

## Neural Network Based STLF Model to Study the Seasonal Impact of Weather and Exogenous Variables

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**Abstract:** Load forecasting is very essential for efficient and reliable operation of the power system. Uncertainties of weather behavior significantly affect the prediction accuracy, which increases the operational cost. In this study, neural network (NN) based 168 hours ahead short term load forecast (STLF) model is proposed to study seasonal impact of calendar year. The affect of the model inputs such as, weather variables, calendar events and type of a day on load demand is considered to enhance the forecast accuracy. The weight update equations of gradient descent algorithm are derived and Mean Absolute Percentage Error (MAPE) is used as performance index. The performance of NN is measured in terms of confidence interval, which is based on training, testing, validation and cumulative impact of these phases. The simulations result shows that the forecast accuracy is affected by seasonal variation of input data.

**Keywords:** Artificial Neural Network (ANN), calendar events, gradient based algorithm, Mean Absolute Percentage Error (MAPE), weather variables

### INTRODUCTION

Load forecasting plays a very important role in the energy management system and better planning for the power system. It ensures the reliable operation of power system that leads to uninterruptable power supply to the consumers (Methaprayoon *et al.*, 2003). The operations of power system, for example scheduling, maintenance, adjustment of tariff rates and contract evaluation can be conveniently carried out by accurate load forecast (Ruzic *et al.*, 2003). Energy policy making decision can be carried out based on accurate load forecast.

In the last decade, widespread research has been published on load forecast because of its potential to be utilized in smart grids and buildings. The importance of load forecast is further increased because the efficiency of power system is affected due to under and overestimate of load. The underestimation of the electrical load demand may show a very negative effect on the demand response, moreover it is also difficult to manage overload conditions because the large backup storage cannot be provided. In the case of overestimation, this may increase the production cost (Wei and Ying, 2007).

Load forecasting is divided into three categories by most researchers but some of them divided it into four categories (Harun *et al.*, 2010). Load forecasting is divided based on the time intervals, such as short term, medium term and long term load forecast. The

preceding years have shown that the efforts are mainly concentrated on short load forecasting because its vital role in optimum unit commitment, control of spinning reserve, evaluation of sales/purchase contracts between various companies.

The multiple decisions of energy management system such as power system operation, maintenance and planning can be carried out on basis of accurate load forecasting (De Felice and Xin, 2011). Effective planning of power systems can save millions of dollars, which plays a significant role in the economic growth of a country. There is a strong impact of weather inputs on load demand such as temperature, relative humidity, dew point, dry bulb, wind speed, cloud cover and the human body index.

The multiple loads consumed by individuals also create enormous impact on load forecasting. To accommodate these all factors, the implementation of historical load data as well as weather data needs to be considered as input of forecasting model.

In this modern era of technology to implement the concept of smart grids and buildings, an accurate load forecast plays a vital role. The preceding years have shown that a large number of researches have been published on Short Term Load Forecasting (STLF) due to its impact on the reliable operation of power systems and the economy. Mainly load forecasting techniques can be divided into two categories as discussed below (Sisworahardjo *et al.*, 2006):

- Parametric techniques
- Non-Parametric techniques

The hybrid Kalman filters (Zheng *et al.*, 2000), autoregressive models (Nowicka-Zagrajek and Weron, 2002), Box-Jenkins models (Harun *et al.*, 2010) and regression techniques (Nowicka-Zagrajek and Weron, 2002) and general exponential techniques can be considered as parametric techniques. One of major drawbacks of statistical techniques is that forecasting accuracy is affected by abrupt changes in metrological conditions and the variation of load demand due to social events.

Artificial neural network techniques for load forecasting have much attention by researchers since the mid 1990's because the artificial neural networks has been shown to be a powerful tool for nonlinear inputs and prediction problems. The neural network has the ability to solve complex problems related to the decision making under uncertainty and prediction patterns (Abdul Hamid and Abdul Rahman, 2010), (Tasre *et al.*, 2011). Several techniques have been applied to STLF, for example, radial basis function (Ranaweera *et al.*, 1995; Gonzalez-Romera *et al.*, 2006), self organizing maps for clustering (Beccali *et al.*, 2004) and feed forward neural networks.

