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Electric Load Forecasting Using an Artificial Neural Network

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Abstract: This paper presents an artificial neural network (ANN) approach to electric load forecasting. The ANN is used to learn the relationship among past, current and future temperatures and loads. In order to provide the fore- casted load, the ANN interpolates among the load and temperature data in a training data set. The average absolute errors of the one-hour and 24-hour ahead forecasts in our test on actual utility data are shown to be 1.40% and 2.06%, respectively. This compares with an average error of 4.22% for 24hour ahead forecasts with a currently used forecasting technique applied to the same data.

Key words: Artificial neural network · Electric load forecasting · Load pattern

INTRODUCTION

Various techniques for power system load forecasting have been proposed in the last few decades. Load forecasting with lead-times, from a few minutes to several days, helps the system operator to efficiently schedule spinning reserve allocation. In addition, load forecasting can provide information which is able to be used for possible energy interchange with other utilities. In addition to these economical reasons, load forecasting is also useful for system security. If applied to the system security assessment problem, it can provide valuable information to detect many vulnerable situations in advance. Traditional computationally economic approaches, such as regression and interpolation, may not give suffi- ciently accurate results. Conversely, complex algorithmic methods with heavy computational burden can converge slowly and may diverge in certain cases.A number of algorithms have been suggested for the load forecasting problem. Previous approaches can be generally classified into two categories in accordance with techniques they employ. One approach treats the load pattern as a time series signal and predicts the future load by using various time series analysis techniques [1-7]. The second approach recognizes that the load pattern is heavily dependent on weather variables and finds a functional relationship between the weather variables and the system load. The future load is then predicted by inserting the predicted weather information into the predetermined functional relationship [8-11]. General problems with the time series approach include the inaccuracy of prediction and numerical instability. One of the reasons this method often gives inaccurate results is. that it does not utilize weather information. There is a strong correlation between the be-havior of power consumption and weather variables such as temperature, humidity, wind speed and cloud cover.This is especially true in residential areas. The time series approach mostly utilizes computationally cumbersome matrix-oriented adaptive algorithms which, in certain cases, may be unstable. Most regression approaches try to find functional relationships between weather variables and current load demands. The conventional regression approaches use linear or piecewise-linear representations for the forecasting functions. By a linear combination of these representations, the regression approach finds the functional relationships between selected weather variables and load demand. Conventional techniques assume, without justification, a linear relationship. The functional relationship between load and weather variables, however, is not stationary, but depends on spatio-temporal elements. Conventional regression approach does not have the versatility to address this temporal variation. It, rather, will produce an averaged result. Therefore, an adaptable technique is needed. In this paper, we present an algorithm which combines both time series and regression approaches. Our algorithm utilizes a layered perceptron artificial neural net- work (ANN). As is the case with time series approach,the ANN traces previous load patterns and predicts a load pattern

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using recent load data. Our algorithm uses weather information for modeling. The ANN is able to perform nonlinear modeling and adaptation. It does not require assumption of any functional relationship between load and weather variables in advance. We can adapt the ANN by exposing it to new data. The ANN is also currently being investigated as a tool in other power system problems such as security assessment, harmonic load identification, alarm processing,fault diagnosis and topological observability [12-18].

Algorithm: The activation function of the artificial neurons in ANNs implementing the the sum of the inputs x multiplied by theirrespective weights w_{ji}:

$$A_j\left(\overline{x},\overline{w}\right)=\sum_{t=0}^{n} x_i w_{ji} \tag{1}$$

We can see that the activation depends only on the inputs and the weights.If the output function would be the identity (output=activation), then the neuron would be called linear. But these have severe limitations. The most common output function is the sigmoidal function [19-27]:

$$O_j\left(\overline{x},\overline{w}\right)=\frac{1}{1+e^{A_i\left(\overline{x},\overline{w}\right)}} \tag{2}$$

