Short Term Load Forecasting Using Artificial Neural Network

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***Abstract*—Short term load forecasting is required for power system planning, operation and control. It is used by utilities, system operators, generators, power marketers. In this paper, load forecasting has been done using ANN (Artificial Neural Network). As load profile is different for weekdays and weekends, so for better forecasting performance, training of neural network has been done separately for weekdays and weekends. Accordingly forecasting is done separately for weekdays and weekends. Neural network toolbox with 20 neurons has been used for forecasting load of NEPOOL region of ISO New England. Hourly temperature (Dry bulb), humidity (Dew point) and electricity load of NEPOOL region has been taken from 2004 to 2008. ANN model is trained on hourly data from 2004 to 2007 and tested on out-of-sample data from 2008. The test set is used only for forecasting to test the performance of the model on out-of-sample data. Simulation results obtained have shown the comparison of actual and forecasted load data. Performance of forecaster is calculated using MAE, MAPE and daily peak forecast error.**

***Keywords*— Artificial neural network (ANN); Artificial Intelligence (AI); Short term load forecasting (STLF); Mean absolute percent error (MAPE); Mean absolute error (MAE)**

I. INTRODUCTION

Load forecasting is a very important component in power system energy management system. There are three forecasting horizons – short term, medium term and long term. STLF is hourly or sub-hourly forecasting of load forecasting starting from next hour to next week. It is mainly required by electric utilities for making unit commitment decisions, reduce spinning reserve capacity, for generator type coordination to determine least cost operation, for transmission line loading ,interchange scheduling and energy purchase. In addition to utilities, other newly formed entities such as load aggregators, power marketers, and independent system operators also need good quality of load forecasting for their operations.[1,2]

Accuracy has very significant economic impact. Even a very small fraction reduction in the forecasting error can result in substantial saving. Accurate forecasting leads to ample savings in operating and maintenance costs, increased reliability of power supply and delivery system, and correct decisions for future development. Overestimation in load forecasting leads to unnecessary increase in the reserve and the operating costs. Underestimation of load forecasting results in failure to provide the required spinning and standby reserve and stability to the system, which may lead to collapse of the power system network.

Various factors that affect STLF are geographical location, mix of customer in service area, weather conditions, seasonal effect, time of the day, day of week and random disturbances etc. Estimation of future load has been difficult up to now, especially for the days with extreme weather, on holidays and other anomalous days. With the recent development of new mathematical, data mining and artificial intelligence tools, it is possible to improve the forecasting result.[3]

Different techniques have been developed for load forecasting during the past few years. At first different mathematical models have been proposed but they were unable to accurately model the weather parameters, they had lack of robustness for representing weekends and public holidays and were computational intensive.[4] Regression models are able to analyze the relation between load and the influencing factors but they require heavy computational efforts. With the development of artificial intelligence (AI) techniques research works have been carried out on the application of these techniques to the load forecasting problem as AI tools have performed better than conventional methods in short-term load forecasting.[1]

AI techniques reported in literatures are expert systems, fuzzy inference, neural network, fuzzy-neural models. Among the different techniques on load forecasting, application of ANN to load forecasting in power system has received much attention in recent years. ANN is becoming popular because it has ability to learn complex and nonlinear relationships that are difficult to model with conventional techniques.[5]

Neural network fitting tool of MATLAB has been used to compute STLF for NEPOOL region (ISO New England). Historical hourly data of temperature, humidity and electricity load have been used for load forecasting.

This paper has been organized in five sections. Section II presents the overview of ANN. Section III describes the data preprocessing and modeling of ANN. Results of simulation are

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presented and discussed in Section IV. Section V discusses the conclusion and future work.

