Data Partitioning for Training a Layered Perceptron to Forecast Electric Load

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Abstract

The multi-layered perceptron (MLP) artificial neural network has been shown to be an effective tool for load forecasting. Little attention, though, has been paid to the manner in which data is partitioned prior to training. The manner in which the data is partitioned dictates much of the structure of the corresponding neural network. In many neural network forecasters, a different neural network is used for each day. We compare the performance of a daily partitioned neural network and hourly partitioned neural network. In our experiments, the hourly partitioned neural network forecaster has better performance than the daily partitioned neural network forecaster.

I. Introduction

Load forecasting using the multilayered perceptron (MLP) artificial neural networks has been shown to be quite effective [1-4]. Load forecasting data contains numerous stationary and cyclostationary components. There exists, for example, a daily pseudo-cyclostationary. The expected profile of the load from weekday to weekday is similarly cyclostationary. In many neural network load forecasters, one neural network is trained to forecast the load over a single cycle of a weekday. (Statistics for weekends and holidays are different and required separate neural networks.) Training data in most previously proposed load forecasting neural networks, was partitioned by days.

Alternatively, the data can be partitioned into loads at 8AM, 9PM, etc. and a separate neural network trained for each time. One advantage of such an approach is that the resulting statistics for each neural network are pseudo stationary. One expects, in general, that a feed forward MLP can predict stationary processes better than nonstationary (*e.g.* cyclostationary) processes. In this paper, we compare the results of neural networks trained in each way. We demonstrate that the autocovariance of the load data is maximum every 24 hours, thus suggesting that hour partitioning should give better results. This, indeed, is the case.

II. Problem Description

The electric load of Puget Power is forecasted at 9:00 AM of the previous day. For example, Tuesday forecasting is done on Monday at 9:00 AM. The exceptions are Saturday, Sunday, and Monday where forecasting is done on Friday at 9:00 AM. The available data is the true hourly temperature at Seattle/Tacoma airport, forecasted hourly temperature at Seattle/Tacoma airport, and the current hourly load. We forecast the hourly load based on the above available data.

III. Comparison between Daily Partitioned and Hourly Partitioned Neural Network Forecasters

1. Daily Partitioned Neural Network

We elected to use five neural networks. The neural network are for Monday, Tuesday, Wednesday through Friday, Saturday, and Sunday. The input data is

- Hour of the forecast (k).
- Forecasted temperature.
- Actual temperature and load 48 hours earlier (k-48).
- Actual temperature and load 49 hours earlier (k-49).
- Actual temperature and load 50 hours earlier (k-50).
- Actual temperature and load one week earlier (k-168).

In this simulation, we use the single hidden layer with 8 neurons. This is the manner by which the load was forecast in [3].

2. Hourly Partitioned Neural Network

Here, one neural network is used for each hour regardless of the day of the week. The input data for this structure

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is

- Forecast year.
- T(k) : Forecasted temperature at hour k.
- $[T(k)-60]^2$: The square of the difference between the forecasted temperature and the average indoor temperature.
- T_{max} : Maximum temperature of the forecast day.
- $[T_{max} - 60]^2$.
- T_{max2} : Maximum temperature of two days before.
- $[T_{max2} - 60]^2$.
- T_{min} : Minimum temperature from the forecast day.
- $[T_{min} - 60]^2$.
- T_{min2} : Minimum temperature of two days before.
- $[T_{min2} - 60]^2$.
- Sum of temperature at hour k of previous 7 days.
- Sum of loads at hour k of the previous 7 days.
- Load at hour k of previous day.
- Load at hour k two days earlier.
- Load at 9:00 AM of the current day.

In this simulation, we use the single hidden layer with 8 neurons.

3. Results

For training, we use the winter data from 1986-1987 to 1989-1990 in the Seattle/Tacoma area. The testing is done from November 7, 1990 to March 31, 1991. Figure 1 shows the relative error of the forecasting and the actual load from test data. As can be seen in Figure 1, the performance of the hourly partitioned neural network is better than that of the daily partitioned neural network. Figure 2 shows the autocovariance of the load.

The autocovariance is defined as

$$COV(n) = NUM(n) / DEM \quad (1)$$

where

$$NUM(n) = E[\{L(m+n)-E(L)\}\{L(m)-E(L)\}],$$

$$DEM = E[\{L(m) - E(L)\}^2]$$

and $E(\cdot)$ indicates the mean value. As can be seen in Figure 2, the autocovariance is maximum every 24 hours. This means that the functional relationship of the hourly partitioned neural network is more smooth than that of the daily partitioned neural network. This is why neural networks trained on hourly partitioned data perform better than those trained on daily partitioned data.

