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Short Term Electric Load Forecasting Using An Adaptively Trained Layered Perceptron

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ABSTRACT

This paper addresses electric load forecasting using artificial Neural Network (NN) technology. The paper summarizes research for Puget Sound Power and Light Company. In this study, several structures for NN's are proposed and tested. Features extraction is implemented to capture strongly correlated variables to electric loads. The NN is compared to several forecasting models. Most of them are commercial codes. The NN performed as well as the best and most sophisticated commercial forecasting systems.

Keywords: Electric Load Forecasting, Neural Networks

1. INTRODUCTION

Short-term load forecasting (24 to 48 hour lead) is a very useful tool for electric utilities in several applications such as economic allocation of generation, energy transaction, system security analysis, optimal energy interchange between utilities, unit commitment and maintenance scheduling. Because of the shrinking spinning reserve and the seasonal high energy demand, utilities are dependent more than ever on short term forecasting for daily energy transactions.

Most of the conventional techniques used for load forecasting can be categorized under two approaches. One treats the load demand as a time series signal and predicts the load using different time series analysis techniques. The second method is a regression technique which recognizes the fact that the load demand is heavily dependent on weather variables.

The time series approach is generally inaccurate and numerically instable. Conventional regression approaches use linear or piecewise-linear representations for the forecasting function. The accuracy of this approach is dependent on the functional relationship between the weather variables and electric load which must be known apriori. This approach cannot handle the non stationary temporal relationship between the weather variables and changing load demands.

Electric load forecasting is a challenging problem that requires extensive statistical analysis. The problem formulation as well as modelling may depend to a great extent on the geographical region where the forecasting is needed. Several key issues must be addressed before a reliable forecast is developed, among them are:

- The relevant variables with strong correlation to electric loads such as temperature, clouds, humidity and winds, must be identified.
- A reliable feature extraction techniques to capture the dominant information related to load patterns and profiles must be developed.
- Accuracy of weather forecasting can have a great impact on the accuracy of load forecasting. In some cases, however, statistical properties of the weather forecasting errors can be captured by the load forecasting model.
- One model for load forecasting for all seasons or even all week days may not be possible to develop with a reasonable degree of accuracy.
- The forecasting model must be able to extrapolate with a reasonable degree of accuracy during cold snaps, heat waves, or pickup loads.
- The forecasting model must be able to adapt to the system's thermal inertia. It must also be able to handle the load growth.

To include all the above considerations in the forecasting models is an enormous exercise. It may not even be possible to implement without some form of a rule based system.

Recently, a neural network approach was proposed for the load forecasting problem [1-5]. The NN technique has several key features that makes it highly suitable for this application. For example, it does not require any preassumed functional relationship between electric load and other variables such as weather conditions. A NN provides a nonlinear mapping between weather variables and previous load patterns, and electric load without the need for predetermined model. NNs are usually fault tolerant and robust.

When the NN approach is compared to classification methods such as Classification And Regression Trees (CART), the NN shows superior accuracy [5].

Although the NN is a very promising tool for load forecasting, several key issues must be addressed before it can be effectively used. The size of the ANN for a given problem is determined experimentally rather than theoretically. The improper selection of the NN structure may result in a "memorization" problem [3], which can be viewed as an overfitting of the training data. If NN memorizes the data, the testing error will likely exceed the training error. Another challenge facing NN application is the speed of learning. With the standard multi-layered NN perceptron, learning algorithms such as the *error back propagation* require rather large training time. This is due to the fact that all the training data must be used repeatedly during training. Furthermore, most of the existing training algorithms assume the stationarity of the training data. In load forecasting, however, the load profile is dynamic in nature with temporal seasonal and annual variations.

During the course of this study, several attempts were made to enhance the accuracy of the forecast by selecting different structures of neural networks based on a feature extraction process. The developed NN was tested by Puget Sound Power and Light Company. The NN was used to forecast the real load of the Puget system. Moreover, the performance of the NN is compared to several commercial forecasting systems. The paper will show that when the NN is designed with feature extraction, it can be highly accurate. As a matter of fact, a simple NN can outperform several complex and expensive forecasting systems.