In this study, ANN based load forecast model is proposed using gradient decent learning algorithm of neural network with historical load data, type of day and weather input variables. The objective of this study is to study the impact of seasonal behavior and weather variable on load forecast. In this study, several load forecast model case studies are designed to predict the 168 hours ahead load demand. All four seasons, i.e., winter, spring, summer and autumn are included for the analysis of forecasting accuracy. In order to improve the accuracy of forecast model, dry blub and dew point, type and hour of the day and previous highly correlated load demand are considered as forecast model inputs.

### NEURAL NETWORK TOPOLOGY

**Proposed ANN forecast model:** Load forecasting accuracy depends upon the better input selection of neural networks, however, there is no general rule defined for input selection. An appropriate input selection can be carried out by engineering expertise or a base of experience (Drezga and Rahman, 1998). Some statistical and correlation analyses can be very helpful to determine the input which significantly influences the load forecasting accuracy (Drezga and Rahman, 1998). Figure 1 depicts the highly correlated load inputs of forecast model.

**Input data collection and preprocessing:** For the neural network, training and testing data sets are required for which the ISO New England load data is

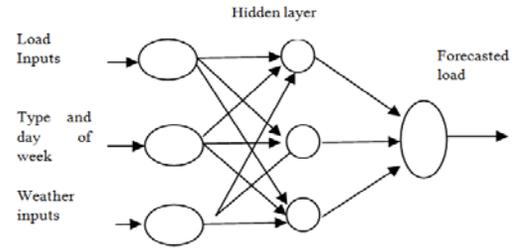


Fig. 1: ANN model for STLF

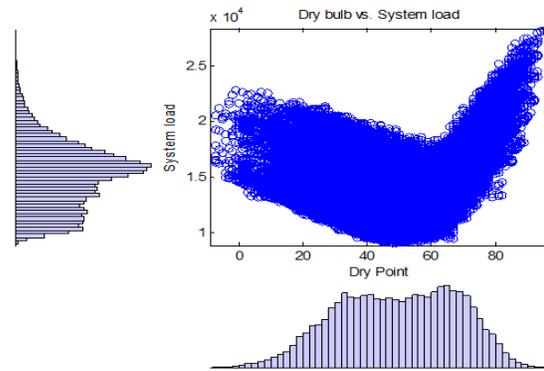


Fig. 2: One year 24 hourly load of the ISO New England grid

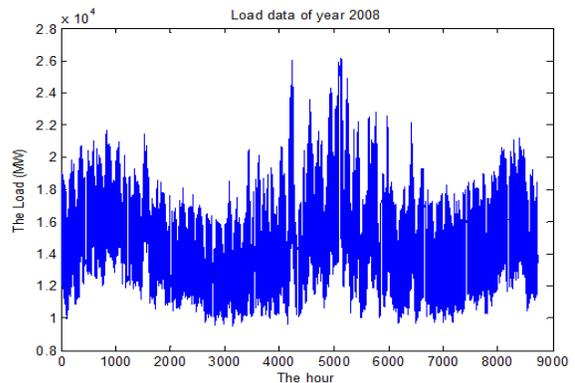


Fig. 3: Relationship dew point vs. system load demand

used. Figure 2 highlights the load profile of peak and low load demand. This analysis is helpful in power system planning and scheduling as in Asians countries the load demand is very high in summer due to increase in the temperature. The load demand is considerable reduced in winter season.

**Impact of dew point and dry blub on load demand:** The graphs in Figure 3 and 4 represent the relationship between the dew point and dry blub with load demand. In Fig. 3 graph shows that as the value of the dew point increases, the power system demand also increases and vice versa. The human perception study shows that the dew point in the range of 40 F to 60 F is suitable for humans. The load demand is low within this range of dew point.

