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Application of Artificial Neural Networks for Hourly Load Forecasting in Distribution Systems

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Abstract— Today's electricity power industry is in the process of up-gradation and modernization. The power system operation has become more competitive in the open market environment. The accuracy of load forecasting is important because it has a direct influence on the planning of the operation schedule of power generation plants. A major part of the operating cost of power generation units depends on the amount of electricity production. To minimize the total operation cost, unit commitment scheduling is used to determine the optimal commitment schedule of power generation units to satisfy the forecasted demand. Load forecasting is an important requirement for unit commitment planning. Hour-ahead load forecasting is necessary for optimally controlling the online resources to supply the next hour load. The objective of this study is to prove the application of Artificial Neural Networks for performing hourly load forecasting in distribution systems. The forecasting results indicate that ANN based load forecasting systems can be used for load forecasting in distribution systems with a good accuracy.

***Keywords**— ANN, Hourly Load Fore Casting. Three Layer MLP network.*

I. INTRODUCTION

With the changing environment and modernization of the electric power system industry, the traditional operating methods of the power system companies are in the process of up-gradation and new methods and technologies are continuously coming up and are being accepted by the industry. The main priority for every electrical utility is the ability to provide reliable and continuous supply of electricity to the consumers. For proper operation of the power system, there must be a balance between the demand and supply of electricity. Therefore, it is important for all electrical utilities to perform effective planning of resources.

Since the economy of the operation and control of power systems is sensitive to the system demand, large amount of savings in operating costs can be obtained if the accuracy of load demand forecast is increased. If there is a large forecast error, then the power system operation can be risky, since there can be a difference between the demand and supply.

These challenges become even more significant in the present situation, when the number of power generation and distribution companies is increasing and there is competition between these companies to provide more reliable and economic supply of electricity to the consumers.

As a result, open market concept was initialized to reduce the operating cost. In the competitive market environment, efficiency has become the top priority for all the electrical utilities and it is closely related to the demand forecasting. An underestimated or overestimated system demand can lead to profit loss. Thus, the basic operational functions of the power system such as generation resource planning and unit commitment scheduling should be effectively carried out so as to perform well in the market competition.

One of the most promising area for the application of ANN is load forecasting. Load forecasting is basically a function-mapping problem. ANN systems are widely used for short-term load forecasting (STLF).

2. LITERATURE SURVEY

Most of the literature published on load forecasting in distribution systems deal with 24-hour-ahead load forecasting or next day peak load forecasting. These methods forecast the demand power by using a forecasted temperature as forecast information. But in case of rapid changes in temperature on the forecast day, load power changes greatly and the load forecast error increases. Therefore, in this case, one-hour-ahead load forecasting which uses the temperature and load values of a few hours before the time at which load is to be forecasted, as input variables to Artificial Neural Network, is more accurate. The forecast error in one-hour-ahead load forecasting is less as compared to day-ahead load forecasting. Hence, it is more accurate. Here, the main idea of this project is to study the application of using Artificial Neural Networks for hourly load forecasting in distribution systems.

The construction of an ANN system for STLF can be divided into following steps:

1) Selection of input variables

2) Design of neural network structure

3) Collection and modification of training data

4) Training of the designed network

5) Validation of the trained network

This chapter aims to provide detailed explanation of the ANN-based model design to perform hourly load forecasting for the Western Farmers Electric Cooperative (WFEC) electric utility.

2.1 SYSTEM DEMAND ANALYSIS

The first step in designing any load forecasting model is to study the load characteristics such as periodicity and trends by analyzing the previous load records. In this study, load analysis is performed on load records from the year 2004 for the western farmers electric cooperative, which is an electricity utility established in Oklahoma, USA to meet the needs of Altus Air Force Base and various other establishments.. According to the record, the yearly maximum load was observed in the first week of August with a load value of 1216 MW. The yearly minimum load was in the last week of April with a load value of 440 MW. Other smaller peaks were recorded in summer from mid-July to the end of August. The daily average demand consumption was also high for a few weeks in the winter season. The system average demand consumption for the year 2004 was 704 MW. Figure 2.1 shows the load characteristics of two parts of load data during the summer season (7/12–7/18) and winter season (1/19–1/25), starting from Monday.

