A REAL-TIME SHORT-TERM LOAD FORECASTING SYSTEM USING FUNCTIONAL LINK NETWORK

P.K.Dash, H.P.Satpathy  
Centre for Intelligent Systems  
Regional Engineering College  
Rourkela, India.

A.C.Liew  
Dept. of Electrical Engineering  
National University of Singapore  
Singapore

S.Rahman  
Virginia Polytechnic Institute and State University  
U.S.A.

Abstract

This paper presents a new functional-link network based short-term electric load forecasting system for real-time implementation. The load and weather parameters are modelled as a nonlinear ARMA process and parameters of this model are obtained using the functional approximation capabilities of an auto-enhanced Functional Link net. The adaptive mechanism with a nonlinear learning rule is used to train the link network on-line. The results indicate that the functional link net based load forecasting system produces robust and more accurate load forecasts in comparison to simple adaptive neural network or statistical based approaches. Testing the algorithm with load and weather data for a period of two years reveals satisfactory performance with mean absolute percentage error (MAPE) mostly less than 2% for a 24-hour ahead forecast and less than 2.5% for a 168-hour ahead forecast.

1. Introduction

The short-term load forecast (one to twenty four hours) is of importance in the daily operations of a power utility. It is required for unit commitment, energy transfer scheduling and load dispatch. With the emergence of load management strategies, the short-term load forecast has played a broader role in utility operations. The development of an accurate, fast and robust short-term load forecasting methodology is of importance to both the electric utility and its customers.

Many algorithms have been proposed in the last few decades for performing accurate load forecasts. The most commonly used techniques include statistically based techniques, expert system approaches and artificial neural network algorithms (ANN). The time series [1] and regression techniques are the two major classes of conventional statistical algorithms, and have been applied successfully in this field for many years. The expert systems based algorithm [2] for short-term load forecasting use a symbolic computational approach to automating intelligence. This approach takes advantage of the expert knowledge of the operator which is, however, neither easy to elicit nor articulate. A major advantage of using ANN [3-5] over expert systems is its non-dependency on an expert. Furthermore ANN also performs non-linear regression among load and weather patterns and can also be used to model the time series method or as a combination of both.

Generally, time series approaches assume that the load can be decomposed into two components. One is weather dependent and the other is weather independent. Each component is modelled separately and the sum of these two gives the total load forecast. The behaviour of weather independent load is mostly represented by Fourier series or trend profiles in terms of time functions. The weather sensitive portion of the load is arbitrarily extracted and modelled by a predetermined functional relationship with weather variables.

An adaptive neural network approach has been recently proposed by Peng et al [6] which incorporates the familiar Box and Jenkins time series model. Instead of off-line simulation, Adalines are used to update the model parameters and simulation results indicate that one-week ahead hourly forecasts can be generated with mean absolute percentage error of less than 3.4 per cent. This forecasting model does not consider the weather dependency of the load, particularly the temperature and uses only past load.

The objective of the present approach is to study the Functional-Link Net [10] architecture to identify a time-series load model incorporating the nonlinearity due to temperature variations. The functional-link-network has an input vector comprising the fourier series functions and nonlinear components comprising the temperature functions and their enhancements. The model parameters are identified during training and once the convergence is achieved, the forecasting model is ready for prediction. This new approach is totally adaptive and generalized and does not depend upon the season and day type. The forecasting accuracy of functional-link net compared to the adaline for one week ahead forecasting is less than 2.5 percent instead of 3.4 percent for the later. The approach is highly flexible and Sundays and holidays can be easily included. The approach presented in this paper is amenable for real-time implementation, as hourly or daily adaptation of model parameters can be done.
2. Overview of the Proposed Approach

The short-term load forecasting model for a power utility is assumed to generally consist of four components: (i) Deterministically known load component, \( L_d(t) \), which represents the abnormal load changes in the future (such as scheduled shut down of a manufacturing unit or scheduled trip off of a transmission line). (ii) Weather independent component, \( L_w(t) \), which represents the system intrinsic load component. (iii) Weather dependent load component, \( L_a(t) \), (iv) Noise residual component, \( L_n(t) \).