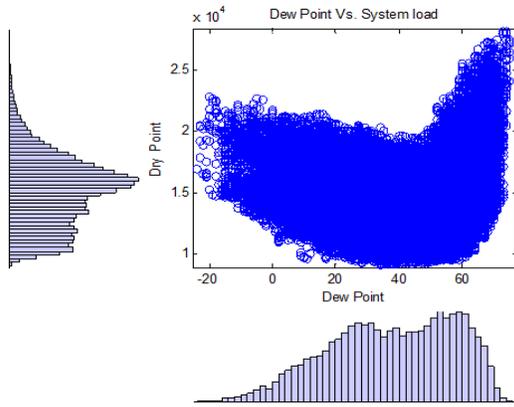


Fig. 4: Relationship dry blub vs. system load demand

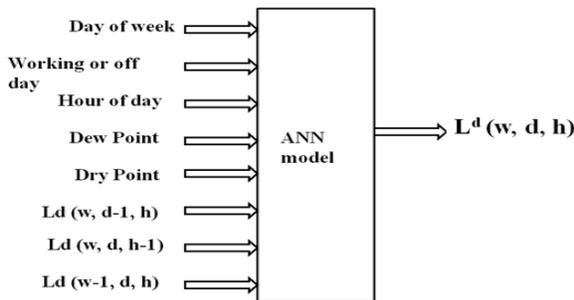


Fig. 5: ANN model inputs for STLF

Dry blub graph shows that, the load demand is relatively low in the range 45 F to 60 F. If the relative humidity is 100%, then the load patterns for dew point and dry blub are similar. From this graph, the effect of dew point and dry blub can be analyzed and better forecasting results can be achieved.

**Input of ANN model:** The load data set is divided into two sets: the training data set is used to train the neural network and the testing data is used to measure the accuracy of the predicted load demand. A one year (2008) 24 hourly load data is used to train to network; it is the called training data set and the 2009 seasonal hourly load data is considered as the testing data set.

The proposed inputs of ANN model for hourly load forecast are shown in Fig. 5.

where  $L_d(w, d, h)$  represents the load demand of a particular hour of the same day and week.

- $L_d(w, d, h-1)$ : represents the load demand for pervious hour of the same day and week.
- $L_d(w, d-1, h)$ : represents the load demand for same hour of the week in previous day.
- $L_d(w-1,d,h)$ : represents the load demand for same hour of a day of the previous week.

Load inputs of the previous hour, day and week are highly correlated.

**Working day or off day:** The type of day includes working days, off days, weekends and special occasion are the inputs of forecast model. The load demand is relatively different in off days from the working day due to change in human activities.

**Day pointer D (k) and hour pointer H (k):** Hour of the day and day of week also considered as forecast model input. (Monday is the first day and Sunday is the seventh day).

**Proposed ANN architecture:** The multilayer perceptrons model is used for forecasting the load demand. The network structure is 8-20-1 in input, hidden and output layer respectively.

### GARDIENT DESCENT LEARNING ALOGORITHM FOR NEURAL NETWORK

G.E. Hinton, Rumelhart and R.O.Williams first proposed the Back-Propagation algorithm to train the neural network. The back propagation neural network consists of input, hidden and output layers connected with each other with a synaptic weight. By feed forward propagation, the inputs are propagated to the output through the hidden layers with synaptic weights. The difference between the network and the desired output generates an error, which is back propagated to the hidden layer and the input layer. The error is repeatedly back propagated and weights are updated on the basis of the error until the desired output is achieved (Reng-Cun *et al.*, 2006).

The Back propagation algorithm is used by the gradient descent method to update the weights and biases. For the network parameters the partial derivative of the error gradient with respect to the weights and biases is calculated. Each node of the network is needed to differentiated in accordance with back propagated error, which is major limitation of back propagation training algorithm (Rey-Chue *et al.*, 2000).

### GRADIENT DECENT LEARNING ALGORITHM MATHEMATICAL FORMULATION

**Step 1:** Initialize all weights and the algorithm will continue until the termination condition becomes true.

**Step 2:** The input signal  $X_i$  is received by each neuron in the input layer of the network and is transmitted to the hidden layer.

