Application of Neural Networks for 24-Hour-Ahead Load Forecasting

Fatemeh Mosalman Yazdi

***Abstract*—**One of the most important requirements for the operation and planning activities of an electrical utility is the prediction of load for the next hour to several days out, known as short term load forecasting. This paper presents the development of an artificial neural network based short-term load forecasting model. The model can forecast daily load profiles with a load time of one day for next 24 hours. In this method can divide days of year with using average temperature. Groups make according linearity rate of curve. Ultimate forecast for each group obtain with considering weekday and weekend. This paper investigates effects of temperature and humidity on consuming curve. For forecasting load curve of holidays at first forecast pick and valley and then the neural network forecast is re-shaped with the new data. The ANN-based load models are trained using hourly historical. Load data and daily historical max/min temperature and humidity data. The results of testing the system on data from Yazd utility are reported.

***Keywords*—**Artificial neural network, Holiday forecasting, pick and valley load forecasting**,** Short-term load-forecasting.

I. Introduction

SHORT term load forecasting has an essential role in the operation and planning of electric power systems. It is one of the requirements for activities such as economic dispatch, unit commitment, fuel allocation and maintenance scheduling. There are many good works in short term load forecasting using ANN approach. Some researchers just dealt with normal weekdays [1,2], while other who tried to deal with weekdays and holidays, tested their approach on a very small residential area which is highly weather sensitive [3].

In this study, ANN techniques have been used to forecast the daily peak and valley load, daily load curve and so on. The ANN is regarded as a powerful method for handling nonlinear complex phenomenon, and it is able to develop a forecasting model automatically only by training with stored actual data. In the methods used, ANN training data are observed for a few weeks before the target day. However the ANN method, using data from the few weeks proceeding the target day as training data, can not accurately forecast seasonal trends mainly due to insufficient learning pattern [4]. The developed method is based on a three-layered perceptron ANN building block. The back propagation (BP) method has been used for the ANN training to increase the speed of convergence. The purpose of this study is to forecast load accurately, using actual data from the same period of previous several years are training data in order to expand learning pattern. The method has satisfactory results for one hour up to a week prediction. Moreover, the forecasting errors of the methods in this paper have became smaller than the errors of the method using data only previous year of the target year as ANN training data. This confirms the effectiveness of the training using actual data from several years. This study used actual power load and weather conditions during the one at Yazd electric power co., Yazd, Iran.

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II. ANN

A generic feed forward neural network (FNN) is shown in Fig. 1, which has input, hidden and output layer of processing elements. Processing elements in an ANN are also known as neurons. These neurons are interconnected by means of information channels called interconnections. Each neuron can have multiple inputs, while there can be only one output. Inputs to a neuron could be from external stimuli or could be from output of other neurons. Copies of the single output that comes from a neuron could be input to many other neurons in the network. It is also possible that one of the copies of a neuron's output could be input to itself as a feedback. In this case, the network is called self recurrent neural network.

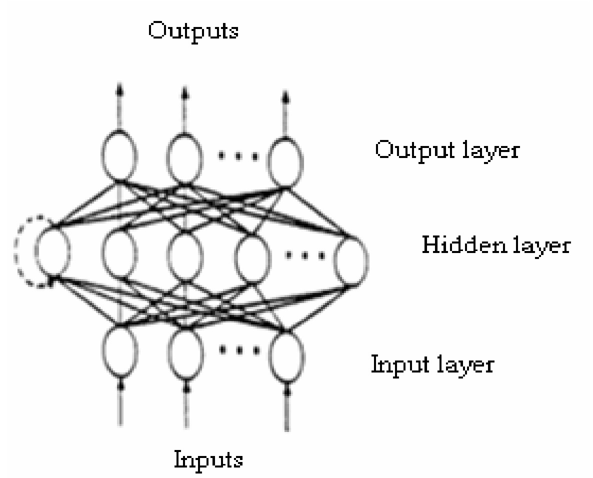

Fig. 1 Artificial neural network

There is connection strength, synapses or weight associated with each connection. When the weighted sum of the inputs to a neuron exceeds a certain threshold, the neuron is fired and output signal is produced. The network can recognize input patterns once the weights are adjusted or tuned via some kind of learning process. The back propagation learning algorithm is the most frequently used method in training the feed forward neural networks. In order to train the self recurrent neural networks, a modified learning algorithm called dynamic back propagation learning algorithm [5] is used.