Thus total load is the sum of the above four components and is given by

\[
L(t) = L_d(t) + L_w(t) + L_a(t) + L_n(t)
\]

Out of the above four components, the deterministic component does not require any prediction. The weather independent load \( L_w(t) \) is modelled as a Fourier series and comprises a constant part, \( q_0 \), and a time varying part that is function of \( m \) frequencies with a daily periodicity. This component is represented by

\[
L_w(t) = a_0 + \sum_{i=1}^{m} q_i \sin(k_i t)
\]

\( \omega_i = \frac{2\pi}{T} \) radius per hour. The fundamental time period \( T \) is defined as 24 hours for 24-hour ahead forecasting and 168-hours for one week ahead forecasting. The most suitable value of \( m \) is either chosen by spectral analysis or trial-and-error. In the present implementation \( m \) is chosen as 12.

In general weather conditions affecting electric load behaviour include temperature, humidity, wind speed, cloud cover and other abnormal situations such as thunderstorms, etc. Investigations have shown that, in most situations temperature is usually the leading factor affecting the load behaviour among all weather variables. However, relative humidity has some importance when the temperature condition is abnormal in summer and wind speed is an important factor in winter with low temperature conditions. Thus the weather dependent load component is modelled as

\[
L_a(t) = \beta_1 T_a(t) + \beta_2 T_a^2(t) + \beta_3 T_a^3(t)
\]

where \( \beta_1, \beta_2, \) and \( \beta_3 \) are the nonlinear temperature model coefficients. It may be worthwhile to use an equivalent temperature \( T_{eq}(t) \) to account for humidity. Here \( T_{eq}(t) \) represents the temperature (°C) for the hour \( t \) of the day of forecast.

3. Auto-Enhanced Functional Link Network

The load forecasting model described in equation (1) is realised by using a special kind of neural network called "Auto enhanced functional link net"[10]. Functional Link Net (FLN) represents the network architecture that allows unsupervised learning, supervised learning and associative retrieval to be carried out with the same net configuration and with the same data structure. The basic idea behind a Functional Link Net is the use of links for affecting the nonlinear transformations of the input pattern before it is fed to the input layer of the actual network. The concept of the functional link network is illustrated in Fig.1.

The idea is that activation of node \( K \) offers the possibility that different additional processes \( f_1(y(k)), \ldots, f_n(y(k)) \) may also be used to activate through a functional link network. In a normal feedforward neural network, vector-to-vector mapping can be represented by a series of linear matrix multiplications, each of which is followed by a nonlinear activation function transformation. The form for the activation function is fixed to be one of several standard varieties and only the values of the threshold parameter are varied in the learning process. In contrast to this, the learning of the functional form of mapping approximating the unknown nonlinear function \( y(k) \) in terms of an expansion with unknown coefficient is attempted. In this way the generation of an enhanced pattern in place of an actual pattern is performed. The flat architecture of the FLN exhibits highly desirable learning capabilities and in some applications like the load forecasting, reduces the convergence time drastically. A single layer auto-enhanced functional-link net is described in this section to correctly represent the load forecasting model as shown in Fig.2. The input to the net comprises a linear harmonic series and nonlinear weather sensitive portion as

\[
X = [X_1, X_2]^T
\]

where

\[
X_1 = \begin{bmatrix}
1 \\
\cos\omega_1t \\
\sin\omega_1t \\
\cos\omega_2t \\
\sin\omega_2t \\
\vdots \\
\cos\omega_m t \\
\sin\omega_m t
\end{bmatrix}
\]

\[
X_2 = \begin{bmatrix}
x \ G(A_1 x + b_1) \ldots \ G(A_n x + b_n)
\end{bmatrix}^T
\]

where, \( x = \begin{bmatrix} T_a(t) \\ T_a(t)^2 \\ T_a(t)^3 \end{bmatrix} \)

\( T_a \) = temperature of the forecasted hour and \( (A_j x + b_j) \) represents a linear transformation of the input temperature pattern vector with \( G \) representing any squashing function. The estimated output of the net is given by

\[
\hat{y} = W^T X
\]

where \( W \) is the weight vector.

In the one-hidden layer neural network, two sets of weights \( W \) and \( A_j \) and thresholds \( b_j \) need to be learned, through back propagation of error. But in the auto-enhancement version of the functional-link net, the \( \{A_j\} \) and \( b_j \) are generated randomly. This results in a flat-net architecture for which only weights \( W \) need to be learnt. The hyperbolic tangent function is used as the activation function \( G \) in (5). Thus the total input vector \( X \) becomes

\[
X^T = [1 \ \cos\omega_1t \ \cos\omega_2t \ \ldots \ \cos\omega_m t \ \sin\omega_1t \ \sin\omega_2t \ \ldots \ \sin\omega_m t \ \tan h(a_1 T_a(t)) + a_2 T_a^2(t) + a_3 T_a^3(t) + b_1) \]

\[
\ldots \tan h(a_n T_a(t)) + a_2 T_a^2(t) + a_3 T_a^3(t) + b_n]
\]
The forecasting error generated by the autoenhanced flat link net model can be used to improve the accuracy of the final forecast. This error is based on the models most recent performance for 24-hour ahead forecast, the forecasting error is available at the end of each day when the actual load for all the 24-hours will be available. Thus the final model will be

\[ X(k) = [X_1(k)X_2(k)\epsilon(k-1)]^T \]  

