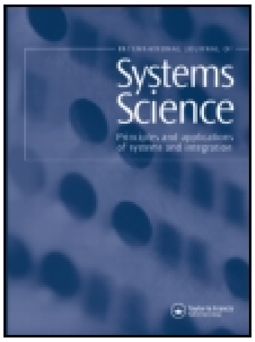

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Electric load forecasting: literature survey and classification of methods

HESHAM K. ALFARES* and MOHAMMAD NAZEERUDDIN

A review and categorization of electric load forecasting techniques is presented. A wide range of methodologies and models for forecasting are given in the literature. These techniques are classified here into nine categories: (1) multiple regression, (2) exponential smoothing, (3) iterative reweighted least-squares, (4) adaptive load forecasting, (5) stochastic time series, (6) ARMAX models based on genetic algorithms, (7) fuzzy logic, (8) neural networks and (9) expert systems. The methodology for each category is briefly described, the advantages and disadvantages discussed, and the pertinent literature reviewed. Conclusions and comments are made on future research directions.

1. Introduction

Load forecasting is a central and integral process in the planning and operation of electric utilities. It involves the accurate prediction of both the magnitudes and geographical locations of electric load over the different periods (usually hours) of the planning horizon. The basic quantity of interest in load forecasting is typically the hourly total system load. However, according to Gross and Galiana (1987), load forecasting is also concerned with the prediction of hourly, daily, weekly and monthly values of the system load, peak system load and the system energy. Srinivasan and Lee (1995) classified load forecasting in terms of the planning horizon's duration: up to 1 day for short-term load forecasting (STLF), 1 day to 1 year for medium-term load forecasting (MTLF), and 1–10 years for long-term load forecasting (LTLF).

Accurate load forecasting holds a great saving potential for electric utility corporations. According to Bunn and Farmer (1985), these savings are realised when load forecasting is used to control operations and decisions such as dispatch, unit commitment, fuel allocation and off-line network analysis. The accuracy of load forecasts has a significant effect on power system operations, as economy of operations and control of power systems may be quite sensitive to forecasting errors. Haida and Muto (1994) observed that both positive and negative forecasting errors resulted in increased operating costs. Hobbs *et al*. (1999) quantified the dollar value of improved STLF for a typical utility; a 1% reduction in the average forecast error can save hundreds of thousands or even millions of dollars.

The system load is a random non-stationary process composed of thousands of individual components. The system load behaviour is influenced by a number of factors, which can be classified as: economic factors, time, day, season, weather and random effects.

A wide variety of models, varying in the complexity of functional form and estimation procedures, has been proposed for the improvement of load forecasting accuracy. Matthewman and Nicholson (1968) conducted an early survey of electric load forecasting techniques. Abu El-Magd and Sinha (1982), Bunn and Farmer (1985), and Gross and Galiana (1987) also reviewed load demand modelling and forecasting. Recently, Moghram and Rahman (1989) surveyed electric load forecasting techniques.

The aim of this paper is to survey and classify electric load forecasting techniques published since the last comprehensive review of Moghram and Rahman (1989). In comparison with those earlier literature reviews, this survey not only covers newer papers, but also includes new categories that reflect recent research trends. It also provides up-to-date brief verbal and mathematical

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descriptions of each category. Load forecasting techniques are classified into nine categories. In subsequent sections, one section is devoted to each category, where a brief description is given of the technique and a literature review offers a representative selection of principal publications in the given category. Arranged in roughly chronological order, the nine categories of load forecasting techniques to be discussed are:

- multiple regression;
- exponential smoothing;
- iterative reweighted least-squares;
- adaptive load forecasting;
- stochastic time series;
- ARMAX models based on genetic algorithms;
- fuzzy logic;
- neural networks; and
- knowledge-based expert systems.

2. Multiple regression

Multiple regression analysis for load forecasting uses the technique of weighted least-squares estimation. Based on this analysis, the statistical relationship between total load and weather conditions as well as the day type influences can be calculated. The regression coefficients are computed by an equally or exponentially weighted least-squares estimation using the defined amount of historical data. Mbamalu and El-Hawary (1993) used the following load model for applying this analysis:

$$Y_t = v_t a_t + \varepsilon_t, \tag{1}$$

where

t sampling time,
Y_t measured system total load,
v_t vector of adapted variables such as time, temperature, light intensity, wind speed, humidity, day type (workday, weekend), etc.,
a_t transposed vector of regression coefficients, and
ε_t model error at time t.

The data analysis program allows the selection of the polynomial degree of influence of the variables from 1 to 5. In most cases, linear dependency gives the best results. Moghram and Rahman (1989) evaluated this model and compared it with other models for a 24-h load forecast. Barakat *et al.* (1990) used the regression model to fit data and check seasonal variations. The model developed by Papalexopulos and Hesterberg (1990) produces an initial daily peak forecast and then uses this initial peak forecast to produce initial hourly forecasts. In the next step, it uses the maximum of the initial hourly forecast, the most recent initial peak forecast error, and exponentially smoothed errors as variables in a regression model to produce an adjusted peak forecast.

Haida and Muto (1994) presented a regression-based daily peak load forecasting method with a transformation technique. Their method uses a regression model to predict the nominal load and a learning method to predict the residual load. Haida *et al.* (1998) expanded this model by introducing two trend-processing techniques designed to reduce errors in transitional seasons. Trend cancellation removes annual growth by subtraction or division, while trend estimation evaluates growth by the variable transformation technique. Varadan and Makram (1996) used a least-squares approach to identify and quantify the different types of load at power lines and substations.

Hyde and Hodnett (1997a) presented a weather-load model to predict load demand for the Irish electricity supply system. To include the effect of weather, the model was developed using regression analysis of historical load and weather data. Hyde and Hodnett (1997b) later developed an adaptable regression model for 1-day-ahead forecasts, which identifies weather-insensitive and -sensitive load components. Linear regression of past data is used to estimate the parameters of the two components. Broadwater *et al.* (1997) used their new regression-based method, Nonlinear Load Research Estimator (NLRE), to forecast load for four substations in Arkansas, USA. This method predicts load as a function of customer class, month and type of day.

Al-Garni *et al.* (1997) developed a regression model of electric energy consumption in Eastern Saudi Arabia as a function of weather data, solar radiation, population and per capita gross domestic product. Variable selection is carried out using the stepping-regression method, while model adequacy is evaluated by residual analysis. The non-parametric regression model of Charytoniuk *et al.* (1998) constructs a probability density function of the load and load effecting factors. The model produces the forecast as a conditional expectation of the load given the time, weather and other explanatory variables, such as the average of past actual loads and the size of the neighbourhood.

