A.P. Alves da Silva, A.J. Rocha Reis, M.A. El-Sharkawi, R.J. Marks II, "Enhancing Neural Network Based Load Forecasting Via Preprocessing", IEEE ISAP2001, Budapest, Hungary, June 18-21,2001, pp.118-123.

Enhancing Neural Network Based Load Forecasting Via Preprocessing

A.P. Alves da Silva[1], A.J. Rocha Reis[1]
[1] Federal Engineering School at Itajuba / Institute of Electrical Engineering
Av. BPS, 1303 - Itajuba, MG, 37500-176, Brazil

M.A. El-Sharkawi[2], R.J. Marks II[2]
[2] University of Washington / Department of Electrical Engineering
Box 352500 - Seattle, WA, 98195-2500, USA

Abstract: The importance of Short-Term Load Forecasting (STLF) has increased, lately. With deregulation and competition, energy price forecasting has become a big business. Load bus forecasting is essential for feeding the analytical methods used for determining energy prices. The variability and nonstationarity of loads are getting worse due to the dynamics of energy tariffs. Besides, the number of nodal loads to be predicted does not allow frequent interventions from load forecasting specialists. More autonomous load predictors are needed in the new competitive scenario. Despite the success of neural network based STLF, techniques for preprocessing the load data have been overlooked. In this paper, different techniques for preprocessing a load series have been investigated. The main goal is to induce stationarity and to emphasize the relevant features of the series in order to produce more robust load forecasters. One year of load data from a Brazilian electric utility has been used to validate the proposed methodology.

Keywords:Digital Filters, Neural Networks, Load Forecasting.

I. INTRODUCTION

Artificial Neural Networks (NNs) have been successfully applied to Short-Term Load Forecasting (STLF) [1-4]. Many electric utilities that had previously employed STLF tools based on classical statistical techniques, now are using NN based STLF programs [5, 6]. It is one of those rare cases in history where science has become technology after a short period of development. Nevertheless, this technology is far from reaching its limitations. Data preprocessing for load series analysis has been extensively studied by classical statistics [7]. However, due to the robustness of NN models, the benefits of data preprocessing has been underestimated in NN based load forecasting.

Techniques such as signal centralization, standardization, transformation, detrending, differencing, seasonal differencing, and filtering have been almost completely ignored. References [8, 9] are among the few exceptions. These techniques are useful for emphasizing important features of the load series, improving stationarity, and removing outliers. Without them, linear models for prediction would be completely useless [10]. On the other hand, as NN models can include nonlinear effects, can deal, to a certain extent, with trends, seasonal components and outliers, data preprocessing for NNs has not been common practice. Nevertheless, it seems reasonable to remove from the load series the almost deterministic information, saving the NN learning capability for modeling the not so obvious regularities.

Paper ISAP2001–N° 56 accepted for presentation at the IEEE ISAP2001 Conference, Budapest, Hungary, June 18-21, 2001.

In other words, if the designer knows beforehand any information, then it should be incorporated in the model rather than requiring the network to learn it from examples.

The two main contributions of this paper are related to improving stationarity and emphasizing important features of load series for NN training. It is well known that differencing improves stationarity. Even a NN model is expected to have a better performance if differencing is applied. The high frequency components of the load series, mostly related to random noise, can obscure the important regularities of the data, making the NN training harder. Filtering can smooth the load curves, removing outliers and bringing up important information. However, not all high frequency fluctuations are meaningless. The idea is to smooth the data, for the clarity it brings to lower frequency components, feeding the NN also with the original series and/or the differenced series, to find high frequency patterns, too.

This paper is divided as follows. In Section II, data normalization, centralization, differencing and seasonal differencing are analyzed. Filtering is the subject of Section III. In Section IV, the proposed load forecasting models are described. These models are compared through forecasting simulations in Section V. Finally, Section VI presents the main conclusions of this paper and indicates some directions for future work.