4. Simulation Results and Evaluation

For identifying the parameters of the load model, four data categories are used depending upon their seasonal characteristics i.e. Winter, Spring, Summer and Fall. Further data on the weekdays are traced separately from the weekends. For this purpose the data on the weekends are separated from the load database for the purpose of identification of the parameters of the week days load model during neural network training. In a similar way, the parameters of the weekends load model are identified by using the proper load database. Similar load patterns are used during the training of the network to obtain fast convergence.

To evaluate the performance of the proposed network architecture, it is used to forecast both one-week ahead hourly load and 24-hour ahead hourly load. In the simulations, the data from an utility in the state of Virginia, USA are used. A mathematical software, MATLAB is used for obtaining load forecasts. The input vector contains twenty five Fourier series functional inputs, three temperature inputs \( T(t), T_2(t), T_3(t) \). Here \( T \) either represents the hourly temperatures or equivalent hourly temperatures including the effect of humidity measurements. In addition there are auto-enhancements which are hyperbolic tangent functions of random linear combinations of temperature inputs and one recurrent error input. Thus the total number of inputs is thirty one for two extensions and forty four for fifteen extensions.

4.1 Training and Testing

The training of the auto-enhanced functional link network was started with a random set of weights along with a random set of tangent hyperbolic coefficients. The number of enhancements is initially chosen as 2. For sets of given input data and output load patterns, an optimum weight vector is found with the minimum RMSE (root mean square error). Then the number of hyperbolic tangent extensions is increased and the tuning of \( a_n \) an \( b_i \) coefficients is attempted to reduce the prediction error to within 1% of the actual load on the forecasted day. The load model presented in this paper showed the best result with 15 extensions during Winter/Spring season and 18 extensions during Summer/Fall. During training nearly 200 iterations are required to reduce the error between the computed load and actual load to a value less than \( 10^{-14} \). The learning parameter \( \alpha \) is chosen between 0<\( \alpha \)<1 and is flexible enough to be varied for faster convergence and lower error.
4.2 Adaptive Mechanism

While operating in real-time environment, it is imperative that the load forecasting system should be able to adapt to changing conditions. In order to achieve this objective, daily, weekly or monthly adaptation is performed on the load forecast model.

For daily adaptation, the optimized weights are used from the training set to forecast the first day load. After the end of the day of forecast model parameters are updated till the error becomes insignificantly small. The number of iterations required for this purpose is extremely small as the error is reduced at the rate of \((1-\alpha)\) every iteration. Once the new weights are established, the forecast for the next day is attempted using this weight vector and the new set of input data for the day. As the weekends are excluded from the 1st set of data base, the weight vector obtained after the forecast of Friday load, is used to predict the load on Monday. For one week ahead forecasts, the adaptation is done once a week, i.e., at the end of the week when the entire load profile for the whole week will be available.

The mean absolute percentage error (MAPE) is used to compute the performance of the real-time algorithm and is defined as follows:

\[
MAPE = (\frac{1}{N} \sum_{i=1}^{N} |\text{forecast load} - \text{actual load}| \times 100)/\text{actual load}
\]

where \(N\) is the number of patterns in the data set used to evaluate the forecasting capability of the model.

Abnormal weather and system conditions, such as thunderstorms or transmission outages, are treated as abnormal events with bad real-time readings and are not considered in the forecasting models. The influence of standard holidays is also considered in the real-time forecast and is treated separately along with weekdays.

The special holiday data occurring in the past and the week end data are used to train the functional link net before the prediction for the holiday is attempted. By collecting similar days from the past, we ensure that the characteristic of only that type of holiday is reflected in the data set.

4.3 Forecasting Results

Fig.3 shows the results of the 24-hour ahead forecast over one week period in Winter and Summer seasons. The MAPE, actual and forecasted loads are shown in this figure over the entire week. From the figure it is observed that the MAPE for any day over the entire week is less than 2% in both Summer and Winter seasons.

Fig.4 shows the MAPEs over one week period during Winter and Summer seasons for 168-hour ahead forecasting. From the figure, it is observed that the maximum value of the MAPE during a week in January is less than 2.4% and in July, the corresponding value is less than 3.6%.