The goal of the training process is to obtain a desired output when certain inputs are given. Since the error is the difference between the actual and the desired output, the error depends on the weights and we need to adjust the weights in order to minimize the error. We can define the error function for the output of each neuron:

$$E_j\left(\overline{x},\overline{w},d\right)=\left(O_j\left(\overline{x},\overline{w}\right)-d_j\right)^2 \tag{3}$$

We take the square of the difference between the output and the desired target because it will be always positive and because it will be greater if the difference is big and lesser if the difference is small. The error of the network will simply be the sum of the errors of all the neurons in the output layer:

$$E\left(\overline{x},\overline{w},\overline{d}\right)=\sum_j\left(O_j\left(\overline{x},\overline{w}\right)-d_j\right)^2 \tag{4}$$

We can adjust the weights using the method of gradient descendent:

$$\Delta w_{ji}=-\eta\frac{\partial E}{\partial w_{ji}} \tag{5}$$

We “only” need to find the derivative of E in respect to w_{ji}.

$$\frac{\partial E}{\partial O_j}=2\left(O_j-d_j\right) \tag{6}$$

And then, how much the output depends on the activation, which in turn depends on the weights (from (1) and (2)):

$$\frac{\partial O_j}{\partial w_{ji}}=\frac{\partial O_j}{\partial A_j}\frac{\partial A_j}{\partial w_{ji}}=O_j\left(1-O_j\right)x_i \tag{7}$$

And we can see that (from (6) and (7)):

$$\frac{\partial E}{\partial w_{ji}}=\frac{\partial E}{\partial O_j}\frac{\partial O_j}{\partial w_{ji}}=2\left(O_j-d_j\right)O_j\left(O_j-d_j\right)x_i \tag{8}$$

And so, the adjustment to each weight will be (from (5) and (8)):

$$\Delta w_{ji}=-2\eta\left(O_j-d_j\right)O_j\left(1-O_j\right)x_i \tag{9}$$

We also need to see how the error of ik the network depends on the adjustment of v_{ik}. So:

$$\Delta w_{ji}=-\eta\frac{\partial E}{\partial v_{ik}}=-\eta\frac{\partial E}{\partial v_{ik}}\frac{\partial xi}{\partial v_{ik}} \tag{10}$$

Where:

$$\frac{\partial E}{\partial w_{ji}}=2\left(O_j-d_j\right)O_j\left(1-O_j\right)w_{ji} \tag{11}$$

And, assuming that there are inputs u into the neuron with v_{ik} (from (7)):

$$\frac{\partial xi}{\partial v_{ik}}=x_i\left(1-x_i\right)v_{ik} \tag{12}$$

Test Cases and Result: Hourly temperature and load data for Seattle/Tacoma area in the interval of Nov. 1, 1988 - Jan. 30, 1989 were collected by the Puget Sound Power and Light Company We used this data to train the ANN and test its perfor-mance [15-18]. Our focus is on a normal weekday (i.e. no holiday or weekends).

This approach of classifier evaluation is known as a jack-knife method.The ANN was trained to recognize the following cases

Case 1: Peak load of the day
Case 2: Total load of the day
Case 3: Hourly load

Case 1: The topology of the ANN for the peak load forecasting is as follows;

Input Neurons: Tl(k), T2(k) and T3(k)
Hidden Neurons: 5 hidden neurons
Out,put Neuron: L(k)

Where
k = day of predicted load,
L(k) = Peak load at day k,
Tl(k) = Average temperature at day k,
T2(k) = Peak temperature at day k,
T3(k) = Lowest temperature at day k.

Case 2: The topology of the ANN for the total load forecasting is as follows:

Input Neurons: Tl(k), T2(k) and T3(k)
Hidden Neurons: 5 hidden neurons
Output Neuron: L(k)

Where
k = day of predicted load,
L(k) = Total load at day k,
Tl(k) = Average temperature at day k,
T2(k) = Peak temperature at day k,
T3 (k) = Lowest temperature at day k.