II. NORMALIZATION & DIFFERENCING

Depending on the type of activation function used in the NN output neuron(s), it is necessary to normalize the output variable(s) in order to consider the activation function output range. Even when the activation function output is unbounded (e.g., a linear activation function), it is still useful to normalize the output and the input variables in compatible ranges. This procedure usually helps to improve training efficiency. The basic motivation for normalizing input and output variables is to make them equally important to the training process. Normalization also helps to improve the NN mapping interpretability.

The most common normalization procedure is the one in which the variables are linear transformed according to pre-specified minimum and maximum values. However, a complementary normalization procedure based on the standardization of variables, i.e. transforming the variables such that they have zero mean and unit standard deviation, can be very useful. This complementary transformation makes different variables directly comparable. Notice that it is still necessary to apply the first mentioned ordinary transformation afterwards, in order to guarantee the plausibility of the transfer function output range.

The process of differencing computes the differences of adjacent values of a load series, i.e. the new series represents the variations of the original one. Differencing helps to improve stationarity. For instance, a linear trend can be easily removed applying differencing. For more complex data, it can be necessary to apply differencing more than once. Another reason for differencing is that, depending on the variable, the variations can be more important than the original values (e.g., temperature). Differencing can be interpreted as a kind of high-pass filter.

Electric load series have very strong seasonal components. They are always characterized by daily, weekly and annual seasonal patterns. Except when dealing with certain special holidays (Christmas, New Years', etc.), the annual seasonality is irrelevant for STLF purposes. This is because the training window does not usually exceed a few weeks, in order to preserve stationarity. Seasonal differencing, i.e. computing the differences for the corresponding seasonal period, is also important for inducing stationarity. With seasonal differencing, the importance of the seasonal lag is implicitly embedded into the model, without the need of explicitly including the corresponding lagged term as an input variable.

III. FILTERING

Electric load series (global, regional or per bus) are formed by the aggregation of individual consumers of different natures (residential, commercial and industrial). A good piece of the information provided by a load series is useful for forecasting purposes. The rest is related to a random component (noise). Therefore, there are three main reasons for filtering an electric load time series. First, the noise can be reduced. Second, important features of the load series can be emphasized. Finally, a partition in different components of the load series can be produced, decreasing the learning effort.

Digital filters have been used in this work. It is necessary to avoid losing important information contained in the original time series when applying filters to forecasting. Linear filters have been suggested for avoiding this problem [11]. The idea can be illustrated by the application of one single filter. In order to not lose any relevant information, the filtered series is subtracted from the original one. Therefore, by adding the output of the filter with the result of the subtraction, the original series is perfectly reconstructed.

Usually, more input variables feed the NN load forecasters when filters are applied to preprocessing the original data (e.g., lagged variables related to the filtered series plus lagged variables related to the complementary series). However, as these variables are nearly independent, the forecasting models are not significantly affected by the curse of dimensionality. Filters can be characterized by their cutoff frequencies and widths. The width parameter needs a careful specification. The smaller it is (producing a narrow transition zone from the cutoff frequency to total cutoff), more load values are used for filtering each value. It is not appropriate to use too many load values before and after a certain time slot in order to filter its value. A few adjacent neighbors are supposed to contain the most useful information for this purpose, without excessively enlarging the filter width.

Digital filters in the frequency domain are employed in this work. An important point to be taken into account is the problem known as circular convolution. The discrete Fourier-transformer wraps the time series around in a circle. This is equivalent to appending the beginning of the series at its end and vice-versa. Therefore, for forecasting purposes, where the last known load values are usually among the most relevant data, circular convolution is a major concern. As it is not possible to avoid circular convolution, padding is adopted. Padding means attaching convenient data at the end and/or at the beginning of the load series. The objective is to avoid the influence of circular convolution on both sides of the load series used for training and on the data required for prediction.

No padding and two different padding schemes have been compared in this work. The first padding scheme includes zeros at the beginning and at the end of the load series. The second one appends the previous load values at the beginning of the series and forecasted values at the end of it. Another important question is related to the length of the attached information. A conservative estimation for the attachment length can be determined by the following procedure. Initially, the minimum attachment to both sides of the series is determined, considering the filter width. Then, the next power of two greater than the sum of the original load series length with the minimum attachment is used to define the final attachment length. The extra padding to reach a power of two does not affect the filtering of the first and last original load series values. It is included to improve the discrete Fourier transformer efficiency, i.e. to allow the application of the FFT.