Alfares and Nazeeruddin (1999) presented a regression-based daily peak load forecasting method for a whole year including holidays. To forecast load precisely throughout a year, different seasonal factors that effect load differently in different seasons are considered. In the winter season, average wind chill factor is added as an explanatory variable in addition to the explanatory variables used in the summer model. In transitional seasons such as spring and Fall, the transformation technique is used. Finally for holidays, a holiday effect load is deducted from normal load to estimate the actual holiday load better.

3. Exponential smoothing

Exponential smoothing is one of the classical methods used for load forecasting. The approach is first to model the load based on previous data, then to use this model to predict the future load. In exponential smoothing models used by Moghram and Rahman (1989), the load at time t, $y(t)$, is modelled using a fitting function and is expressed in the form:

$$y(t) = \beta(t)^{\mathrm{T}} f(t) + \varepsilon(t), \tag{2}$$

where

- $f(t)$ fitting function vector of the process,
- $\beta(t)$ coefficient vector,
- $\varepsilon(t)$ white noise, and
- T transpose operator.

The Winter's method is one of several exponential smoothing methods that can analyse seasonal time series directly. This method is based on three smoothing constants for stationarity, trend and seasonality. Results of the analysis by Barakat *et al.* (1990) showed that the unique pattern of energy and demand pertaining to fast-growing areas was difficult to analyse and predict by direct application of the Winter's method. El-Keib *et al.* (1995) presented a hybrid approach in which exponential smoothing was augmented with power spectrum analysis and adaptive autoregressive modelling. A new trend removal technique by Infield and Hill (1998) was based on optimal smoothing. This technique has been shown to compare favourably with conventional methods of load forecasting.

4. Iterative reweighted least-squares

Mbamalu and El-Hawary (1992) used a procedure referred to as the iteratively reweighted least-squares to identify the model order and parameters. The method uses an operator that controls one variable at a time. An optimal starting point is determined using the operator. This method utilizes the autocorrelation function and the partial autocorrelation function of the resulting differenced past load data in identifying a sub-optimal model of the load dynamics. The weighting function, the tuning constants and the weighted sum of the squared residuals form a three-way decision variable in identifying an optimal model and the subsequent parameter estimates. Consider the parameter estimation problem involving the linear measurement equation:

$$Y = X\beta + \varepsilon, \tag{3}$$

where Y is an $n \times 1$ vector of observations, X is an $n \times p$ matrix of known coefficients (based on previous load data), β is a $p \times 1$ vector of the unknown parameters and ε is an $n \times 1$ vector of random errors. Results are more accurate when the errors are not Gaussian. β can be obtained by iterative methods (Mbamalu and El-Hawary 1992). Given an initial β, one can apply the Newton method. Alternatively, one can also use the Beaton–Turkey iterative reweighted least-squares algorithm (IRLS). In a similar work, Mbamalu and El-Hawary (1993) proposed an interactive approach employing least-squares and the IRLS procedure for estimating the parameters of a seasonal multiplicative autoregressive model. The method was applied to predict load at the Nova Scotia Power Corporation.

5. Adaptive load forecasting

In this context, forecasting is adaptive in the sense that the model parameters are automatically corrected to keep track of the changing load conditions. Adaptive load forecasting can be used as an on-line software package in the utilities control system. Regression analysis based on the Kalman filter theory is used. The Kalman filter normally uses the current prediction error and the current weather data acquisition programs to estimate the next state vector. The total historical data set is analysed to determine the state vector, not only the most recent measured load and weather data. This mode of operation allows switching between multiple and adaptive regression analysis. The model used is the same as the one used in the multiple regression section, as described by equation (1).

Lu *et al.* (1989) developed an adaptive Hammerstein model with an orthogonal escalator structure as well as a lattice structure for joint processes. Their method used a joint Hammerstein non-linear time-varying functional relationship between load and temperature. Their algorithm performed better than the commonly used RLS (Recursive Least-square) algorithm. Grady *et al.* (1991) enhanced and applied the algorithm developed by Lu *et al.* An improvement was obtained in the ability to forecast total system hourly load as far as 5 days. McDonald *et al.* (1989) presented an adaptive-time-series model, and simulated the effects of a direct load-control strategy.

Park *et al.* (1991b) developed a composite model for load prediction, composed of three components: nominal load, type load and residual load. The nominal load is modelled such that the Kalman filter can be used and the parameters of the model are adapted by the exponentially weighted recursive least-squares method. Fan and McDonald (1994) presented a practical real-time implementation of weather adaptive STLF. Implementation is performed by means of an ARMA model, whose parameters are estimated and updated on-line, using the WRLS (Weighted Recursive Least-squares) algorithm.

Paarmann and Najar's (1995) adaptive online load-forecasting approach automatically adjusts model parameters according to changing conditions based on time series analysis. This approach has two unique features: autocorrelation optimization is used for handling cyclic patterns and, in addition to updating model parameters, the structure and order of the time series is adaptable to new conditions. An important feature of the regression model of Hyde and Hodnett (1997b) is adaptability to changing operational conditions. The load-forecasting software system is fully automated with a built-in procedure for updating the model. Zheng *et al*. (2000) applied a wavelet transform-Kalman filter method for load forecasting. Two models are formed (weather sensitive and insensitive) in which the wavelet coefficients are modelled and solved by the recursive Kalman filter algorithm.

6. Stochastic time series

It has been observed that unique patterns of energy and demand pertaining to fast-growing areas are difficult to analyse and predict by direct application of time-series methods. However, these methods appear to be among the most popular approaches that have been applied and are still being applied to STLF. Using the time-series approach, a model is first developed based on the previous data, then future load is predicted based on this model. The remainder of this section discusses some of the time series models used for load forecasting.

6.1. *Autoregressive (AR) model*

If the load is assumed to be a linear combination of previous loads, then the autoregressive (AR) model can be used to model the load profile, which is given by Liu *et al*. (1996) as:

$$\hat{L}_k = -\sum_{i=1}^{m} \alpha_{ik} L_{k_{-i}} + w_k \tag{4}$$

where $\hat{L}_k$ is the predicted load at time k (min), w_k is a random load disturbance, $\alpha_i, i = 1, \ldots, m$ are unknown coefficients, and (4) is the AR model of order m. The unknown coefficients in (4) can be tuned on-line using the well-known least mean square (LMS) algorithm of Mbamalu and El-Hawary (1993). The algorithm presented by El-Keib *et al*. (1995) includes an adaptive autoregressive modelling technique enhanced with partial autocorrelation analysis. Huang (1997) proposed an autoregressive model with an optimum threshold stratification algorithm. This algorithm determines the minimum number of parameters required to represent the random component, removing subjective judgement, and improving forecast accuracy. Zhao *et al*. (1997) developed two periodical autoregressive (PAR) models for hourly load forecasting.