II. ANN FOR STLF

ANN fundamentally performs like a human brain. A neural network is a massively parallel-distributed processor made up of simple processing units, known as neurons. This network consists of number of layers containing neurons and weights associated with the connection between neurons where the information is passed in feed-forward manner. A model of artificial neuron is shown in Fig. 1. Neurons of ANN consists of 3 main components:- weights connecting the nodes, the summation function within the node and transfer function. In this model there is 1 input layer, 1 hidden layer and 1 output layer, as this structure of MLP is proven to address almost any kind of non-linear relationship. The neural network consists of two-layer feed-forward network with sigmoid activation function in hidden neurons and linear in output neurons.[6] First the information is passed in feed forward manner via input to output then weight is adjusted via back propagation. Adjustment of weight and bias is called learning which is done by Levenberg-Marquardt back propagation algorithm.

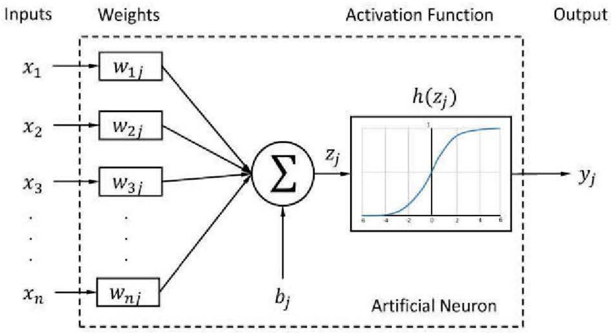

Fig. 1. Model of an Artificial Neuron

III. LOAD FORECASTING METHODOLOGY

Hourly raw data in form of dry bulb, dew point and electricity load from ISO NEW ENGLAND has been taken from year 2004-2008[7]. Dry bulb is taken for temperature and Dew point for humidity as load depends on both these parameters.

A. Data preprocessing

In this paper data from 2004-2007 has been used for ANN training and 2008 data for testing of trained neural network. As the load profile is different for weekdays and weekends, separate analysis has been done for both. As load at any particular hour is similar to some previous days loads so preprocessing of data has been done to train neural network.

The input to neural network is as follows:-

- Dry bulb temperature
- Dew point temperature
- Hour of the day
- Day of the week
- Working day or holiday/weekend indicator(0 for holiday and 1 for working day)
- Previous day same hour load
- Previous week same day same hour load
- Previous 24 hr average load

These hourly data is used as input and hourly load is used as output to train neural network. Separate training and forecasting has been done for working days and weekends.

B. Modelling

The default neural network fitting toolbox of matlab consisting three layers and 20 neurons has been used. Activation function is sigmoid for the hidden layer and linear for output layer. [8]

IV. SIMULATION AND RESULTS

Now neural network is trained with above 8 inputs and one output separately for working days, weekends only and weekends including holidays using training set (2004-2007). The training set is used for building the model (estimating its parameters). This trained neural network is tested on testing data of year 2008. The test set is used only for forecasting to test the performance of the model on out-of-sample data.

Then a plot is created to compare the actual load and the predicted load and to compute the forecast error. In addition to the visualization, the performance of the forecaster is quantified using metrics such as mean average error (MAE), mean absolute percent error (MAPE) and daily peak forecast error.

$$\text{M.A.P.E.} = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{A_t - F_t}{A_t}\right| \times 100$$

$$\text{M.A.E.} = \frac{1}{N}\sum_{i=1}^{N}\left|A_t - F_t\right|$$

Where A_t is actual load, F_t is forecasted load and N is number of observation points.

A. Forecasting for weekdays

- Neural network is trained on weekdays data of 2004-2007 and tested on 2008 weekdays data.