The following procedure for filtering a load series has been adopted [12]. Initially, pad as previously described. Reference [11] suggests that the minimum padding on each side of the series can be estimated dividing 0.8 by the filter width. Then, compute the discrete Fourier transformer (1):

$$w_j = \sum_{k=0}^{n-1} [P_k \cos\left(\frac{2\pi jk}{n}\right) + P_k \sin\left(\frac{2\pi jk}{n}\right)]. \qquad (1)$$

Following that, perform a low-pass filtering in the frequency domain applying an energy decay factor (2) to w_j, after the filter cutoff frequency j_c. The parameter l determines the filter width.

$$H(j) = e^{-\left(\frac{j-j_c}{l}\right)^2} \quad \text{for } j > j_c \qquad (2)$$

Next, apply the inverse transform to return to the time domain (3). Finally, disregard the filtered values corresponding to padding.

$$P_k^f = \frac{1}{n}\sum_{j=0}^{n-1} [w_j^f \cos\left(\frac{2\pi jk}{n}\right) - w_j^f \sin\left(\frac{2\pi jk}{n}\right)] \qquad (3)$$

IV. LOAD FORECASTING MODELS

This section describes load forecasters that employ different combinations of preprocessing. Six possibilities have been compared. The first four do not apply filtering in the frequency domain to the load series. The idea is to incorporate different alternatives of preprocessing, one by one, and to verify the corresponding performance gain. The basic set of input variables correspond to the lagged values of the hourly load series by 1h, 2h, 24h and 168h, and two additional inputs, $HS(k)=\sin(2\pi k/24)$ and $HC(k)=\cos(2\pi k/24)$, codifying the hour of the day. The output corresponds to the one step ahead load forecast.

It has been recently shown that the best input variables for linear load predictors are not necessarily among good input variables for nonlinear ones [13]. The present work keeps using the most popular input variables for load forecasting purposes. This is because the main goal of this paper is to show that the preprocessing of a load series is very beneficial for nonlinear predictors, too.

The selected architectures for each input set (Sections A-F) vary with respect to the number of hidden neurons. One to three hidden neurons have been used depending on the period of the year. Wintertime, because of weather stability, is usually the easiest season for load prediction, therefore requiring less hidden neurons. Summer and the transition seasons, for the opposite reason, are more difficult, consequently demanding more hidden neurons. One single hidden layer has been used. Hyperbolic activation functions and a linear activation function have been employed in the hidden and output layers, respectively.

A. Model 1 (M1)

The first load forecaster is the simplest one. It uses the basic set of input variables with ordinary normalization (e.g., minimum and maximum values in the [0;1] range). The output variable is also normalized with the same procedure. Fig. 1 shows this Multi-Layer Perceptron (MLP) load predictor.

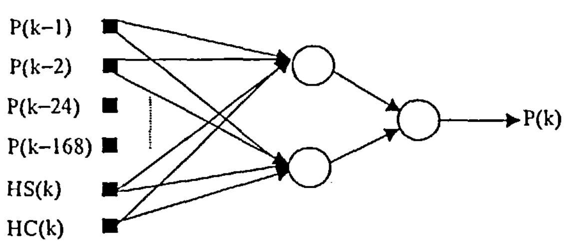

Fig. 1. Load forecaster with basic inputs.

B. Model 2 (M2)

The second model uses the same structure and the same type of inputs as M1. However, the normalization procedure for the input and output variables is not the same. For M2, the normalization is also based on standardization of the variables (zero mean and unit variance). Fig. 2 shows the diagram for M2.