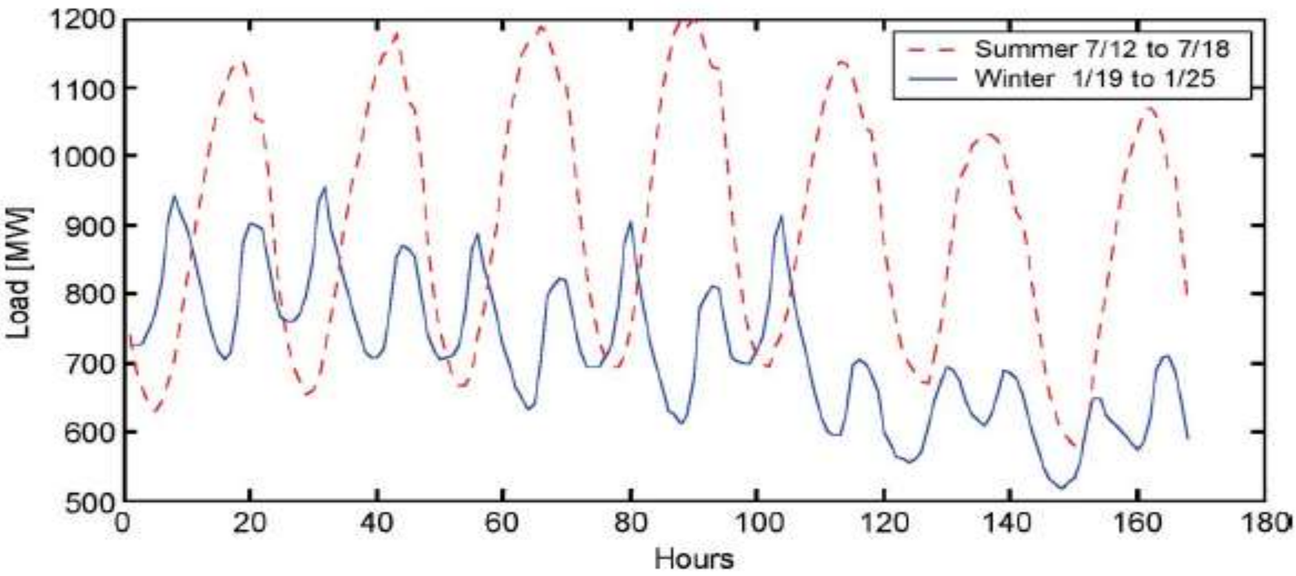


Figure 1.

2.2 Network Structure Design

In this study, a forward approach is used to test for the proper number of hidden neurons. The method is started by first setting the estimated optimal number of hidden neurons by using the following equation:

$$\text{Number of hidden neurons} = \sqrt{\text{number of inputs} \times \text{number of outputs}} \quad \text{.......... (1.1)}$$

The number of hidden neurons is then gradually increased by one. Each of the time, the model is trained and then the forecasting error from the testing data set is recorded for comparison. The proper number of hidden units is selected from the case in which the forecasting error is minimum. The mean absolute percentage error for a test data set is calculated by applying this method as shown in table 2.1. It can be seen that on increasing the number of neurons first the error decreases and becomes minimum for four neurons and after that it starts increasing. This is because if there are too many hidden neurons, the network will start to memorize the data in the training set and will begin to lose its generalization property, and therefore the network will not be able to perform well for other load patterns. The optimal number of hidden units is selected as the point before such a condition is observed. Thus, the optimal number of hidden neurons is selected to be four in this study.

Number of hidden neurons	Mean absolute percentage error
2	2.065
3	1.6475
4	1.26
5	1.58

Table 1. Variation of Mean absolute percentage error with no. of hidden neurons.

$$f(x)=\tanh(kx)=\frac{e^{kx}-e^{-kx}}{e^{kx}+e^{-kx}} \quad \ldots\ldots\ldots(1.2)$$

The exact shape of the sigmoid function has a little effect on the network performance, but it may have a strong effect on the training speed. The hyperbolic tangent function as given in equation 2.2 is selected as the activation function for hidden units in this study. The function is shown in figure 1.2.