Fig.5 presents the average MAPE for both 24-hour and 168-hour ahead load forecasts including all day types over one year period. From the figure it is observed that maximum value of MAPE is 2% for 24-hour ahead forecast and 3.8% for 168-hour ahead forecast.
Fig. 4 MAPEs over one week period during Winter and Summer seasons for 168-hour ahead forecasting.

Fig. 5 Average MAPE for both 24-hour and 168-hour ahead load forecast including all day types (Monday to Sunday) over one year period.

The results for 24-hour ahead peak load forecast over 30 days period for both Winter and Fall seasons are shown in Fig. 6. The forecasting results for the peak load show excellent accuracy and the MAPE is found to be less than 2% over a 90 day period during Winter and Fall.
term load forecasting model combines the familiar theory of flat net computing. The functional link net based variations using an adaptive e mechanism built into the 24-hours ahead time frame. 

Numerical results obtained with a load data from a typical Virginia utility in U.S.A. reveal the superior performance of the auto enhanced net in predicting load in both in Singapore, Malaysia and Indonesia. He was Director of VPSU, Blacksburg in 1978. He has taught at Bangladesh University of Engineering and Technology in 1973 with a B.Sc. degree in Electrical Engineering. He obtained M.S. degree in Electrical Science from SUNY at Stony brook in 1975 and Ph.D. from VPSU, Blacksburg in 1978. He has taught at Bangladesh University of Engineering and Technology, the Texas A&M University, VPSU, Blacksburg, where he is currently a professor. He serves on the System Planning and demand Side Management Subcommittees of IEEE Power Engineering group.


P.K.Dash was educated at the Utkal University and I.I.Sc., Bangalore. He was a post-doctoral fellow at the University of Calgary, Canada and held several visiting appointments with North-American Universities, BBC Brown Boveri, Switzerland, and Bristol Aerospace, Canada. His recent collaborations are with Virginia Polytechnic Institute and State University, U.S.A. Dr. Dash is a Professor of Electrical Engineering and Chairman of the Centre of Applied Artificial Intelligence, Regional Engineering College, Rourkela, India. During 1993-94 he was a visiting staff at the National University of Singapore.

Ah.Choy Liew received the B.E. and Ph.D. Degree from the University of Queensland, Australia in 1969 and 1972 respectively. From 1972 to 1979, he was with the Electrical Engineering Department of the university of Malaya. He is presently with the National University of Singapore where he is associate professor and head of department. His man areas of interest are lightning and lightning protection, high voltage and power systems engineering. He has over 140 publications in international and regional journals and has acted as specialist consultant to many lightning related and other electrical projects, both in Singapore, Malaysia and Indonesia. He was Director of IEEE Region 10 in 1987-1988.

Saifur Rahman graduated from the Bangladesh University of Engineering and Technology in 1973 with a B.Sc. degree in Electrical Engineering. He obtained M.S. degree in Electrical Science from SUNY at Stony brook in 1975 and Ph.D. from VPSU, Blacksburg in 1978. He has taught at Bangladesh University of Engineering and Technology, the Texas A&M University, VPSU, Blacksburg, where he is currently a professor. He serves on the System Planning and demand Side Management Subcommittees of IEEE Power Engineering group.

H.P.Satpathy received his M.Sc. degree in Physics in 1991 and Diploma in Computer Application in 1993. Currently he is a Ph.D. student at R.E.C., Rourkela working on Load Forecasting using Neural Networks & Intelligent Fuzzy Systems.

The paper presents a new on-line load forecasting technique using functional link neural network. The short-term load forecasting model combines the familiar autoregressive moving average time series model with the theory of flat net computing. The functional link net based load forecasting produces a robust and accurate on-line forecast and is capable of taking the weather and seasonal variations using an adaptive e mechanism built into the network. Numerical results obtained with a load data from a typical Virginia utility in U.S.A. reveal the superior performance of the auto enhanced net in predicting load in 24-hours ahead time frame.

5. Conclusions

The paper presents a new on-line load forecasting technique using functional link neural network. The short-term load forecasting model combines the familiar autoregressive moving average time series model with the theory of flat net computing. The functional link net based load forecasting produces a robust and accurate on-line forecast and is capable of taking the weather and seasonal variations using an adaptive e mechanism built into the network. Numerical results obtained with a load data from a typical Virginia utility in U.S.A. reveal the superior performance of the auto enhanced net in predicting load in 24-hours ahead time frame.

7. References