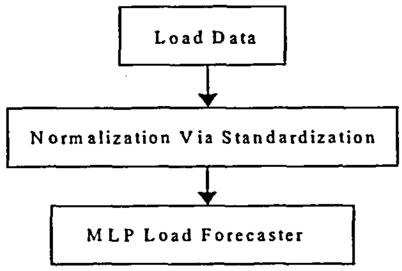

Fig. 2. Load forecaster with standardized variables.

C. Model 3 (M3)

The third load predictor adds differenced variables to the set of inputs of M2. Therefore, two time series are employed: the standardized and the differenced one. Differencing is applied to the standardized series. For M3, only the first-order time differences (D) are considered. Fig. 3 illustrates the new set of inputs.

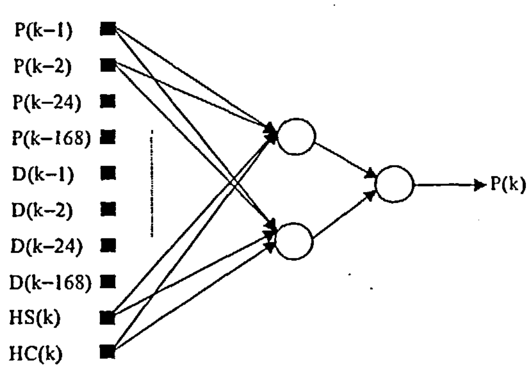

Fig. 3. Input set for model 3.

D. Model 4 (M4)

In M4, seasonal differencing is incorporated (Fig.4). Taking the first-order differenced series (D), a twenty four hour differencing period is applied, producing a new series SD. Since the 24 hour seasonal pattern is removed from series D, there is no need for the input variable SD(k−24).

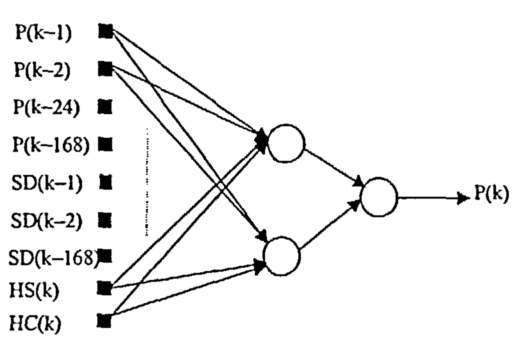

Fig. 4. Adding seasonally differenced inputs.

A.P. Alves da Silva, A.J. Rocha Reis, M.A. El-Sharkawi, R.J. Marks II, "Enhancing Neural Network Based Load Forecasting Via Preprocessing", IEEE ISAP2001, Budapest, Hungary, June 18-21,2001, pp.118-123.

E. Model 5 (M5)

Model 5 adds filtered variables to the M2 inputs, removing P(k−1), P(k−2), P(k−24) and P(k−168) to avoid redundancy (Fig.5). Only a low-pass filter is applied. The cut-off frequency is 1/24 cycles per sample and the filter width is 0.025. For this filter width, a minimum padding of 32 points is required for each side of the load series. The forecasts for padding are provided by M3. The new filtered series (LOW) describes the daily load behavior in a very smooth way. The complementary series (COM), i.e. the standardized load series minus the filtered series, is also used in order to provide higher frequencies information.

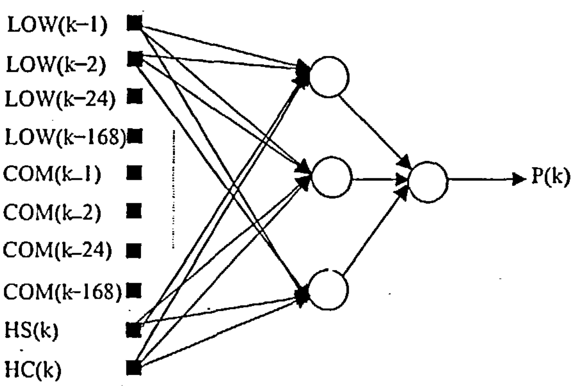

Fig. 5. Incorporating filtered inputs to the load forecaster.