Case 3: The topology of the ANN for the hourly load forecasting with one hour of lead time is as follows;

Input Neurons: k, L (k-2), L (k-1), T (k-2), T(k-1) and □(k)
Hidden Neurons: 10 hidden neurons
Output Neuron: L(k)

k = Hour of predicted load
L(x) = Load at hour x,
T(x) = Temperature at hour x,
□(x) = predicted temp. for hour x

In training stage, T(x) was used instead of □ (x). The lead times of predicted temperatures, □ (x),vary from 16 to 40 hours.Figure 1 shows examples of the hourly actual and fore- casted loads with one-hour and 24-hour lead times. the error gradually increases as the lead hour grows. This is true up to 18 hours of lead time. One of the reasons for this error pattern is the periodicity of temperature and load pattern. Even though they are not

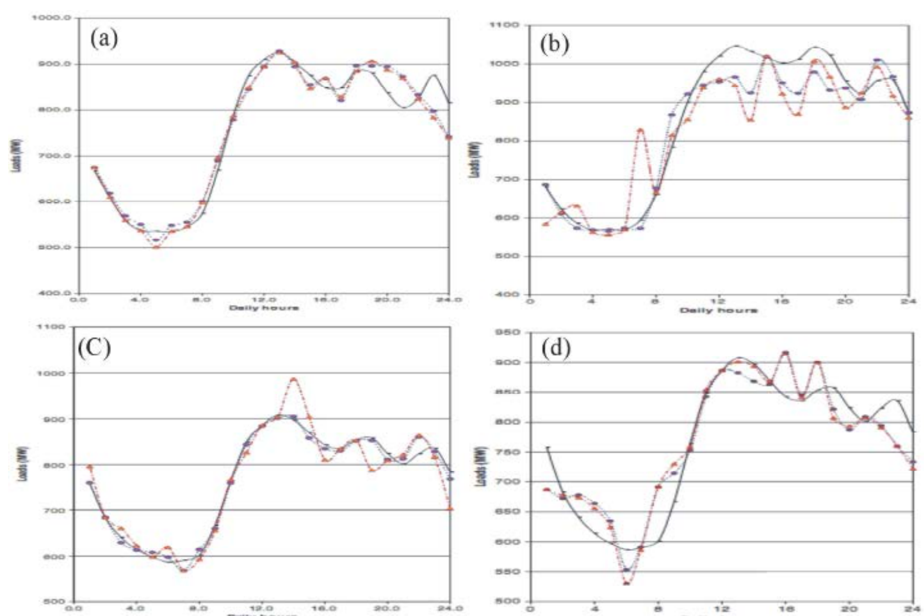

Fig. 1: a,b,c,d: Hourly Load Forecasting and Actual Load (in MW) (black: actual load, blue:1-hour lead forecast, red: 24hour lead forecast)

quite the same as those of the previous day, the temperature and system load are very similar to those of the previous day.

CONCLUSION

We have presented an electric load forecasting methodology using an artificial neural network(ANN). This technique was inspired by the work of Lapedes and Farber [28]. The performance of this technique is similar to the ANN with locally tuned receptive field [29]. The results shows that the ANN is suitable to interpolate among the load and temperature pattern data of training sets to provide the future load pattern. In order to forecast the future load from the trained ANN, we need to use the recent load and temperature data in addition to the predicted future temperature. Compared to the other regression methods, the ANN allows more flexible relationships between temperature and load pattern. A more intensive comparison can be found in [30]. Since the neural network simply interpolates among the training data, it will give high error with the test data that is not close enough to any one of the training data.In general, the neural network requires training data well spread in the feature space in order to provide highly accurate results. The training times required in our experiments vary, depending on the cases studied, from 3 to 7 hours of CPU time using the SUN SPARK Station 1. However, a trained ANN requires only 3 to 10 milliseconds for testing. The neural network typically shows higher error in the days when people have specific startup activities such as Monday or variant activities such as during the holiday seasons .In order to have more accurate results, we may need to have more sophisticated topology for the neural network which can discriminate startup days from other days. We utilize only temperature information among weather variables since it is the only information available to us. Use of additional weather variables such as cloud coverage and wind speed should yield even better results.

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