M.A.P.E. = 1.38%
M.A.E. = 214.66 MWh
Daily Peak M.A.P.E. = 1.34%

- A comparison of actual and forecasted load data of one week and residual of that data is shown in fig.2.:-

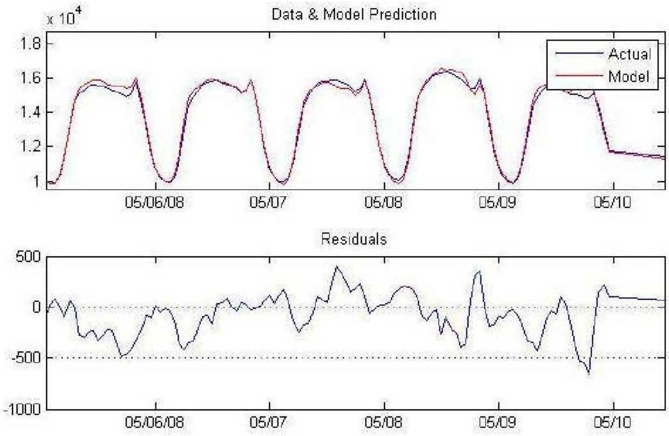

Fig. 2. Comparison of actual and forecasted load for a weekday of year 2008.

- Plot of percent forecast errors by hour of day, day of week and month of the year for weekdays has been shown to check performance of forecaster.

Forecasting error as a function of hour of the day is shown in Fig. 3.

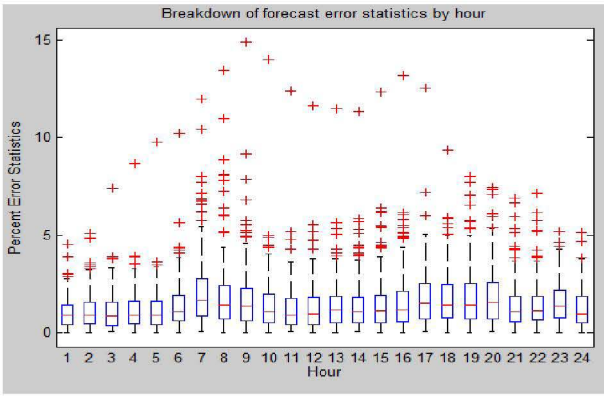

Fig. 3. Box-plot of the error distribution of forecasted load as a function of hour of the day for weekdays of year 2008.

- Forecasting error as a function of weekdays is shown in Fig.4.

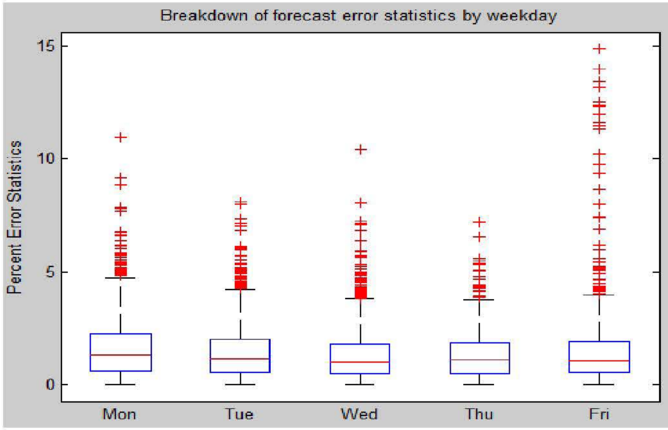

Fig. 4. Box-plot of the error distribution of forecasted load as a function of weekdays for year 2008.

- Forecasting error as a function of month is shown in Fig.5.

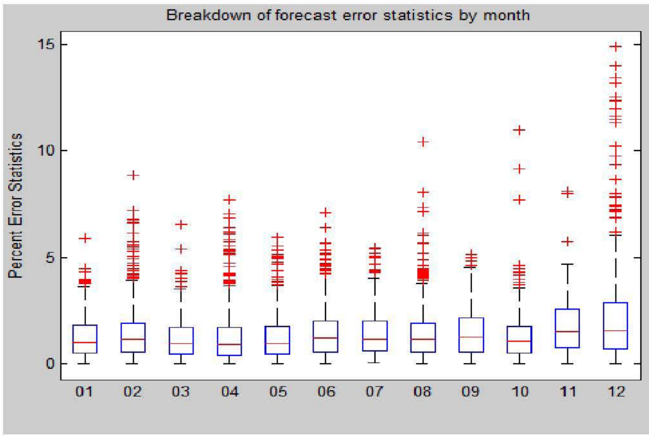

Fig. 5. Box-plot of the error distribution of forecasted load as a function of month of weekdays for year 2008.