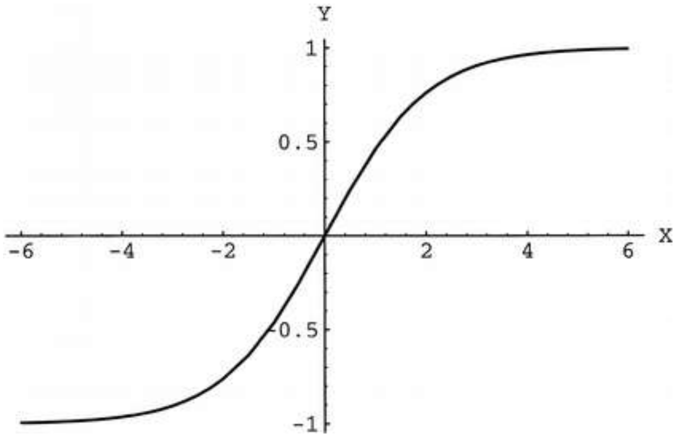


Figure 2. Activation function of hidden units

A linear function can be selected as the activation function for the output neurons. Since it is given that a nonlinear function is used in the hidden layer, the output generated by the sigmoid function at the output layer will be close to the output obtained for the case when a linear function is used. The difference between both the cases is just the resources needed in the calculation process. It has been set as a default in the program to use a linear output activation function in order to reduce the calculation resources.

Thus, an optimal final structure of the ANN system has now been selected after a long procedure of proper observations and calculations and is shown in figure 1.3

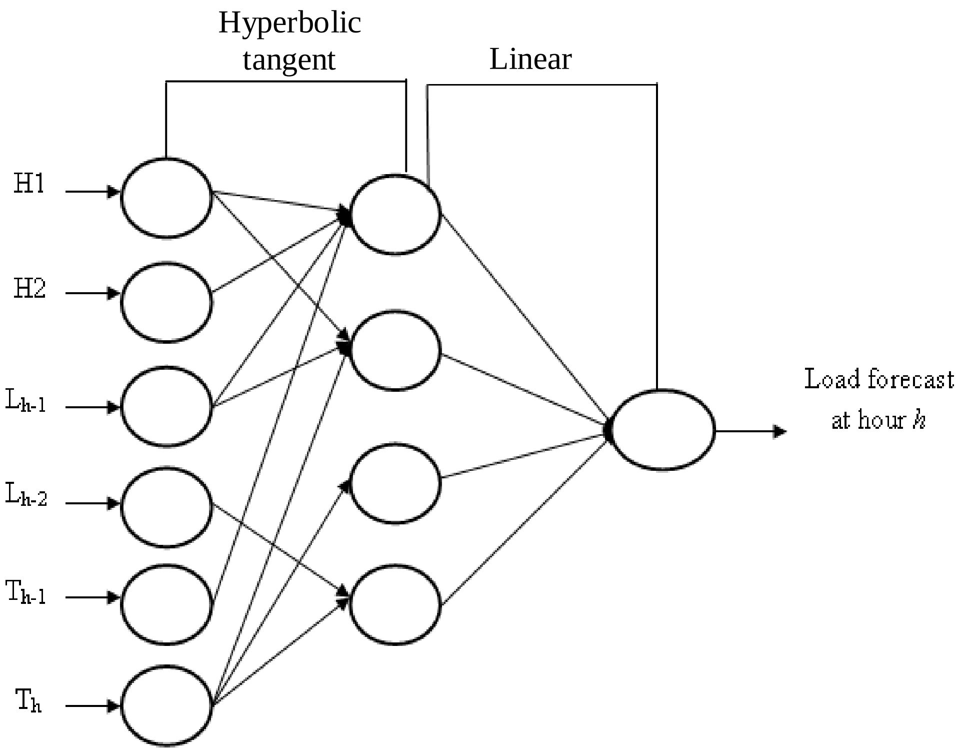
When the activation function is chosen to be a sigmoid function, the following two identities can be applied to calculate the derivative:

Logistic $f(x) = \frac{1}{1+e^{-kx}} \Rightarrow f'(x) = k.\ f(x).[1 - f(x)]$ ....(1.2)

Hyperbolic tangent $f(x) = \frac{e^{kx} - e^{-kx}}{e^{kx} + e^{-kx}} = \tanh(kx) \Rightarrow$

$f'(x) = [1 - (f(x))^2]$ ....(1.3)

There are two ways to present the training samples. If the weights are updated every time each single pattern is presented to the network, the learning is said to be incremental or pattern learning. Because of the fact that the purpose of ANN learning is to reduce the average error over the entire training set, there is another learning method that is more effective. In this method, all the training data is processed at the same time, and then the weights are adjusted according to the average error of the entire training set. This method of learning is known as the batch learning. One complete set of the entire training data is known as an epoch.