**Step 3:** The sum of the input weighted signal ( $L_j, J = 1,2,3,...,p$ ):

$$Lm_k = D_{oj} + \sum_{i=1}^n x_i * D_{ij} \quad (1)$$

To compute the output, we have applied the activation function:

$$L_j = f(L_m) \tag{2}$$

**Step 4 :** The sum of weighted inputs generates the output, accordingly ( $G_{in_k}$  where  $k = 1, 2, 3, \dots, m$ ):

$$G_{in_k} = W_{ok} + \sum_{j=1}^p L_j * W_{jk} \tag{3}$$

And, to compute the output, we have applied the activation function:

$$G_k = f(G_{in_k}) \tag{4}$$

Error back propagation:

**Step 5 :** For error computation, each output unit ( $G_k$  where  $k = 1, 2, 3, \dots, m$ ) receives a target pattern corresponding to the input training pattern:

$$\delta_k = (T_k - G_k) f'(G_{in_k}) \tag{5}$$

Calculates the correction term of its weight

$$\Delta W_{jk} = \alpha \delta_k L_j \tag{6}$$

Calculates the correction term of its bias:

$$\Delta W_{ok} = \alpha \delta_k \tag{7}$$

And sends  $\delta_k$  to its units in the layer below:

$$\delta_{in_j} = \sum_{k=1}^m \delta W_{jk} \tag{8}$$

**Step 6 :** Each hidden neuron ( $L_j$ , where  $j = 1, 2, 3, \dots, p$ ) in the layer above (from neurons) takes the sum of its delta:

$$\delta_j = \delta_{in_j} * f'(L_m) \tag{9}$$

Calculates the correction term of its weight:

$$\Delta D_{ij} = \alpha \delta_j x_i \tag{10}$$

Calculates the correction term of its bias and updates the weights and biases:

$$\Delta D_{oj} = \alpha \delta_j \tag{11}$$

**Step 7 :** Weights and biases are updated:

$$(j = 0, \dots, p)_{jk}(new) = w_{jk}(old) + \Delta w_{jk} \tag{12}$$

Each output unit and each hidden unit also update the weights and biases:

$$O_{ij}(new) = o_{ij}(old) + \Delta V_{ij} \tag{13}$$

## RESULTS AND DISCUSSION

In order to assess the forecast model performance, the error is calculated. The difference of the testing data set and the network predicted output gives the error, which can be calculated as:

$$MAPE = 1 / M \sum_{i=1}^m |L_{actual} - L_{predicted}| / L_{actual} \tag{14}$$

$$MAE = 1 / M \sum_{i=1}^m |L_{actual} - P_{predicted}| \tag{15}$$

where  $L_{actual}$  is the actual load,  $L_{predicted}$  is forecasted load and  $M$  is the number of data points.

In order to assess the prediction quality of the forecasting model, the Mean Absolute Percent Errors (MAPE) as given in Table 1. The neural network forecast model is applied with weather inputs for 168 h ahead load forecasting for four seasons. Normally, each season has 2 month for typical season such as: December and January are considered as winter; March and April as spring; July and August are seen as summer; and September and October as the autumn season. For seasonal forecasts, 168 hours ahead forecast is implemented. The first week of January, March, June and September of 2009 are the data points for winter, spring, summer and autumn respectively (Niu *et al.*, 2012). Figure 6, 7, 8 and 9 shows the 168 hour STLF for the four seasons.