F. Model 6 (M6)

The last predictor is similar to M5, except that new input variables are added to it. These new variables are the first-order differences D(k−1), D(k−2), D(k−24) and D(k−168) of the standardized load series. It is worthwhile to mention that the combination of the first-order differencing with the daily/weekly seasonal differencing has also been tried. However, it has degraded the predictor's performance. It seems that the NNs prefer to receive the seasonal information directly. The following diagram describes M6.

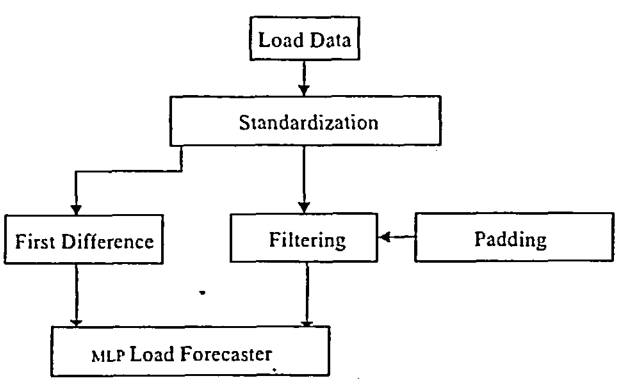

Fig. 6. Adding differenced inputs to model 5.

Fig. 7 illustrates the effect of applying the low-pass filter specified for models 5 and 6. Notice that as a side effect of smoothing, the peaks and valleys of the original load curve are attenuated. However, important features of the original series are emphasized, such as load levels, slopes and trend reversals.

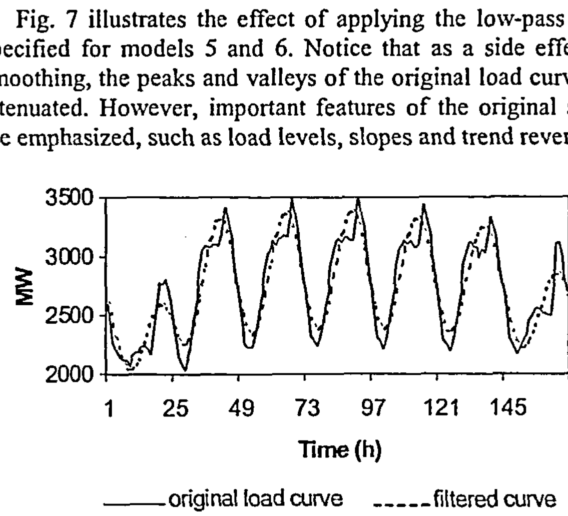

Fig. 7. Application of the low-pass filter.

V. TESTS

A comparison of the six previously mentioned models has been performed. Six-week windows have been taken for training (and testing), with data grouping according to the day of the week. For each day of the week, a MLP has been trained, applying the backpropagation algorithm with cross-validation. Different partitions for the training and testing sets are randomly created every 50 epochs. During the NNs training, there is no particular treatment for holidays. Special days have been excluded from the training set. A load series from an electric utility in Rio de Janeiro, Brazil, has been used (maximum load around 3,900 MW).

After the one-step ahead training, the one to twenty four steps ahead recursive load forecasts are computed. The load forecasters are retrained at the end of the day. The six-week training window is moved one day forward, and the forecasts for the next 24 hours are performed (predictions always start at midnight). This validation procedure is repeated for one year. The Mean Absolute Percentage Error (MAPE), Mean Square Error (MSE), Mean Error (ME) and Maximum percentage error (MAX) have been used to evaluate the load forecasting models. The following tables present the forecasters performances for different days of the week (Table I), for 1-24 steps ahead predictions (Table II), and a global average evaluation (Table III).