6.2. *Autoregressive moving-average (ARMA) model*

In the ARMA model the current value of the time series $y(t)$ is expressed linearly in terms of its values at previous periods $[y(t-1), y(t-2), \ldots]$ and in terms of previous values of a white noise $[a(t), a(t-1), \ldots]$. For an ARMA of order (p, q), the model is written as:

$$y(t) = \phi_1 y(t-1) + \cdots + \phi_p y(t-p) + a(t) - \theta_1 a(t-1) - \cdots - \theta_q a(t-q). \tag{5}$$

The parameter identification for a general ARMA model can be done by a recursive scheme, or using a maximum-likelihood approach, which is basically a non-linear regression algorithm. Barakat *et al*. (1992) presented a new time-temperature methodology for load forecasting. In this method, the original time series of monthly peak demands are decomposed into deterministic and stochastic load components, the latter determined by an ARMA model. Fan and McDonald (1994) used the WRLS (Weighted Recursive Least-Squares) algorithm to update the parameters of their adaptive ARMA model. Chen *et al*. (1995) used an adaptive ARMA model for load forecasting, in which the available forecast errors are used to update the model. Using minimum mean square error to derive error learning coefficients, the adaptive scheme outperformed conventional ARMA models.

6.3. *Autoregressive integrated moving-average (ARIMA) model*

If the process is non-stationary, then transformation of the series to the stationary form has to be done first. This transformation can be performed by the differencing process. By introducing the ∇ operator, the series $\nabla y(t) = (1 - B)y(t)$. For a series that needs to be differenced d times and has orders p and q for the AR and MA components, i.e. ARIMA(p, d, q), the model is written as:

$$\phi(B)\nabla^d y(t) = \theta(B)a(t). \tag{6}$$

The procedure proposed by Elrazaz and Mazi (1989) used the trend component to forecast the growth in the system load, the weather parameters to forecast the weather sensitive load component, and the ARIMA model to produce the non-weather cyclic component of the weekly peak load. Barakat *et al*. (1990) used a seasonal ARIMA model on historical data to predict the load with seasonal variations. Juberias *et al*. (1999) developed a real time load forecasting

ARIMA model that includes the meteorological influence as an explanatory variable.

7. ARMAX Model based on genetic algorithms

The genetic algorithm (GA) or evolutionary programming (EP) approach is used to identify the autoregressive moving average with exogenous variable (ARMAX) model for load demand forecasts. By simulating natural evolutionary process, the algorithm offers the capability of converging towards the global extremum of a complex error surface. It is a global search technique that simulates the natural evolution process and constitutes a stochastic optimization algorithm. Since the GA simultaneously evaluates many points in the search space and need not assume the search space is differentiable or unimodal, it is capable of asymptotically converging towards the global optimal solution, and thus can improve the fitting accuracy of the model.

The general scheme of the GA process is briefly described here. The integer or real valued variables to be determined in the genetic algorithm are represented as a D-dimensional vector P for which a fitness $f(p)$ is assigned. The initial population of k parent vectors P_i, $i = 1, \ldots, k$, is generated from a randomly generated range in each dimension. Each parent vector then generates an offspring by merging (crossover) or modifying (mutation) individuals in the current population. Consequently, $2k$ new individuals are obtained. Of these, k individuals are selected randomly, with higher probability of choosing those with the best fitness values, to become the new parents for the next generation. This process is repeated until f is not improved or the maximum number of generations is reached.

Yang *et al*. (1996) described the system load model in the following ARMAX form:

$$A(q)y(t) = B(q)u(t) + C(q)e(t), \tag{7}$$

where

- $y(t)$ load at time t,
- $u(t)$ exogenous temperature input at time t,
- $e(t)$ white noise at time t, and
- q^{-1} back-shift operator.

and $A(q)$, $B(q)$, and $C(q)$ are parameters of the autoregressive (AR), exogenous (X), and moving average (MA) parts, respectively. Yang *et al*. (1996) chose the solution(s) with the best fitness as the tentative model(s) that should further pass diagnostic checking for future load forecasting. Yang and Huang (1998) presented a fuzzy autoregressive moving average with exogenous variable (FARMAX) model for load demand forecasts. The model is formulated as a combinatorial optimization problem, then solved by a combination of heuristics and evolutionary programming. Ma *et al*. (1995) used a genetic algorithm with a newly developed knowledge-augmented mutation-like operator called the forced mutation. Lee *et al*. (1997) used genetic algorithms for long-term load forecasting, assuming different functional forms and comparing results with regression.

8. Fuzzy logic

It is well known that a fuzzy logic system with centroid defuzzification can identify and approximate any unknown dynamic system (here load) on the compact set to arbitrary accuracy. Liu *et al*. (1996) observed that a fuzzy logic system has great capability in drawing similarities from huge data. The similarities in input data ($L_{-i} - L_0$) can be identified by different first-order differences (V_k) and second-order differences (A_k), which are defined as:

$$V_k = (L_k - L_{k-1})/T, \quad A_k = (V_k - V_{k-1})/T. \tag{8}$$

The fuzzy logic-based forecaster works in two stages: training and on-line forecasting. In the training stages, the metered historical load data are used to train a $2m$-input, $2n$-output fuzzy-logic based forecaster to generate patterns database and a fuzzy rule base by using first- and second-order differences of the data. After enough training, it will be linked with a controller to predict the load change online. If a most probably matching pattern with the highest possibility is found, then an output pattern will be generated through a centroid defuzzifier.

Several techniques have been developed to represent load models by fuzzy conditional statements. Hsu (1992) presented an expert system using fuzzy set theory for STLF. The expert system was used to do the updating function. Short-term forecasting was performed and evaluated on the Taiwan power system. Later, Liang and Hsu (1994) formulated a fuzzy linear programming model of the electric generation scheduling problem, representing uncertainties in forecast and input data using fuzzy set notation. Al-Anbuky *et al*. (1995) discussed the implementation of a fuzzy-logic approach to provide a structural framework for the representation, manipulation and utilization of data and information concerning the prediction of power commitments. Neural networks are used to accommodate and manipulate the large amount of sensor data.

Srinivasan *et al*. (1992) used the hybrid fuzzy-neural technique to forecast load. This technique combines the neural network modelling and techniques from fuzzy logic and fuzzy set theory. The models were later enhanced by Dash *et al*. (1995a, b). This hybrid approach can accurately forecast on weekdays, public holidays, and days before and after public holidays. Based on the work of Srinivasan *et al*., Dash *et al*.