Table 1: MAPE of the seasons with the number of hidden neurons of NN

Season	Number of hidden units	MAPE (%)
Spring	20	3.81
Summer	20	4.59
Autumn	20	4.25
Winter	20	3.98

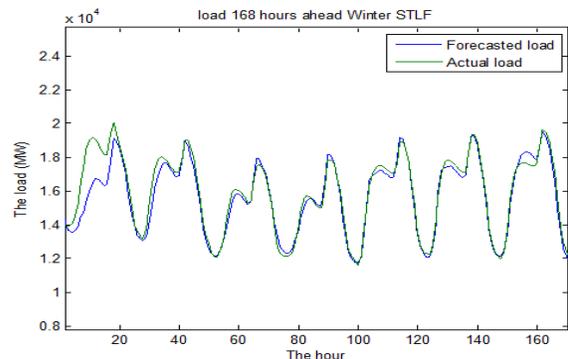


Fig. 6: 168 h ahead STLF of the winter season

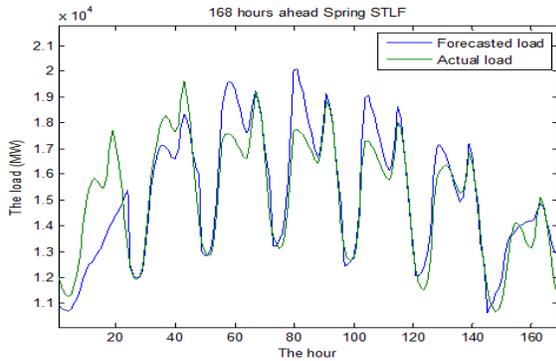


Fig. 7: 168 h ahead STL of the spring season

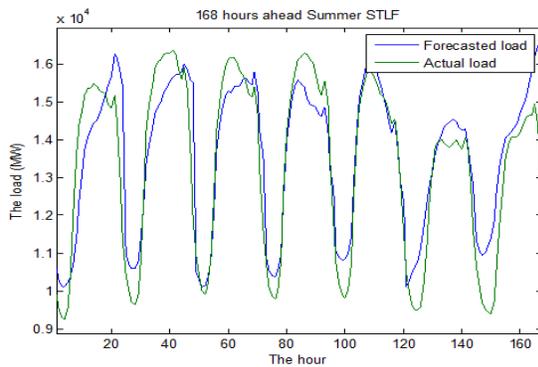


Fig. 8: 168 h ahead STL of the summer season

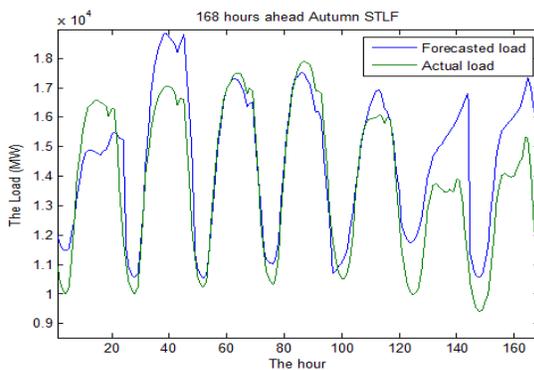


Fig. 9: 168 h ahead STL of the autumn season

The MAPE of the load forecasting is affected due to uncertain changes in the weather and load demand which is due to certain social activities (Niu *et al.*, 2012), (Ruth and Lin, 2006). In the ANN model, the type of day (working or off day) is considered as an input to the system to evaluate its effect on load demand. Different special and public events increases load uncertainty such as Eid, Charismas, New Year’s night. Moreover, the neural network output also depends upon the weather inputs, correlated load inputs, network configuration and training algorithm. To achieve the higher forecasting accuracy these factors should be considered in the forecast model.

Seasonal forecasting shows that the winter load forecast produce more error than the other seasons due to social events and improper training of the neural network with respect to other seasonal forecast. The regression analysis shows that the high confidence interval of the training of the neural network produce better forecast results.

### PERFORMANCE ANALYSIS OF FORECAST MODEL

The neural network inputs are large data set that has correlated inputs with a significant impact on the training process of network. As the data analysis study shows that, the load demand of pervious hour, day and week had more correlated inputs to forecast for the specific hour load demand. The similar day selection method considering weather inputs is used to select the better input to train the network, otherwise, it could cause a large forecasting error (Ching-Lai *et al.*, 2005). A large number of training data may lead to a long training time and slow convergence, which would affect the accuracy (Wei and Ying, 2007).