B) Forecasting for weekends:-

Now neural network is trained on weekends data of 2004-2007 and tested on weekends data of 2008.

M.A.P.E. = 1.40%
M.A.E. = 202.22 MWh
Daily Peak M.A.P.E. = 1.78%

- A comparison of actual and forecasted load data of one weekend and residual of that data is shown:-

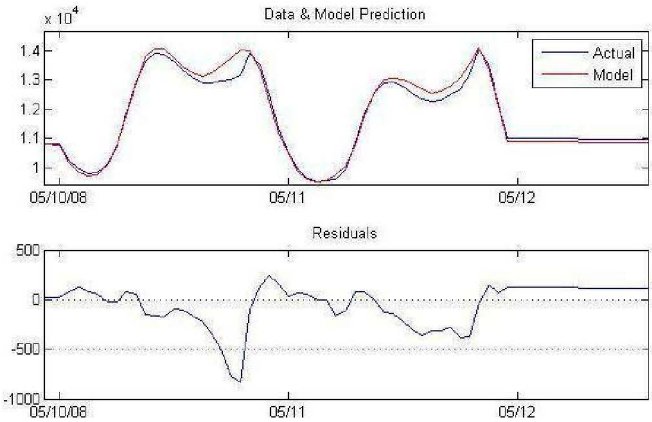

Fig. 6. Comparison of actual and forecasted load for a weekend of year 2008

- Plot of percent forecast errors by hour of day, day of week and month of the year for weekends has been shown to check performance of forecaster.

Forecasting error as a function of hour of the day is shown in Fig. 7.

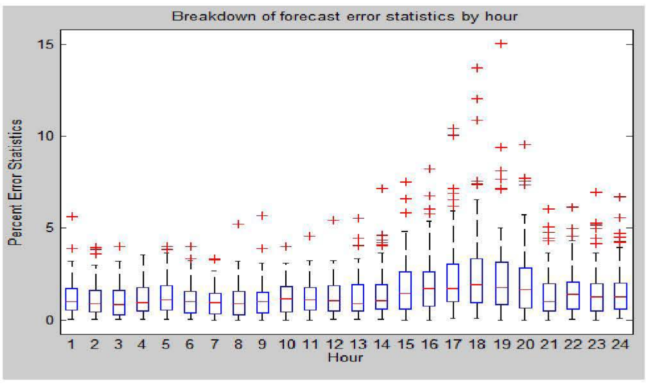

Fig. 7. Box-plot of the error distribution of forecasted load as a function of hour of the day of weekends for year 2008.

- Forecasting error as a function of weekends is shown in Fig. 8.

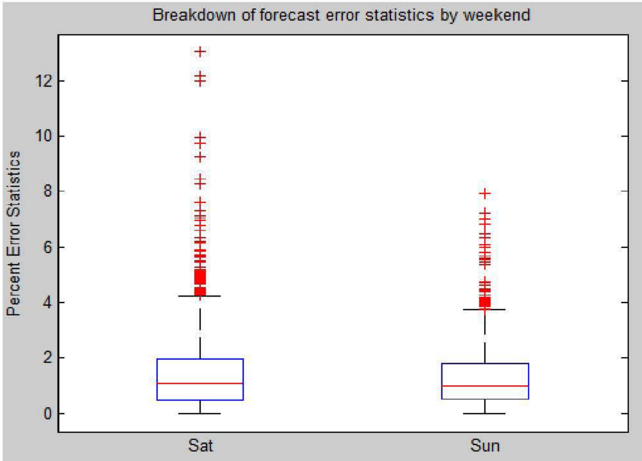

Fig. 8. Box-plot of the error distribution of forecasted load as a function of weekends for year 2008.