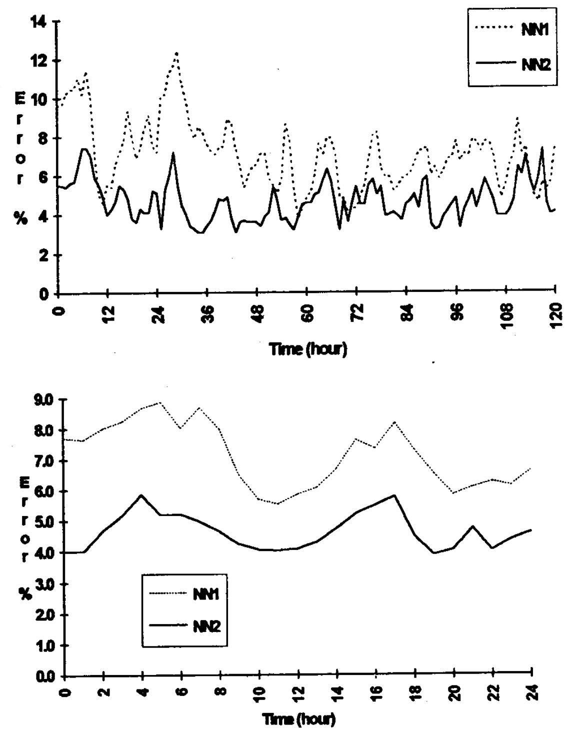

Figure 1: Comparison for the error of two structures. The solid line is for an hourly partitioned network and the broken line is for a daily partitioned network.

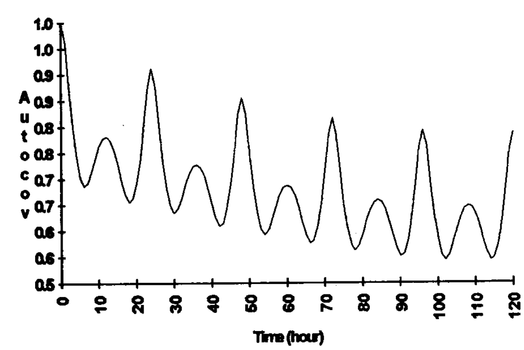

Figure 2: The autocovariance of the load after normalization by the maximum and minimum load of each hour. The peak occurs every 24 hours.

IV. Forecast Temperature Bias Effect

The performance of load forecasting depends highly on the accuracy of the forecasted temperature. One might expect that the error between the forecast temperature and the true temperature is unbiased. This, however, is not the case. The error is biased for certain time intervals. One solution to adjust for this bias is to train the neural network on the forecasted and the true temperature. In the data base available to us, however, the forecasted temperature data is not included. Another method is use of a correction term to augment the forecasted load. We choose the linear fit

$$L = C_1 * NN + C_2 * (T_f - T_a) + C_3 \qquad (2)$$

where L is forecast load, NN is neural network forecasted load, T_f is forecast temperature, and T_a is actual temperature. The coefficient values, C_1, C_2 and C_3 are determined by minimum mean square error. In the adaptive training mode, we used the above equation. In the testing mode, however, we do not have knowledge of the actual temperature. The second term of the above equation is therefore dropped.

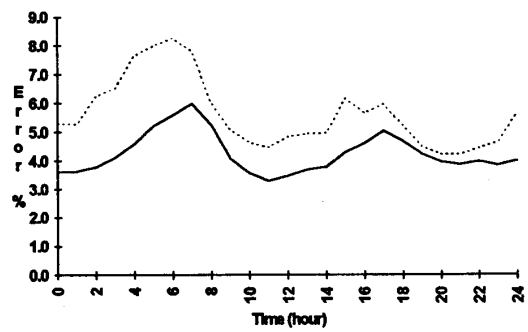

Figure 3: The error of the temperature compensating network. Solid line is for compensated network and broken line is for normal hourly partitioned network.

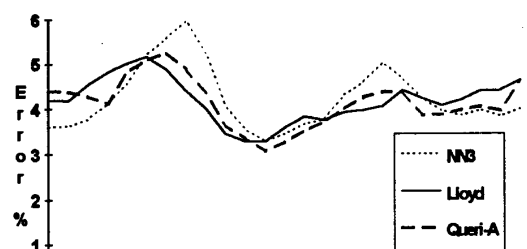

Figure 4: Forecasting contest (Courtesy of Puget Sound Power and Light Company).

Figure 3 and 4 show the comparison of the error between the forecast and actual load with this consideration and without this consideration in the period of November 7, 1991 to November 30, 1992. The results using (2) are clearly better. This forecast was placed into competition with other techniques in competition coordinated by the Puget Sound Power and Light Company. It did quite well. The interested reader is refereed to Brace et.al. [5] for details. Figure 4 shows the performance of the NN as compared to human forecaster (Lloyd) and a comprehensive regression method (Queri-A). These tests are reported in reference [5]

V. Conclusion

We compared the daily partitioned neural network and hourly partitioned neural network. The hourly partitioned neural network forecaster had better performance than the daily partitioned neural network forecaster. In addition, we demonstrated a technique whereby the effect of the forecasted and actual temperature can be corrected.

Acknowledgments

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