TABLE I - MAPEs ACCORDING TO THE DAY OF WEEK

Day	M1	M2	M3	M4	M5	M6
Sunday	3.2	3.2	2.7	3.6	2.5	2.6
Monday	3.0	3.0	2.3	3.1	2.4	2.4
Tuesday	2.7	2.6	2.4	2.7	2.2	2.0
Wednesday	2.4	2.2	1.7	2.4	1.7	1.6
Thursday	2.8	2.7	2.4	2.8	2.1	1.9
Friday	2.1	2.5	2.0	2.4	1.7	1.9
Saturday	3.3	3.1	2.5	3.1	2.5	2.5

TABLE II - FORECASTING PERFORMANCES (MAPEs) FOR EACH LEAD-TIME

Steps Ahead	M1	M2	M3	M4	M5	M6
1	2.6	2.5	1.3	2.6	1.6	1.5
2	3.7	3.6	1.8	4.0	1.7	1.7
3	4.0	3.8	2.3	4.5	2.1	2.1
4	3.8	3.7	2.6	4.2	2.2	2.1
5	3.6	3.5	2.5	3.7	2.1	2.0
6	3.4	3.2	2.6	3.3	2.2	2.1
7	3.0	3.0	2.5	2.9	2.3	2.3
8	2.7	2.5	2.4	2.6	2.2	2.3
9	2.4	2.1	2.2	2.4	2.0	2.1
10	2.0	2.0	2.2	2.5	2.1	2.1
11	1.9	2.1	2.0	2.2	2.0	1.9
12	1.9	2.0	1.8	1.9	1.8	1.8
13	2.1	2.1	1.9	2.1	1.9	1.8
14	2.1	2.1	2.0	2.0	2.0	2.0
15	2.6	2.4	2.1	2.3	2.1	2.2
16	2.7	2.7	2.5	2.7	2.4	2.6
17	2.9	2.9	2.6	2.8	2.6	2.7
18	3.2	2.9	2.4	2.7	2.4	2.6
19	2.8	2.7	2.1	2.8	2.2	2.2
20	3.1	3.3	2.6	3.5	2.5	2.5
21	2.2	2.4	2.1	2.6	1.8	1.8
22	2.0	2.2	2.2	2.4	2.1	1.9
23	2.7	2.7	2.7	2.7	2.4	2.2
24	3.6	3.6	3.3	3.4	2.7	2.4

TABLE III - OVERALL EVALUATION OF THE LOAD PREDICTORS

Index	M1	M2	M3	M4	M5	M6	Gain (%)
MAPE (%)	2.8	2.7	*2.3*	2.9	2.1	*2.1*	*8.7*
MSE (MW^2)	10,930	10,618	*7,486*	11,371	6,655	*6,392*	*14.6*
ME (MW)	−1.4	−9.1	*−7.3*	−2.2	−10.0	*−8.2*	*−12.3*
MAX (%)	8.6	8.6	*7.0*	9.2	6.7	*6.5*	*7.1*

Model 3 has been the most accurate among the predictors which have not applied filtering in the frequency domain for preprocessing the input data. That justifies the option of taking its forecasts for padding the data to be used by M5 and M6. Models 5 and 6 are not as precise as model 3 for one step ahead forecasts (see Table II). This is the bad side effect of filtering, i.e. the model takes longer to react to sudden changes in the load behavior. However, for multiple steps ahead, filtering decreases the forecasting errors.

It is clear that a larger forecasting lead-time does not necessarily imply in a larger forecasting error. That depends on the data variability for the different periods of the day [14]. Notice that the MSE, in Table III, points out a greater number of high errors for M3. The incorporation of differencing has made M6 more precise and less biased than M5 (see ME in Table III). The Gain column in Table III compares models 3 and 6.

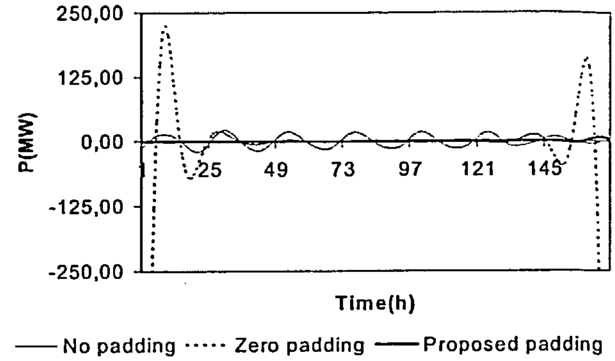

Fig. 8. Distortions generated by different padding schemes.