- Forecasting error as a function of month is shown in Fig. 9.

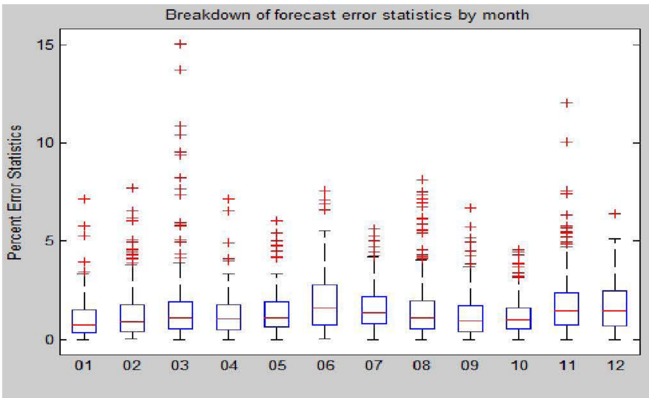

Fig. 9. Box-plot of the error distribution of forecasted load as a function of month of weekends for year 2008.

C) Then the neural network is trained using weekends (including holidays) data and tested upon it.

M.A.P.E. = 1.73%
M.A.E. = 245.73 MWh
Daily Peak M.A.P.E. = 1.82%

The testing error for different testing days is shown in Table 1

Table I

Hourly Load Forecast Summary		
Testing Days	**MAPE**	**MAE(MWh)**
Weekdays(Mon-Fri)	1.38	214.66
Weekends(Sat, Sun)	1.39	202.22
Weekends(including holidays)	1.73	245.73

- To forecast the load for any particular day take raw data from database. Create the predictor matrix and then predict load using trained neural network. For example load profile of 3 April 2008 is forecasted below. This 24 hour (Day ahead) forecasting is required by system operator for various energy transactions.

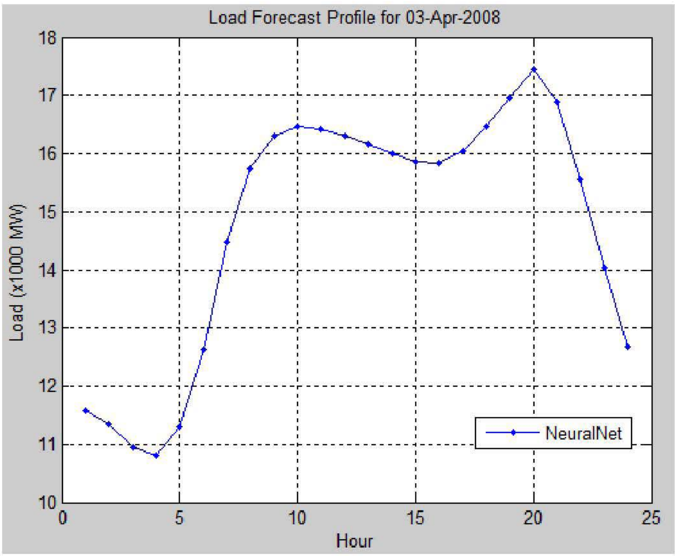

Fig.10 Load profile of 03 April 2008

V. Conclusion and Future Work

This paper presents hourly short-term electricity load forecast using artificial neural network (ANN) in NEPOOL region (ISO New England). Performance of ANN is calculated by M.A.P.E. Separate analysis has been done for weekdays and weekends to improve forecasting accuracy. A M.A.P.E. of 1.38% for weekdays and 1.39% for weekends has been obtained which shows good prediction with less error in forecasting.

Other parameters that affect short term load are weather parameters like precipitation, wind velocity and customer class (Industrial, Residential and commercial). If these parameters will also be taken into account, result of forecasting can be further improved.

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