III. Load Model Description

The most of the forecaster used a multilayer perceptron network. The MLP must be trained with historical data to find the appropriate values for w_{ij} and the number of required neurons in the hidden layer. Prior to the training of neural networks, the weights in the network are set randomly. Multiple training cases are then applied to adjust the weights using a parameter optimization technique based on back propagation. In this technique, the steepest descent algorithm is used to minimize the error square function.

$$E = \frac{1}{2}\sum_{i=1}^{k}(L(i) - \hat{L}(i))^2 \tag{1}$$

Where k is the number of training cases used. The weights in between the hidden/output layers and input/hidden layers are adjusted by propagation back from the output layer the error difference between the actual load and predicated load.

IV. Adaptive Scaling

The adaptive scaling employed in the daily forecaster and temperature forecaster are identical exert for the number of temperatures considered. In either case, the outputs of the ANN are scaled so that the network forecast matches the desired high and low temperatures. Scaling uses a linear transformation

$$T_S(k) = m(k).T_U(k) + b(k) \tag{2}$$

Where $T_U(k)$ and $T_S(k)$ are the unscaled and scaled temperature, respectively, at hour k and m(k) and b(k) are scale and offset parameters, respectively. Note the dependence of the scale parameters (m and b) on time k typically, the scale parameters change at the hour of the day where a high or low occurs in the network forecast [6].

V. The Weather Forecasting

Although temperature is one of the effective climate variety on consuming curvature, but other climate factors such as relative humidity and wind speed have considerable effect on consuming ration. In this research we only affect the humidity effect.

A. The Hourly Temperature Forecaster

One of the input data of neural network for load forecast is temperature. Therefore it is necessary to forecast temperature, other way temperature of each day can be forecasted from temperature of previous day. The resultant of considering temperature information of 3 years and test different training set are for getting high accuracy must use information of 5 days prior to the day to be forecast. By this the accuracy will be about 100%. Network has 28 inputs and 24 outputs. The inputs of the temperature forecaster are 24 hourly temperatures of the previous day, the high and low temperatures of the day to be forecast, and the high and the low temperatures of two days prior to the day to be forecast. The outputs are the 24 hourly temperatures of the day to be forecast.

B. The Hourly Relative Humidity Forecaster

Relative humidity data affect the consuming rate therefore relative humidity data of forecasting day must be forecasted. Input to the forecasting network humidity is the same as temperature therefore has training set, that is consist information of 5 days prior to the day to be forecast**.** Network has 26 inputs and 24 outputs. The inputs of the relative humidity forecaster are 24 hourly relative humidity of the previous day, the high and low relative humidity of the day to be forecast. The outputs are the 24 hourly temperatures of the day to be forecast.

VI. The Load Forecasting

For load forecasting must divide days of year to many groups with considering temperature. Information of 3 years used to increase accuracy. 3 samples exist for every day, must calculate average curve of years then obtain average from it's 24 hours. Therefore there is an average for each day and an average curve for each year. With dividing this curve can divide a year to groups. Groups make according linearity rate of curve, linear parts have little variety and are in one group. For load forecasting of ordinary days of a year must divide days of a week to weekdays and weekend days. For each group there is one network. The network of weekdays has 124 inputs and 24 outputs. The inputs of the load forecaster are 24 hourly loads of the previous day, 24 hourly temperature of the previous day, 24 hourly relative humidity of the previous day, 24 hourly temperature forecasts for the coming day, 24 hourly relative humidity forecasts for the coming day, 4 day type indicators for each day of the week. The outputs are the 24 hourly load of a day. The network of weekends has 120 inputs and 24 outputs. The inputs of the load forecaster are 24 hourly loads of the previous day, 24 hourly temperature of the previous day, 24 hourly relative humidity of the previous day, 24 hourly temperature forecasts for the coming day, 24 hourly relative humidity forecasts for the coming day, 2 day type indicators for each day of the week. The outputs are the 24 hourly load of the day to be forecast.