An important decision regarding the estimation of models 5 and 6 is related to the type of padding to be used. Three possibilities were mentioned in Section III: no padding, padding with zeros, and padding with measured values at the beginning of the series and with forecasted values at the end of it. Fig. 8 shows the deviations of these three schemes from the result of the ideal padding, i.e. measurements attached to the beginning and to the end of the series, too. Notice that for forecasting purposes the measured values at the end of the series are, in principle, unknown. The filtered series with no padding presents oscillations allover. The zero padding scheme introduces very heavy oscillations on both sides of the filtered series. The proposed padding scheme (the third one) produces a filtered series quite similar to the one generated by the ideal padding, i.e. almost zero deviation.

Fig. 9 shows a typical case for the training/testing (cross-validation) of predictors 3 and 6. Besides being more stable, the training process for M6 always has lower testing errors along the epochs than M3.

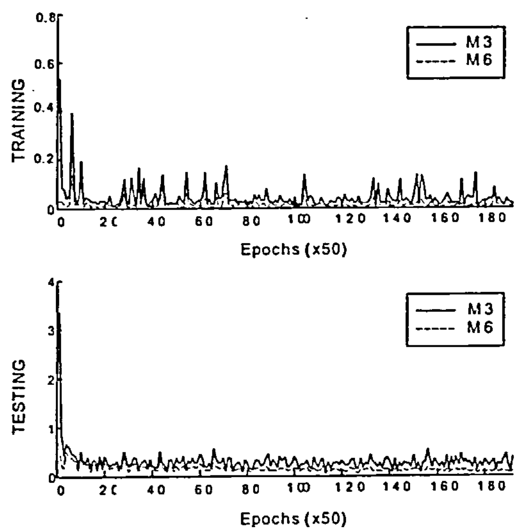

Fig. 9. Improving the learning capability through filtering

VI. CONCLUSIONS

With power systems growth and the increase in their complexity, many factors have become influential to the electric power generation and consumption. Therefore, the forecasting process has become even more complex, and more accurate forecasts are needed. Short-term load forecasting is essential for feeding the analytical methods used for determining the short-term energy prices. The variability and nonstationarity of electric loads are increasing because of the dynamics of energy tariffs. More autonomous and robust load predictors are needed in the new competitive environment.

In this work, the implications of preprocessing a load series for prediction have been investigated. Six procedures for preprocessing a load series have been compared. The combination of standardization, first-order differencing and linear filtering has been the most effective. It has been shown that the padding scheme for the low-pass filter is very important. Attaching load measurements to the beginning of the series and forecasted values on the other side has been the best way to avoid distortion due to circular convolution.

The best load predictor without filtering in the frequency domain, i.e. the one responsible for padding, applies standardization and first-order differencing to the load data. It is true that the computational effort increases with the application of preprocessing based on filtering in the frequency domain. Although, using the fast Fourier transformer, the filtering itself does not introduce a heavy computational burden, the number of NNs doubles (since M3 MLPs are also required). However, considering the performance gains, filtering is worthwhile.

Future work will focus on the incorporation of input variables related to weather. Due to climatic diversity over the geographical zone of interest, many meteorological stations are necessary to establish a significant correlation with the load. Installation of such devices is still being planned by the local electric utility. Although it would be desirable to count on such information, the univariate adaptive procedure proposed in this paper implicitly tracks the weather induced load changes over the short-term. Nevertheless, the same idea, i.e. preprocessing, applies to multivariable time series as well. The application of other types of filters, such as the ones based on wavelets, will also be investigated.

VII. ACKNOWLEDGMENTS

This work was supported by the Brazilian Research Council (CNPq), under grant No. 300054/91-2, and by FINEP/RECOPE, project 0626/96-SAGE. The paper was concluded while the first author was on Sabbatical in the Department of Electrical Eng. at University of Washington.

VIII. REFERENCES

[1] K. Liu, S. Subbarayan, R.R. Shoults, M.T. Manry, C. Kwan, F.L. Lewis, and J. Naccarino, "Comparison of very short-term load forecasting techniques". IEEE Trans. Power Systems, vol. 11, no. 2, May 1996, pp. 877-882.

