	06/03/12-06/16/12	3.40	1.12
13	06/17/12-06/30/12	4.80	1.63
14	07/01/12-07/14/12	3.51	1.60
15	07/15/12-07/28/12	3.99	1.45
16	07/29/12-08/11/12	2.78	1.46
17	08/12/12-08/25/12	2.50	1.42
18	08/26/12-09/08/12	3.38	1.59
19	09/09/12-09/22/12	3.72	1.89
20	09/23/12-10/06/12	2.36	1.33
21	10/07/12-10/20/12	2.01	1.68
22	10/21/12-11/03/12	2.23	2.61
23	11/04/12-11/17/12	2.24	1.73
24	11/18/12-12/01/12	2.63	1.78
25	12/02/12-12/15/12	2.97	1.75
26	12/16/12-12/29/12	3.67	2.21

V. CONCLUSION AND FUTURE WORK

This paper presented a comprehensive model for day-ahead short-term electricity loads forecasting by using artificial neural network (ANN) approach in NEPOOL region (ISO New England) and PJM electricity market (RTO region). It has also been observed that temperature plays an important role in electricity load forecasting thus temperature and weather data must be considered as an input to forecast the electricity load. The ANN model used has performed well in the case of sudden weather changes. The results suggest that 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 forecasting may be worked out. Its forecasting results are evaluated by computing the MAPE between the exact and predicted electricity load values. We were able to obtain an MAPE 3.14% for PJM electricity market (RTO region) and MAPE 1.59% for NEPOOL region (ISO New England) in the year 2012.

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