(1995a) presented two fuzzy neural network (NN) models capable of fuzzy classification of patterns. The first network uses the membership values of the linguistic properties of the past load and weather parameters, where the output of the network is defined as the fuzzy class membership values of the forecasted load. The second network is based on the fact that any expert system can be represented as a feedforward NN.

Mori and Kobayashi (1996) used fuzzy inference methods to develop a non-linear optimization model of STLF, whose objective is to minimize model errors. The search for the optimum solution is performed by simulated annealing and the steepest descent method. Dash *et al.* (1996) used a hybrid scheme combining fuzzy logic with both neural networks and expert systems for load forecasting. Fuzzy load values are inputs to the neural network, and the output is corrected by a fuzzy rule inference mechanism. Ramirez-Rosado and Dominguez-Navarro (1996) formulated a fuzzy model of the optimal planning problem of electric energy. Computer tests indicated that this approach outperforms classical deterministic models because it is able to represent the intrinsic uncertainty of the process.

Chow and Tram (1997) presented a fuzzy logic methodology for combining information used in spatial load forecasting, which predicts both the magnitudes and locations of future electric loads. The load growth in different locations depends on multiple, conflicting factors, such as distance to highway, distance to electric poles, and costs. Therefore, Chow *et al.* (1998) applied a fuzzy, multi-objective model to spatial load forecasting. The fuzzy logic approach proposed by Senjyu *et al.* (1998) for next-day load forecasting offers three advantages. These are namely the ability to (1) handle non-linear curves, (2) forecast irrespective of day type and (3) provide accurate forecasts in hard-to-model situations.

Mori *et al.* (1999) presented a fuzzy inference model for STLF in power systems. Their method uses tabu search with supervised learning to optimize the inference structure (i.e. number and location of fuzzy membership functions) to minimize forecast errors. Wu and Lu (1999) proposed an alternative to the traditional trial and error method for determining of fuzzy membership functions. An automatic model identification is used, that utilizes analysis of variance, cluster estimation, and recursive least-squares. Mastorocostas *et al.* (1999) applied a two-phase STLF methodology that also uses orthogonal least-squares (OSL) in fuzzy model identification. Padmakumari *et al.* (1999) combined fuzzy logic with neural networks in a technique that reduces both errors and computational time. Srinivasan *et al.* (1999) combined three techniques—fuzzy logic, neural networks and expert systems—in a highly automated hybrid STLF approach with unsupervised learning.

9. Neural networks

Neural networks (NN) or artificial neural networks (ANN) have very wide applications because of their ability to learn. According to Damborg *et al.*, (1990), neural networks offer the potential to overcome the reliance on a functional form of a forecasting model. There are many types of neural networks: multilayer perceptron network, self-organizing network, etc. There are multiple hidden layers in the network. In each hidden layer there are many neurons. Inputs are multiplied by weights ω_i, and are added to a threshold θ to form an inner product number called the net function. The net function NET used by Ho *et al.* (1992), for example, is put through the activation function y, to produce the unit's final output, $y(NET)$.

The main advantage here is that most of the forecasting methods seen in the literature do not require a load model. However, training usually takes a lot of time. Here we describe the method discussed by Liu *et al.* (1996), using fully connected feed-forward type neural networks. The network outputs are linear functions of the weights that connect inputs and hidden units to output units. Therefore, linear equations can be solved for these output weights. In each iteration through the training data (epoch), the output weight optimization training method uses conventional back-propagation to improve hidden unit weights, then solves linear equations for the output weights using the conjugate gradient approach.

Srinivasan and Lee (1995) surveyed hybrid fuzzy neural approaches to load forecasting. Park and Osama (1991) used a NN approach for forecasting which, compared to regression methods, gave more flexible relations between temperature and load patterns. Extending this work, Park *et al.* (1991a) presented a NN algorithm that combines time series and regression approaches. Park *et al.* proposed an improved training procedure for training the ANN. Atlas *et al.* (1989) earlier compared a similar technique with other regression methods. Hsu and Yang (1992) estimated the load pattern of the day under study by averaging the load patterns of several past days, which are of the same day type (ANN being used for the classification). To predict the daily peak load, a feed-forward multilayer neural network was designed.

Peng *et al.* (1992) used a minimum distance measurement to identify the appropriate historical patterns of load and temperature weights to be used to find the network weights. They also proposed an improved algorithm that combined linear and non-linear terms to map past load and temperature inputs to the load forecast output. This work was an extension to a strategy by Peng *et al.* (1990) which was applied on daily load. The major difference lies in the alternate method for the selection of the training cases. Later, Peng *et al.* (1993) applied a neural network approach to one-week ahead load forecasting based on an adaptive linear combiner called the adaline.

Ho and Hsu (1992) designed a multilayer ANN with a new adaptive learning algorithm for short term load forecasting. In this algorithm the momentum is automatically adapted in the training process. Lee and Park (1992) proposed a non-linear load model and several structures of ANNs were tested. Inputs to the ANN include past load values, and the output is the forecast for a given day. Lee and Park demonstrated that the ANN could be successfully used in STLF with accepted accuracy. Chen *et al.* (1992) presented an ANN, which is not fully connected, to forecast weather sensitive loads for a week. Their model could differentiate between the weekday loads and the weekend loads. Lu *et al.* (1993) conducted a computational investigation to evaluate the performance of the ANN methodology.

Djukanovic *et al.* (1993) proposed an algorithm using an unsupervised/supervised learning concept and historical relationship between the load and temperature for a given season, day type and hour of the day. They used this algorithm to forecast hourly electric load with a lead time of 24 h. Papalexopoulos *et al.* (1994) developed and implemented the ANN based model for the energy control centre of the Pacific Gas and Electric Company. Attention was paid to accurately model special events, such as holidays, heat waves, cold snaps and other conditions that disturb the normal pattern of the load. Ho *et al.* (1992) extended the three-layered feedforward adaptive neural networks to multilayers. Dillon *et al.* (1991) proposed a multilayer feedforward neural network, using a learning algorithm for adaptive training of neural networks.

Srinivasan *et al.* (1991) used an ANN based on back propagation for forecasting, and showed its superiority to traditional methods. Liu *et al.* (1991) compared an econometric model and a neural network model, through a case study on electricity consumption forecasting in Singapore. Their results show that a fully trained NN model with a good fitting performance for the past may not give a good forecasting performance for the future. Kalra *et al.* (1992) demonstrated how present methods for solving such problems could be converted to NN approaches.