[2] A.G. Bakirtzis, V. Petridis, S.J. Klartzis, M.C. Alexiadis, and A.H. Maissis, "A neural network short-term load forecasting model for the Greek power system". IEEE Trans. Power Syst., vol. 11, no. 2, May 1996, pp. 858-863.

[3] O. Mohammed, D. Park, R. Merchant, T. Dinh, C. Tong, A. Azeem, J. Farah, and C. Drake, "Practical experiences with an adaptive neural network short-term load forecasting system". IEEE Trans. Power Systems, vol. 10, no. 1, February 1995, pp. 254-265.

[4] D.C. Park, M.A. El-Sharkawi, R.J. Marks II, L.E. Atlas, and M.J. Damborg, "Electric load forecasting using an artificial neural network". IEEE Trans. Power Systems, vol. 6, no. 2, May 1991, pp. 442-449.

[5] A. Khotanzad, R. Afkhami-Rohani, and D. Maratukulam, "ANNSTLF – artificial neural network short-term load forecaster – generation three". IEEE Trans. Power Syst., vol. 13, no. 4, November 1998, pp. 1413-1422.

[6] H. Mori, "State-of-the-art overview on artificial neural networks in power systems". in A Tutorial Course on Artificial Neural Networks with Applications to Power Systems, IEEE Catalog no. 96TP112-0, Edited by M.A. El-Sharkawi and D. Niebur, 1996, pp. 51-70.

[7] G. Gross and F.D. Galiana, "Short term load forecasting". Proceedings of IEEE, vol. 75, no. 4, December 1987, pp. 1558-1573.

[8] E. Doveh, P. Feigin, D. Greig, and L. Hyams, "Experience with FNN models for medium term power demand predictions". IEEE Trans. Power Systems, vol. 14, no. 2, May 1999, pp. 538-546.

[9] T.W.S. Chow and C.-T. Leung, "Nonlinear autoregressive integrated neural network model for short-term load forecasting". IEE Proc.-Gener. Transm. Distrib., vol. 143, no. 5, September 1996, pp. 500-506.

[10] G.E. Box and G.M. Jenkins, Time Series Analysis, Forecasting and Control. Holden-Day, 1976.

[11] T. Masters, Neural, Novel and Hybrid Algorithms for Time Series Prediction. John Wiley & Sons, 1995.

[12] C.B. Rorabaugh, Digital Filter Designer's Handbook: with C++ algorithms. McGraw-Hill, Second Edition, 1997.

[13] I. Drezga and S. Rahman, "Input variable selection for ANN-based short-term load forecasting". IEEE Trans. Power Systems, vol. 13, no. 4, November 1998, pp. 1238-1244.

[14] A.P. Alves da Silva and L.S. Moulin, "Confidence intervals for neural network based short term load forecasting", IEEE Trans. Power Systems, vol. 15, no. 4, November 2000, pp. 1191-1196.

IX. BIOGRAPHIES

Alexandre P. Alves da Silva (SM) received the Ph.D. degree in Electrical Engineering (EE) from University of Waterloo, Canada, in 1992. He is a Professor of EE at the Federal Engineering School at Itajuba (EFEI), Brazil. <alex@iee.efei.br>

Agnaldo J. Rocha Reis (S) received the B.Sc. and M.Sc. degrees in EE from Catholic University of Minas Gerais and EFEI, in 1996 and 1999, respectively. He is currently working towards the D.Sc. degree in EE at EFEI. <agnreis@iee.efei.br>

Mohamed A. El-Sharkawi (F) received the Ph.D. degree in EE from University of British Columbia, Canada, in 1980. He is a Professor of Electrical Engineering at University of Washington (UW), US. <elsharkawi@ee.washington.edu>

Robert J. Marks II (F) received the Ph.D. degree in EE from Texas Tech University, US, in 1977. He is a Professor of EE at UW. <marks@ee.washington.edu>