VII. HOLIDAYS

Load curve of holidays differ from a typical weekday also number of these days in historical information in compression with a typical weekdays is less. Because of unormal load behavior in these days and not enough samples neural network can't trained. Special holidays are either national celebrations or religious holidays. In Iran, some of the holidays are lunar calendar dependent. Thus, the special holidays of Iran are divided in to 2 groups: solar and lunar calendar special days [7]. For each group there is one network separately. For forecasting load curve of holidays at first calculate pick and valley and then the neural network forecast is re-shaped with the new data. In this paper we use two different neural networks to predict peak and valley load separately. The network of peak load forecasting has 23 inputs and 1 output. These inputs are daily high temperature and relative humidity on that day, high temperature and relative humidity and Peak loads on seven preceding days of the same day type as the particular day. The output is peak load of the day to be forecast.

The structure of the neural network for valley load forecasting is the same as that for peak load forecasting, but low temperature and relative humidity and valley employed.

VIII. PERFORMANCE

The performance of the proposed neural network is tested on real data from yazd power system. Three years of historical data is used to train the neural network. Actual weather data is used so that the effect of weather forecast errors do not alter the modeling error. One-to-seven-day-ahead forecasts are generated for each test set. To extend the forecast horizon beyond one day ahead, the forecast load of the previous day is used in place of the actual load to obtain the next day’s load forecast. The load forecast accuracy is reported in terms of the mean absolute percentage error (MAPE) defined as:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{\left| Actual(i) - Forecast(i) \right|}{Actual(i)}\times 100 \tag{3}$$

Where N is the total number of test data, and Actual(i) and Forecast(i) are the actual and forecast values of the ith data point, respectively. The MAPE measure is the accepted industry standard for examining load forecast performance. With the proposed method, the mean absolute forecasting error was below 2%. Fig. 2 is a plot of one-to-seven-day-ahead load forecasts.

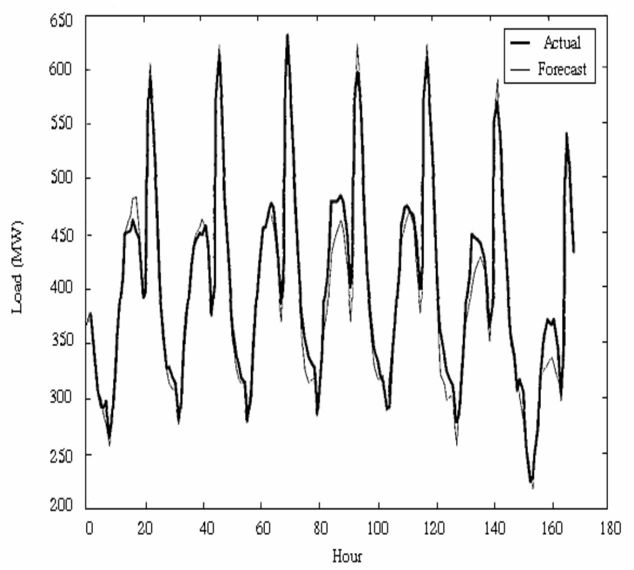

Fig. 2 Actual and forecasted hourly loads from June. 12 to June. 18, 2005,MAPE=1.7%

Tables I and II illustrates the result of our approach for forecasting peak and valley load several holidays in yazd.

TABLE I
PEAK LOAD FORECAST RESULT FOR MARCH 2005

Day	Actual peak	Forecasting peak
20	635	630
21	615	614
22	620	622
23	620	617
24	615	605

TABLE II
VALLEY LOAD FORECAST RESULT FOR MARCH 2005

Day	Actual peak	Forecasting valley
20	330	333
21	330	329
22	331	333
23	333	332.2
24	332	333.5

IX. CONCLUSION

An artificial neural network-based approach has been applied to forecast the hourly electric load of the power system of yazd. The ANN multi-layer structure has been trained using the back propagation technique. For load forecasting must divide days of year with using average temperature, Groups make according linearity rate of curve. Ultimate forecast for each group obtain with considering weekday & weekend. For forecasting load curve of holidays, high and low load is first estimated then the neural network forecast is re-shaped with the new data.

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