2. Problem Description

The electric load of Puget Power is forecasted at 9:00 AM of each weekday. For example, Tuesday forecasting is done on Monday at 9:00 AM. The exceptions are Saturday, Sunday and Monday forecasting which are done on 9:00 AM on Friday. The purpose of this study is to provide the following information:

1. AM peak load
2. PM peak load
3. Average load of the day
3. Hourly forecasting

Several NN's were developed in the early stage of this study [1]. Although they were generally acceptable, they had two major drawbacks:

1) Updating the NN using more recent data is a very time consuming process. This is because the *error back propagation* algorithm can not be used in an adaptive mode. When a new data set is to be used, it must be added to the old set and the NN is retrained by using the new and old data sets.

2) Using raw weather variables without any form of feature extraction may not be adequate.

To solve the first problem. we have developed an adaptive training technique for NN's [2]. The NN is updated using the new data set without the old training data. The adaptive training also substantially reduces the training time and ensures convergence to global optimality within a specified region. This technique shows substantial improvement over the existing methods [2,4]

The second problem (feature extraction) was addressed by using the experience of forecasters from the Pacific Northwest region. In this paper, we will show these features and show how can they substantially improve the forecast.

3. Available Data for Forecasting

Puget Power furnished the data used for training and testing of the NN. The main forecasting periods of this project were the winter seasons. We had access to the winter data starting from 1986. The data included the following variables.

- o Actual hourly temperature at Seattle/Tacoma airport
- o Forecast hourly temperature at Seattle/Tacoma airport
- o Actual hourly system load

Other variables such as wind speed and cloud coverage were also available but were not used in this study.

4. Neural Network Structures

Several structures were considered during this study. Some were acceptable in terms of accuracy. To evaluate the different structures, the NN was compared to several forecasting methods used at Puget Power. Among these were several commercial codes developed specifically for the Northwest region.

Several structures were developed over the research period. In this paper, however, two key structures are presented. One of these structures (Structure I) was developed in the earlier stages of this study. The input variables of this structure were selected based on common sense. The second structure was developed taking into account the recommendation of the forecasting experts. This structure was found to be more successful.

<u>Structure I:</u>

In the earlier stages of this study, we evaluated the load patterns of every day of the week. We found that almost every day is unique, particularly Mondays, Saturdays and Sundays. Monday morning was usually higher than the rest of the week because of the pickup loads. Weekend loads were mainly residential and partially commercial with some light industrial component. Based on this analysis, we elected to use five neural networks: one NN to forecast Wednesdays, Thursdays and Fridays; and one for each of the other days.

<u>Structure II:</u>

This structure was developed when we could not enhance the accuracy of the NN of structure I beyond a certain level. We solicited the assistance of forecasting experts to suggest different variables to be used in load forecasting. As a result, 24 NNs were developed. One NN per hour regardless of the day of the week. Only weekdays were considered.

5. Training Data

The training data used for structure I were the following:

Input data:

- o Hour of the forecast (k)
- o Forecast temperature at hour k
- o Actual temperature and load 48 hours earlier (k-48)

- o Actual temperature and load 49 hours earlier (k-49)
- o Actual temperature and load 50 hours earlier (k-50)
- o Actual temperature and load one week earlier (k-168)

output data: Load at time k

Structure II has the following training data:

Input data:

- o Forecast year; to allow for load growth
- o T(k): Forecast temperature at hour k
- o [T(k) - 60]2: The square of the difference between the forecast temperature and the average indoor temperature.
- o T_{max}: Maximum temperature of previous week
- o $[T_{max} - 60]^2$
- o T_{max2}: Maximum temperature two days earlier
- o $[T_{max2} - 60]^2$
- o T_{min}: Minimum temperature of previous week
- o $[T_{min2} - 60]^2$
- o Sum of temperature at hour k of the previous 7 days
- o Sum of loads at hour k of the previous 7 days
- o Load at hour k of previous day
- o Load at hour k two days earlier
- o Load at 9 AM of the current day. This is the time where the following day forecasting is done.