The performance of the training algorithm is also measured by the rate of the convergence for a specific forecast model and network topology. The relationship between the mean absolute error and the number of epochs of the NN based STL model, as shown in Fig. 10. It shows that the networks converged as the number of epochs increased. The best validation performance of the back propagation method is 1106 in 719 epochs for STL networks. Figure 3 shows that the training, validation and testing simultaneously moved towards the convergence of the STL model.

The regression analysis of the NN model for the 168 h ahead load forecasting is shown in Fig. 11. The confidence interval of the neural network is also analyzed for the training, testing, validation and overall performance of the neural network for the particular network architecture.

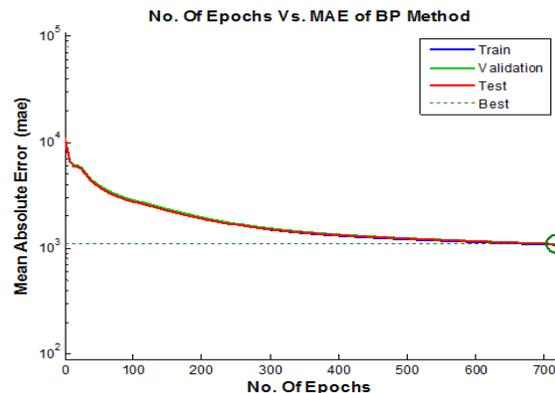


Fig. 10: Number Of epochs vs. mean absolute error

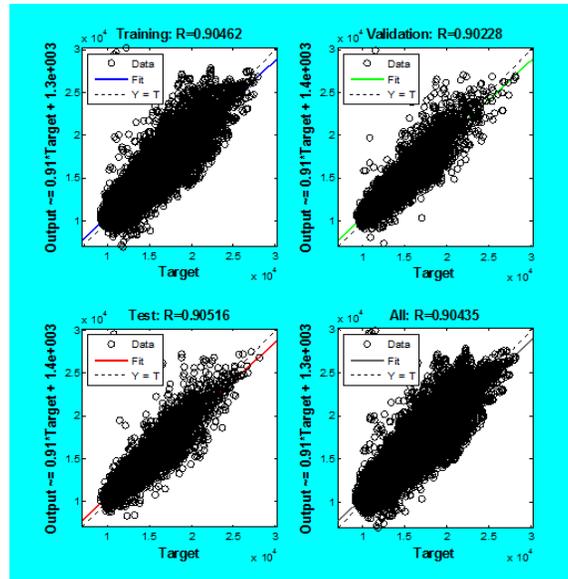


Fig. 11: Regression analysis of neural network model

The confidence interval is 90% of the model; it meant that 90% of the estimated data is statistically significant for the network. The measure of the validation is the generalization ability of NN. Testing of NN provides the independent measure of the performance during and after training. A significant increase in the range of the confidence interval may increase the accuracy, which is the main objective of forecasting problem.

### CONCLUSION

In this study, 168 hours ahead load forecast of four seasons using NN based model is proposed with weather inputs. As the results shows, weather inputs such as dry bulb, dew point and correlated load inputs have a significant impact on forecasting output. The back propagation training algorithm is used to update the weights of neural network. One year load data is used to train the neural network having 8 inputs, 20 hidden and one output neuron. As the year's seasonal forecast results shows, the spring season shows relatively less forecast error due to fewer uncertain events, which have an effect on the forecast output and training. The load forecast model converged in 719 epochs with a 90% confidence interval, which shows that only 10% of the data is not statistically significant. As the regression analysis of the network shows, the overall confidence interval is 90% for training, testing and validation of the network.

This research will serve as a basis for future studies and provide a chance to save expenditure by providing an increase in the accuracy of load forecasting. For future research, forecast accuracy can be enhanced by better training of the neural network, more correlated

inputs and by including the other weather parameters like humidity- information, wind speed, cloud cover, rainfall and the human body index.

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