Azzam-ul-Asar and McDonald (1994) trained a family of ANNs and then used them in line with a supervisory expert system to form an expert network. They also investigated the effectiveness of the ANN approach to short term load forecasting, where the networks were trained on actual load data using back-propagation. Al-Anbuky *et al.* (1995) presented fuzzy logic based neural networks for load forecasting. Dash *et al.* (1995a, b, 1996) also used fuzzy logic in combination with neural networks for load forecasting. Their work has been discussed in the previous section.

Chen *et al.* (1996) applied a supervisory functional ANN technique to forecast load for three substations in Taiwan. To enhance forecasting accuracy, the load was correlated with temperature as well as the type of customers served, which is classified as residential, commercial or industrial. Al-Fuhaid *et al.* (1997) incorporated temperature and humidity effects in an ANN approach for STLF in Kuwait. Vermaak and Botha (1998) proposed a recurrent NN to model the STLF of the South African utility. They utilized the inherent non-linear dynamic nature of NN to represent the load as the output of some dynamic system, influenced by weather, time and environmental variables.

McMenamin and Monforte (1998) used an econometric and statistical approach to NN-based load forecasting. Considering NN models as flexible non-linear equations, they used non-linear least-squares to estimate parameters, and simple statistics such as MAPE to determine the number of nodes. Papadakis *et al.* (1998) developed a three-step fuzzy ANN approach, involving the prediction of load curve peaks and valleys and mapping them to forecasted peak values. Dash *et al.* (1998) presented a fuzzy NN load forecasting system that accounts for seasonal and daily changes, as well as holidays and special situations. An adaptive mechanism is used to train the system on line, providing accurate results when tested with actual data of the Virginia Utility. Another adaptive NN technique, employing genetic algorithms in the design and training phase, was used by Kung *et al.* (1998) on the Taiwan power system.

ANN have been integrated with several other techniques to improve their accuracy. Chow and Leung (1996), for example, combined ANN with stochastic time-series methods, in the form of non-linear autoregressive integrated (NARI) model. They implemented an ANN capable of weather compensation, based on NARI, to forecast electric load in Hong Kong. Choueiki *et al.* (1997) used weighted least-squares procedure in the training phase of developing an ANN for load forecasting. Several other hybrid methods involving ANNs in combination with fuzzy logic and expert systems are discussed in Sections 6 and 10, respectively. It is very hard to keep track of all publications on load forecasting using NN, which is currently a very active area of research. Niebur (1995) and Czernichow *et al.* (1996) surveyed methods and applications of electrical load forecasting with ANNs.

Oonsivilan *et al.* (1999) presented an approach for predicting electric power system commercial load using a wavelet neural network. Their results showed that wavelet NNs may outperform traditional architectures in approximation. Drenza *et al.* (1999) presented a new ANN-based technique for STLF. The technique implemented active selection of training data employing k-nearest neighbours concept. Excellent results were reported using this technique. Yoo and Pimmel (1999) developed a self-supervised adaptive NN to perform STLF for a large power system. They used the self-supervised network to extract correlational features from temperature and load data. Their results showed low forecasting errors. Kandil *et al.* (1999) used multilayer perceptron (MLP) type ANN for STLF using real load and weather data. Leyan and Chen (1999) used variable learning rate method combined with quasi-Newton method to expedite the learning process of ANN for STLF.

Nazarko and Styczynski (1999) presented load-modelling methods useful for long term planning of power distribution systems using statistical clustering and NN approach. Ijumba and Hunsley (1999) applied ANN model to predict hourly peak demands of loads in a newly electrified area. Sinha and Mandal (1999) presented an ANN-based model for bus-load prediction and dynamic state estimation in power systems. Drezga and Rahman (1999a) used phase-space concepts to embed electric load parameters, including temperature and cycle variables, into ANN-based STLF. Drezga and Rahman (1999b) applied another ANN-based technique that features the following characteristics: (1) selection of training data by the k-nearest neighbours concept, (2) pilot simulation to determine the number of ANN units and (3) iterative forecasting by simple moving average to combine local ANN predictions.

10. Knowledge-based expert systems

Expert systems are new techniques that have emerged as a result of advances in the field of artificial intelligence. An expert system is a computer program that has the ability to reason, explain, and have its knowledge base expanded as new information becomes available to it. To build the model, the 'knowledge engineer' extracts load forecasting knowledge from an expert in the field by what is called the knowledge base component of the expert system. This knowledge is represented as facts and IF-THEN rules, and consists of the set of relationships between the changes in the system load and changes in natural and forced condition factors that effect the use of electricity. This rule base is used daily to generate the forecasts. Some of the rules do not change over time, while others have to be updated continually.

The logical and syntactical relationships between weather load and the prevailing daily load shapes have been widely examined to develop different rules for different approaches. The typical variables in the process are the season under consideration, day of the week, the temperature and the change in this temperature. Illustrations of this method can be found in Rahman (1990, 1993) and Ho *et al.* (1990). The algorithms of Rahman and Shreshta (1991) and Rahman and Hazim (1993) combine features from knowledge-based and statistical techniques, using the pairwise comparison technique to prioritize categorical variables. Rahman and Hazim (1996) developed a site-independent expert system for STLF. This system was tested using data from several sites around the USA, and the errors were negligible. Brown *et al.* (1999) used a knowledge-based load-forecasting approach that combines existing system knowledge, load growth patterns, and horizon year data to develop multiple load growth scenarios.

Several hybrid methods combine expert systems with other load-forecasting approaches. Dash *et al.* (1993, 1996) combined fuzzy logic with expert systems. Kim *et al.* (1995) used a two-step approach in forecasting load for Korea Electric Power Corporation. First, an ANN is trained to obtain an initial load prediction, then a fuzzy expert system modifies the forecast to accommodate temperature changes and holidays. Mohamad *et al.* (1996) applied a combination of expert systems and NN for hourly load forecasting in Egypt. Bataineh *et al.* (1996) used neural networks and fuzzy logic for data representation and manipulation to construct the expert system's rule base. Chiu *et al.* (1997a, b) determined that a combined expert system-NN approach is faster and more accurate than either one of the two methods alone. Chandrashekara *et al.* (1999) applied a combined expert system-NN procedure divided into three modules: location planning, forecasting and expansion planning.

11. Comparison of approaches

In addition to classifying load-forecasting approaches, it is important to compare different categories and individual techniques. A number of researchers have attempted to empirically compare some of the methods used in load forecasting. One of the earliest and most comprehensive comparisons is made by Willis and Northcote-Green (1984), who performed comparison tests on 14 load forecasting methods. Atlas *et al.* (1989) compared the performance of different structures of neural networks with regression models. Dash *et al.* (1995a) also compared several fuzzy neural network-based methods. Another comparison between neural networks and econometric models of forecasting electricity consumption was performed by Liu *et al.* (1991).