Figgure.3 Final Structure of the ANN system

2.3 Selection of training period

Training is the process by which the network parameters, i.e., the weights and bias values, are determined. This is done to find out the relationship between the inputs and the target outputs which are based on a set of examples called the training set. Therefore, it is necessary, that the training data set should cover wide ranges of input patterns, that will sufficiently teach the model to identify the relations among the input and output values. The ANNSTLF system is trained with the help of supervised learning method.

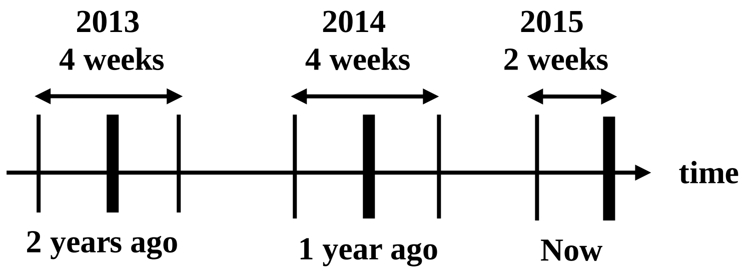


Figure 4. Moving window data collection with 2 weeks and 3 years training

3 HOURLY LOAD FORECAST ANALYSIS USING ANN

3.1 LOAD FORECASTING RESULTS

In this study, hourly load forecast analysis of the load data from the WFEC (western farmers electric cooperative) in Oklahoma, USA is performed on the day of 18 August, 2005 [8]. Load for all the 24 hours of the day is forecasted. In this study, load forecast analysis using ANN is done using MATLAB. To forecast load for each hour, first we have to train the ANN. For training, a two week-three year window covering 10 weeks of current load pattern (two weeks from current year and eight weeks from the past two years) is taken. Thus, the ANN system is trained with 10 previous similar patterns for each hour, i.e., a total of $24 \times 10 = 240$ load patterns for a particular day. After training, the input data pattern for the hour at which load is to be forecasted is fed into the ANN and the output is noted down. The forecasted load is then compared with the actual load. The comparison is illustrated in table 3.1. The percentage error for each hour, MPE (mean percentage error) and MAPE (mean absolute percentage error) for the full day are also calculated by applying the following equations:

$$\%\ \text{error} = \frac{(\text{Actual load} - \text{Forecasted load})}{(\text{Actual load})} \times 100 \qquad (3.1)$$

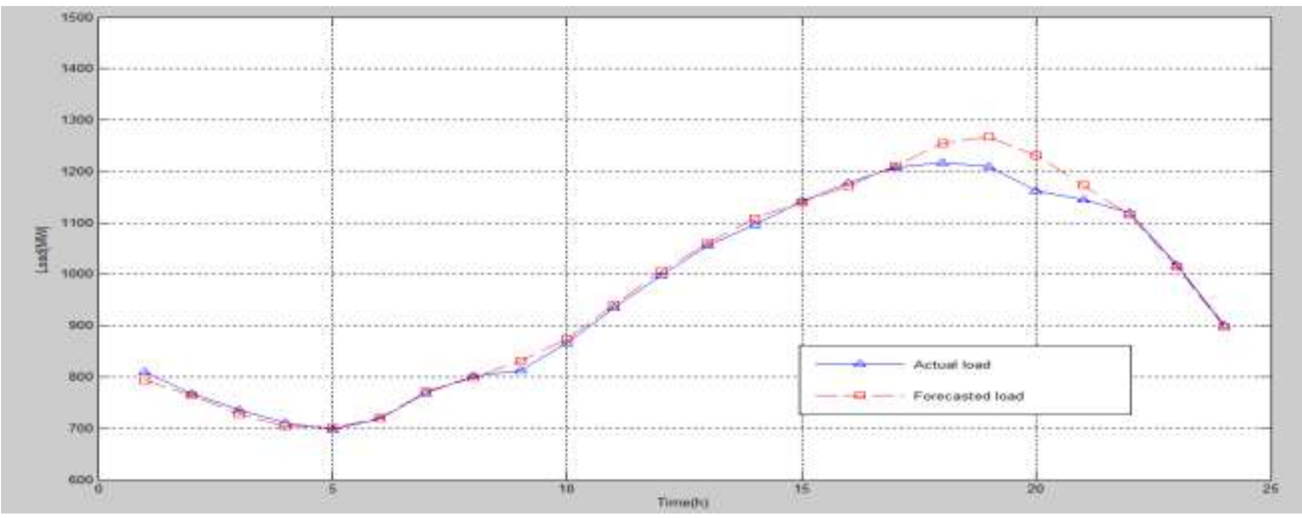


Figure 5. Comparison between actual and forecasted loads for 18 Aug, 2015.