Output data: Load at time k

6. TEST RESULTS OF STRUCTURE I; ADAPTIVE TRAINING

Adaptive training was used in this study since it was more suitable for the forecasting problem compared to the *error back propagation* method. The later method had a number of limitations that made it difficult to use. For example, since the *error back propagation* technique is not designed to be adaptive, all data must be used every time the weights are updated. If a set of old data becomes irrelevant, the NN is retrained by using the entire new data set. Also, when new data is in conflict with old data (data inconsistency), the effect of old data can not be removed unless the NN is retrained without the old data. The importance of some data can not be easily weighted. In addition, the *error back propagation* technique converges slowly.

The adaptive training reported in [2,4] has some key features that makes it ideal for applications such as load forecasting: 1) It is suitable for dynamically varying systems with large data sets such as load forecasting and security assessment; 2) Weights are automatically adjusted based on new data without the need for the original training data; 3) The effect of old and invalid patterns (data) are eventually and automatically deleted (forgotten); 4) No matrix inversion or other computationally intensive operations are needed; 5) Perturbation of the NN weights are restricted to chosen boundaries; 6) Global optimality can be obtained; 7) It does not drift; and 8) Data can be weighted based on its importance.

Figure 1 shows a sample of the result of the NN of structure I. The NN was trained using the adaptive training technique reported in [2]. In this particular study, different numbers of hidden neurons (HN) were selected. As we expected, the number of hidden neurons had great impact on the accuracy and speed of training. When a large number of hidden neurons was selected, the convergence of the NN was poor. This was because the NN was under-determined. The cost index used to identify the NN weights had a flat shape without clearly defined minima. On the other hand, when a small number of hidden neurons was used, the cost index had a clear minima but high error value. The NN in this study was trained for about 80,000 iterations and tested on five days. The testing data were not included in the training. Table 1 shows the testing error which illustrates the above argument. Based on this, one can assume that the two hidden neurons NN is the most suitable for this case.

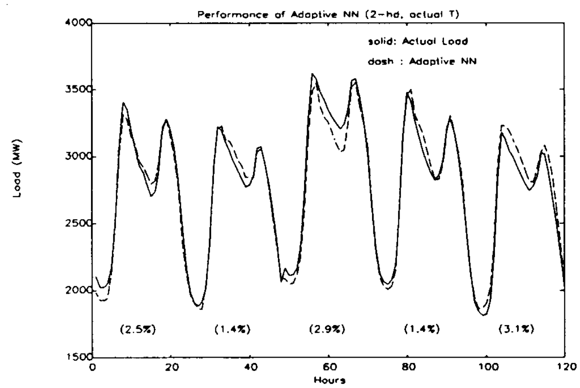

Figure 1: Load Forecasting of Structure I; Adaptive Training

Table 1: Effect of number of hidden Neurons

Testing Error	1 HN	2 HN	7 HN	20 HN
Max error (%)	4.54	3.44	5.65	6.96
Min error (%)	2.45	1.34	1.86	1.94
Ave error (%)	3.34	2.32	3.81	4.98

7. TEST RESULTS OF STRUCTURE II

The following figures show the test results of structure II. The figures show the results of three types of forecasting: NN forecasting, Puget Power forecasting (Lloyd) and the forecasting of a commercial product (Queri-A) designed specifically for the Northwest. This study was part of a Puget Power Forecasting Contest which is the subject of another paper [6]. There were several other forecasting systems. However, the three shown in the figures have the best results. The figures show the magnitude of the hourly error calculated for the weekdays.

In the figures, NN1 is referred to the NN of Structure I. NN2 is for Structure II where one NN is used to forecast three hours. NN3 is also for Structure II but each NN is used to forecast one hour.