Girgis *et al.* (1995) used actual load data to compare estimation errors of one-hour ahead and one-day-ahead forecasts associated with three self-learning forecasting techniques. These techniques are: adaptive Kalman filter, neural networks, and expert systems. On the basis of a simulation study, Liu *et al.* (1996) compared three other techniques—fuzzy logic (FL), neural networks (NN) and autoregressive models (AR)—concluding that NN and FL are much superior to AR models of STLF.

Other limited comparative data exist, provided by many researchers to establish the superiority of their proposed forecasting methods over a limited number of previously published methods. For example, Mbamalu and El-Hawary (1993) compared their interactive autoregressive model to the Box-Jenkins method. Willis *et al.* (1995) compared their simulation-based method to two other simulation methods. Wu and Lu (1999) compared their fuzzy modelling method to Box-Jenkins transfer functions and ANN. Srinivasan *et al.* (1999) compared their NN-fuzzy expert system methodology to a regression-based model, showing significant improvement in forecasting accuracy. The need for up-to-date comprehensive comparisons of the different load forecasting methods provides a challenging opportunity for future research, given the wide variety of objectives and assumptions, and the unlimited possibility of mixing and matching different components of various methods.

12. Conclusions

Different techniques have been applied to load forecasting. Nine approaches have been reviewed in this paper: (1) multiple regression, (2) exponential smoothing, (3) iterative reweighted least-squares, (4) adaptive load forecasting, (5) stochastic time series, (6) ARMAX models based on genetic algorithms, (7) fuzzy logic, (8) neural networks and (9) expert systems. After surveying all these approaches, we can observe a clear trend toward new, stochastic, and dynamic forecasting techniques. It seems a lot of current research effort is focused on three such methods: fuzzy logic, expert systems and particularly neural networks. There is also a clear move towards hybrid methods, which combine two or more of these techniques.

Over the years, the direction of research has shifted, replacing old approaches with newer and more efficient ones. Apparently due to their limited success, a number of old approaches seem to be out of favour nowadays. These include such methods as state space and Kalman filter modelling, on-line load forecasting, and forecasting by pattern recognition. There is also considerably less emphasis on methods such as iterative reweighted least-squares and adaptive load forecasting.

Although the time series approach is still widely used, newer techniques offer a lot of promise for this developing and rapidly changing field. The rapidly increasing power of the personal computer is making it possible to apply more complicated solution techniques. New load forecasting methods based on fuzzy logic, genetic algorithms, expert systems, and neural networks offer new hopes in this direction of research. Over the last few years, the most active research area has been neural network based load forecasting.

References

Abu El-Magd, M. A., and Sinha, N. K., 1982, Short term load demand modeling and forecasting. *IEEE Transactions on Systems Man and Cybernetics*, **12**, 370–382.

Al-Anbuky, A., Bataineh, S., and Al-Aqtash, S., 1995, Power demand prediction using fuzzy logic. *Control Engineering Practice*, **3**, 1291–1298.

Al-Fuhaid, A. S., El-Sayed, M. A., and Mahmoud, M. S., 1997, Neuro-short-term forecast of the power system in Kuwait. *Applied Mathematical Modeling*, **21**, 215–219.

Al-Garni, A. Z., Ahmed, Z., Al-Nassar, Y. N., Zubair, S. M., and Al-Shehri, A., 1997, Model for electric energy consumption in Eastern Saudi Arabia. *Energy Sources*, **19**, 325—334.

Alfares, H. K., and Nazeeruddin, M., 1999, Regression-based methodology for daily peak load forecasting. *Proceedings of the 2nd International Conference on Operations and Quantitative Management*, Ahmedabad, India, 3–6 January, pp. 468–471.

Atlas, L., Connor, J., Park, D., Marks, R. J., Lippman, A., and Muthusamy, Y., 1989, A performance comparison of trained multilayer perceptrons and trained classification trees. *Proceedings of the IEEE International Conference on Systems, Man, and Cybernetics*, pp. 915–920.

Azzam-ul-Asar, A., and McDonald, J. R., 1994, A Specification of neural networks in the load forecasting problem. *IEEE Transactions on Control System Technology*, **2**, 135–141.

Barakat, E. H., Al-Qassim, J. M., and Al-Rashed, S. A., 1992, New model for peak demand forecasting applied to highly complex load characteristics of a fast developing area. *IEE Proceedings - C*, **139**, 136–149.

Barakat, E. H., Qayyum, M. A., Hamed, M. N., and Al-Rashed, S. A., 1990, Short-term peak demand forecasting in fast developing utility with inherent dynamic load characteristics. *IEEE Transactions on Power Systems*, **5**, 813–824.

Bataineh, S., Al-Anbuky, A., and Al-Aqtash, S., 1996, Expert system for unit commitment and power demand prediction using fuzzy logic and neural networks. *Expert Systems*, **13**, 29–40.

Broadwater, R. P., Sargent, A., Yarali, A., Shaalan, H. E., and Nazarko, J., 1997, Estimating substation peaks from research data. *IEEE Transactions on Power Delivery*, **12**, 451–456.

Brown, R. E., Hanson, A. P., and Hagan, D. L., 1999, Long range spatial load forecasting using non-uniform areas. *IEEE Transmission and Distribution Conference Proceedings*, **1**, 369–373.

Bunn, D. W., and Farmer, E. D., 1985, *Review of Short-term Forecasting Methods in the Electric Power Industry* (New York: Wiley), pp. 13–30.

Chandrashekara, A. S., Ananthapadmanabha, T., and Kulkarni, A. D., 1999, A neuro-expert system for planning and load forecasting of distribution systems. *Electrical Power and Energy Systems Research*, **21**, 309–314.

Charytoniuk, W., Chen, M. S., and van Olinda, P., 1998, Nonparametric regression based short-term load forecasting. *IEEE Transactions on Power Systems*, **13**, 725–730.

Chen, C. S., Tzeng, Y. M., and Hwang, J. C., 1996, Application of artificial neural networks to substation load forecasting. *Electric Power Systems Research*, **38**, 153–160.

Chen, J.-F., Wang, W.-M., and Huang, C.-M., 1995, Analysis of an adaptive time-series autoregressive moving-average (ARMA) model for short-term load forecasting. *Electric Power Systems Research*, **34**, 187–196.