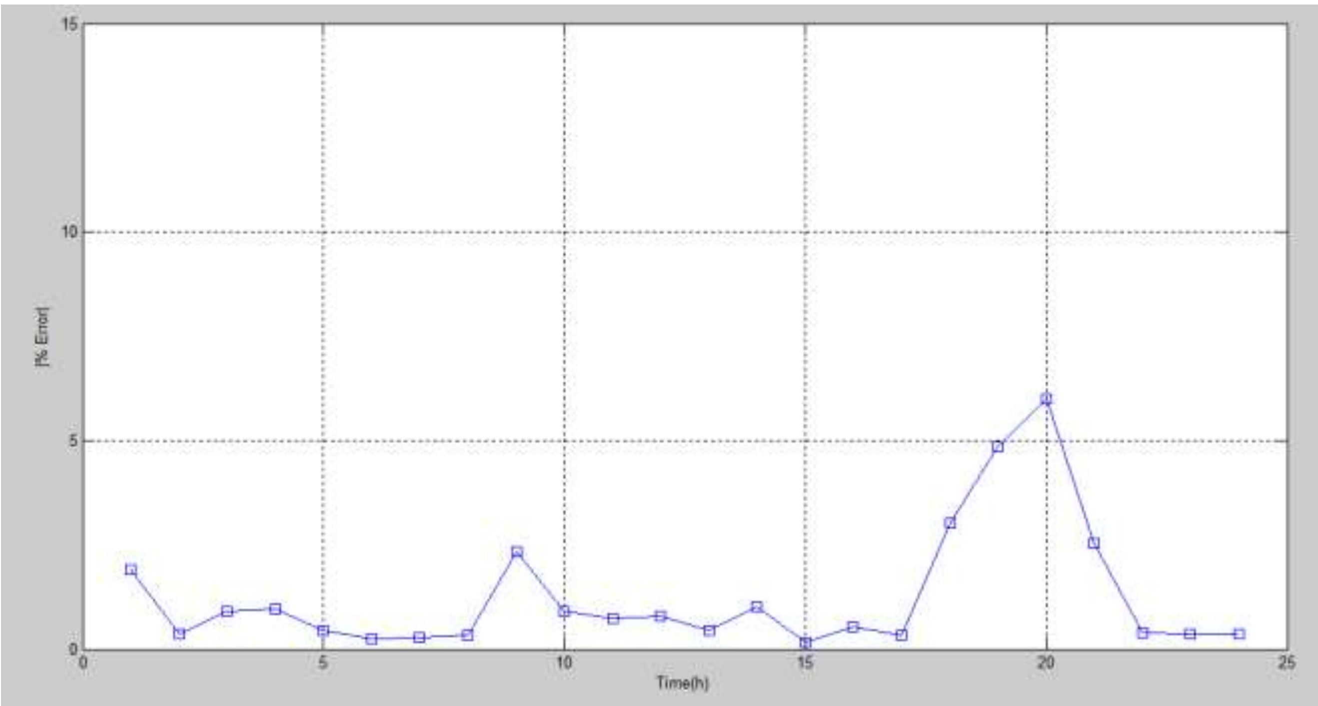


Figure 5. Plot of |% Error| vs Time(h) for Hourly Load Forecasting on 18 Aug, 2015

CONCLUSION

The accuracy of load forecasting has a strong influence on the operating cost of all the electric utilities involved in power generation planning. There is a nonlinear relationship between the load affecting variables and the actual load demand. The Artificial Neural Networks have shown good results for solving difficult nonlinear problems. This project describes the steps to develop an ANN model for hourly load forecasting in distribution systems. The ANN model used in this project is constructed by using a Multi-Layer-Perceptron (MLP) network with only one hidden layer. The model uses the past load and weather data as inputs. The load forecasting results on actual system load data were found to be of good accuracy and this encourages the use of ANN based systems for hourly load forecasting in distribution systems. ANN based short-term load forecasting systems are being widely used today in the power system industry.

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