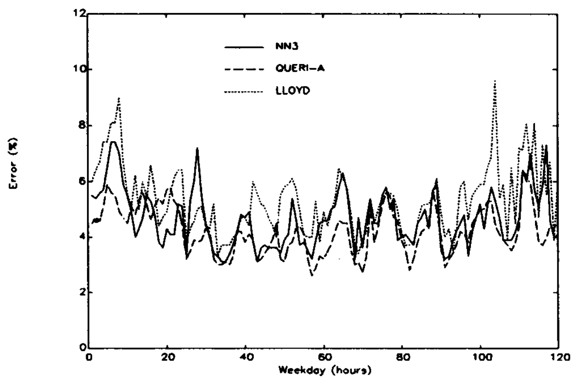

Figure 2: Forecasting Contest (Courtesy of Puget Sound Power and Light Company)

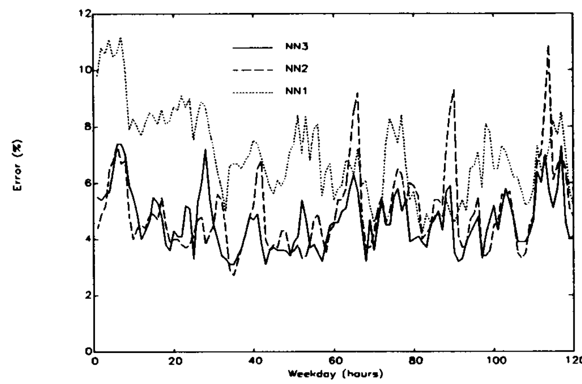

Figure 4: Forecasting Contest (Courtesy of Puget Sound Power and Light Company)

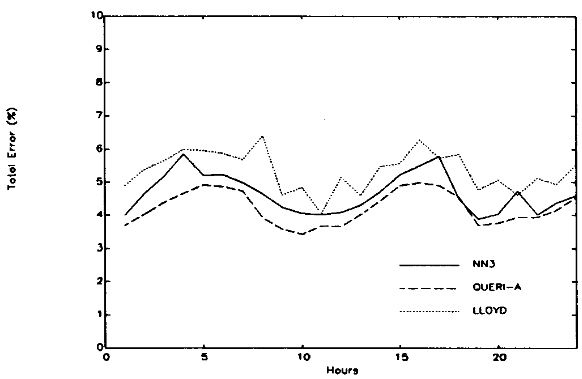

Figure 3: Forecasting Contest (Courtesy of Puget Sound Power and Light Company)

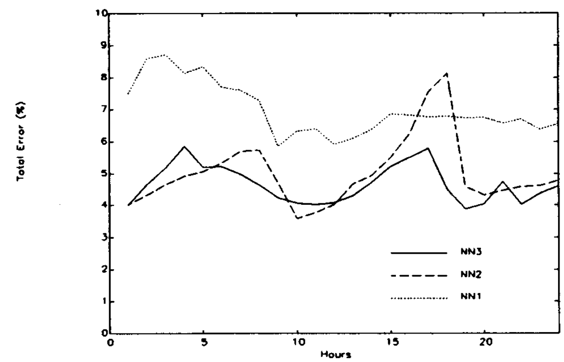

Figure 5: Forecasting Contest (Courtesy of Puget Sound Power and Light Company)

CONCLUSIONS

The study in this paper shows that NN's can be trained to predict the load demand with good accuracy. It is shown that when feature extraction is used, the accuracy of the NN is greatly enhanced. The NN faired well when compared to extensive forecasting methods. Yet NN is simple to build and train compared to the other available commercial, sophisticated forecasting codes.

It is also evident that one network cannot handle all cases where sparse representation exists in the training test. For example, a NN trained to predict electric loads during normal weather conditions, may not predict accurately during extreme weather conditions such as cold snaps and heat waves. To predict electric loads under these conditions, a separate NN may be needed. These comments also apply to all existing techniques.

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