Chen, S.-T., Yu, D. C., and Moghaddamjo, A. R., 1992, Weather sensitive short-term load forecasting using nonfully connected artificial neural network. *IEEE Transactions on Power Systems*, **7**, 1098–1105.

Chiu, C.-C., Cook, D. F., Kao, J.-L., and Chou, Y.-C., 1997, Combining a neural network and a rule-based expert system for short-term load forecasting. *Computers and Industrial Engineering*, **32**, 787–797.

Chiu, C.-C., Kao, L.-J., and Cook, D. F., 1997, Combining a neural network with a rule-based expert system approach for short-term power load forecasting in Taiwan. *Expert Systems with Applications*, **13**, 299–305.

Choueiki, M. H., Mount-Campbell, C. A., and Ahalt, S., 1997, Implementing a weighted least squares procedure in training a neural network to solve the short-term load forecasting problem. *IEEE Transactions on Power Systems*, **12**, 1689–1694.

Chow, M., and Tram, H., 1997, Application of fuzzy logic technology for spatial load forecasting. *IEEE Transactions on Power Systems*, **12**, 1360–1366.

Chow, M., Zhu, J., and Tram, H., 1998, Application of fuzzy multi-objective decision making in spatial load forecasting. *IEEE Transactions on Power Systems*, **13**, 1185–1190.

Chow, T. W. S., and Leung, C.-T., 1996, Nonlinear autoregressive neural network model for short-term load forecasting. *IEE Proceedings: Generation, Transmission, and Distribution*, **143**, 500–506.

Czernichow, T., Piras, A., Imhof, K., Caire, P., Jaccard, Y., Dorizzi, B., and Germond, A., 1996, Short term electrical load forecasting with artificial neural networks. *International Journal of Engineering Intelligent Systems for Electrical Engineering and Communications*, **4**, 85–99.

Damborg, M. J., El-Sharkawi, M. A., Aggoune, M. E., and Marks, R. J., II, 1990, Potential of artificial neural network to power system operation. *Proceedings of the IEEE International Symposium on Circuits and Systems*, New Orleans, LA, pp. 2933–2937.

Dash, P. K., Dash, S., Rama Krishna, G., and Rahman, S., 1993, Forecasting of a load time series using a fuzzy expert system and fuzzy neural networks. *International Journal of Engineering Intelligent Systems*, **1**, 103–118.

Dash, P. K., Liew, A. C., and Rahman, S., 1995a, Comparison of fuzzy neural networks for the generation of daily average and peak load profiles. *International Journal of System Science*, **26**, 2091–2106.

Dash, P. K., Liew, A. C., and Rahman, S., 1996, Fuzzy neural network and fuzzy expert system for load forecasting. *IEE Proceedings: Generation, Transmission, and Distribution*, **143**, 106–114.

Dash, P. K., Liew, A. C., Rahman, S., and Dash, S., 1995b, Fuzzy and neuro-fuzzy computing models for electric load forecasting. *Engineering Applications of Artificial Intelligence*, **8**, 423–433.

Dash, P. K., Satpathy, H. P., and Liew, A. C., 1998, Real-time short-term peak and average load forecasting system using a self-organizing fuzzy neural network. *Engineering Applications of Artificial Intelligence*, **11**, 307–316.

Dillon, T. S., Sestito, S., and Leung, S., 1991, Short term load forecasting using an adaptive neural network. *Electric Power and Energy Systems*, **13**, 186–192.

Djukanovic, M., Babic, B., Sobajic, O. J., and Pao, Y. H., 1993, 24-Hour load forecasting. *IEEE Proceedings — C*, **140**, 311–318.

Drezga, I., and Rahman, S., 1999a, Phase-space based short-term load forecasting for deregulated electric power industry. *Proceedings of the International Joint Conference on Neural Networks*, **5**, 3405–3409.

Drezga, I., and Rahman, S., 1999b, Short term load forecasting with local ANN predictors. *IEEE Transactions on Power Systems*, **14**, 844–850.

El-Keib, A. A., Ma, X., and Ma, H., 1995, Advancement of statistical based modeling for short-term load forecasting. *Electric Power Systems Research*, **35**, 51–58.

Elrazaz, Z. S., and Mazi, A. A., 1989, Unified weekly peak load forecasting for fast growing power system. *IEE Proceedings — C*, **136**, 29–41.

Fan, J. Y., and McDonald, J. D., 1994, A Real time implementation of short-term load forecasting for distribution power system. *IEEE Transactions on Power Systems*, **9**, 988–993.

Girgis, A. A., Varadan, S., El-Din, A. K., and Zhu, J., 1995, Comparison of different approaches to short-term load forecasting. *International Journal of Engineering Intelligent Systems for Electrical Engineering and Communications*, **3**, 205–210.

Grady, W. M., Groce, L. A., Huebner, T. M., Lu, Q. C., and Crawford, M. M., 1991, Enhancement, implementation and performance of an adaptive load forecasting technique. *IEEE Transactions on Power Systems*, **6**, 450–456.

Gross, G., and Galiana, F. D., 1987, Short term load forecasting. *Proceedings of the IEEE*, **75**, 1558–1573.

Haida, T., and Muto, S., 1994, Regression based peak load forecasting using a transformation technique. *IEEE Transactions on Power Systems*, **9**, 1788–1794.

Haida, T., Muto, S., Takahashi, Y., and Ishi, Y., 1998, Peak load forecasting using multiple-year data with trend data processing techniques. *Electrical Engineering in Japan*, **124**, 7–16.

Ho, K., Hsu, Y., Chen, C., Lee, T., Liang, C., Lai, T., and Chen, K., 1990, Short term load forecasting of Taiwan power system using a knowledge based expert system. *IEEE Transactions on Power Systems*, **5**, 1214–1221.

Ho, K. L., Hsu, Y. Y., and Yang, C. C., 1992, Short term load forecasting using a multi layer neural network with an adaptive learning algorithm. *IEEE Transactions on Power Systems*, **7**, 141–149.

Hobbs, B, F., Jitprapaikulsarn, S., Konda, S., Chankong, V., Loparo, K. A., and Maratukulam, D. J., 1999, Analysis of unit commitment of improved load forecasts. *IEEE Transactions on Power Systems*, **14**, 1342–1348.

Hsu, Y. Y., 1992, Fuzzy expert systems: an application to short-term load forecasting. *IEEE Proceedings — C*, **139**, 471–477.

Hsu, Y. Y., and Yang, L.-C., 1992, Design of artificial neural networks for short term load forecasting. *IEEE Proceedings — C*, **138**, 407–413.

Huang, S. R., 1997, Short-term load forecasting using threshold autoregressive models. *IEE Proceedings: Generation, Transmission, and Distribution*, **144**, 477–481.

Hyde, O., and Hodnett, P. F., 1997a, Modeling the effect of weather in short-term electricity load forecasting. *Mathematical Engineering in Industry*, **6**, 155–169.

Hyde, O., and Hodnett, P. F., 1997b, Adaptable automated procedure for short-term electricity load forecasting. *IEEE Transactions on Power Systems*, **12**, 84–94.

Infield, D. G., and Hill, D. C., 1998, Optimal smoothing for trend removal in short term electricity demand forecasting. *IEEE Transactions on Power Systems*, **13**, 1115–1120.

Ijumba, N. M., and Hunsley, J. P., 1999, Improved load forecasting techniques for newly electrified areas. *Africon 1999 IEEE*, **2**, 989–994.

Juberias, G., Yunta, R., Garcia Morino, J., and Mendivil, C., 1999, A new ARIMA model for hourly load forecasting. *IEEE Transmission and Distribution Conference Proceedings*, **1**, 314–319.

Kalra, P. K., Srivastav, A., and Chaturvedi, D. K., 1992, Possible application of neural nets to power system operation and control. *Electric Power Systems Research*, **25**, 83–90.

Kandil, N., Sood, V., and Saad, M., 1999, Use of ANNs for short-term load forecasting. *1999 Canadian Conference on Electrical and Computer Engineering*, **2**, 1057–1061.

Kim, K.-H., Park, J.-K., Hwang, K.-J., and Kim, S.-H., 1995, Implementation of hybrid short-term load forecasting system using artificial neural networks and fuzzy expert systems. *IEEE Transactions on Power Systems*, **10**, 1534–1539.

Kung, C.-H., Devaney, M. J., Huang, C.-M., and Kung, C.-M., 1998, Adaptive power system load forecasting scheme using a genetic algorithm embedded neural network. *Proceedings of the IEEE Instrumentation and Measurement Technology Conference, Part 1*, St Paul, MN, 18–21 May, pp. 308–311.

Lee, D. G., Lee, B. W., and Chang, S. H., 1997, Genetic programming model for long-term forecasting of electric power demand. *Electric Power Systems Research*, **40**, 17–22.

Lee, K. Y., and Park, J. H., 1992, Short-term load forecasting using an artificial neural network. *IEEE Transactions on Power Systems*, **7**, 124–130.

Leyan, X., and Chen, W. J., 1999, Artificial neural network short-term electrical load forecasting techniques. *TENCON 99: Proceedings of the IEEE Region 10 Conference*, **2**, pp. 1458–1461.

Liang, R. H., and Hsu, Y. Y., 1994, Fuzzy linear programming: an application to hydroelectric generation scheduling. *IEE Proceedings: Generation, Transmission and Distribution*, **141**, 568–574.

Liu, K., Subbarayan, S., Shoults, R. R., Manry, M. T., Kwan, C., Lewis, F. L., and Naccarino, J., 1996, Comparison of very short-term load forecasting. *IEEE Transactions on Power Systems*, **11**, 877–882.

Liu, X. O., Ang, B. W., and Goh, T. N., 1991, Forecasting of electricity consumption: a comparison between an econometric model and a neural network model. *IEEE International Joint Conference on Neural Networks*, Singapore, 18–21 November, pp. 1254–1259.

Lu, C. N., Wu, H. T., and Vemuri, S., 1993, Neural network based short term load forecasting. *IEEE Transactions on Power Systems*, **8**, 336–341.

Lu, Q. C., Grady, W. M., Crawford, M. M., and Anderson, G. M., 1989, An adaptive non-linear predictor with orthogonal escalator structure for short-term load forecasting. *IEEE Transactions on Power Systems*, **4**, 158–164.

Ma, X., El-Keib, A. A., Smith, R. E., and Ma, H., 1995, Genetic algorithm based approach to thermal unit commitment of electric power systems. *Electric Power Systems Research*, **34**, 29–36.

Mastorocostas , P. A. Theocharis, J. B., and Bakirtzis, A. G., 1999, Fuzzy modeling for short term load forecasting using the orthogonal least squares method. *IEEE Transactions on Power Systems*, **14**, 29–36.

Matthewman, P. D., and Nicholson, H., 1968, Techniques for load prediction in electricity supply industry. *Proceedings of the IEEE*, **115**, 1451–1457.

Mbamalu, G. A. N., and El-Hawary, M. E., 1992, Load forecasting via suboptimal seasonal autoregressive models and iteratively reweighted least squares estimation. *IEEE Transactions on Power Systems*, **8**, 343–348.

Mbamalu, G. A. N., and El-Hawary, M. E., 1993, Load forecasting via suboptimal autoregressive models and iteratively recursive least squares estimation. *IEEE Transactions on Power Systems*, **8**, 343–348.

McDonald, J. R., Lo, K. L., and Sherwood, P. M., 1989, Application of short-term adaptive forecasting techniques in energy management for the control of electric load. *Transactions of the Institute of Measurement and Control*, **11**, 79–91.

McMenamin, J. S., and Monforte, F. A., 1998, Short term energy forecasting with neural networks. *Energy Journal*, **19**, 43–62.

Moghram, I., and Rahman, S., 1989, Analysis and evaluation of five short-term load forecasting techniques. *IEEE Transactions on Power Systems*, **4**, 1484–1491.

Mohamad, E. A., Mansour, M. M., El-Debeiky, S., Mohamad, K. G., Rao, N. D., and Ramakrishna, G., 1996, Results of Egyptian unified grid hourly load forecasting using an artificial neural network with expert system interfaces. *Electric Power Systems Research*, **39**, 171–177.

Mori, H., and Kobayashi, H., 1996, Optimal fuzzy inference for short-term load forecasting. *IEEE Transactions on Power Systems*, **11**, 390–396.

Mori, H., Sone, Y., Moridera, D., and Kondo, T., 1999, Fuzzy inference models for short-term load forecasting with tabu search. *IEEE Systems, Man, and Cybernetics Conference Proceedings*, **6**, 551–556.

Nazarko J., and Styczynski, Z. A., 1999, Application of statistical and neural approaches to the daily load profiles modelling in power distribution systems. *IEEE: Transmission and Distribution Conference,* **1**, 320–325.

Niebur, D., 1995, Artificial neural networks in the power industry, survey and applications. *Neural Network World*, **5**, 951–964.

Oonsivilan, A., and El-Hawary, M. E., 1999, Wavelet neural network based short term load forecasting of electric power system commercial load. *1999 Canadian Conference on Electrical and Computer Engineering*, **3**, 1023–1028.

Paarmann, L. D., and Najar, M. D., 1995, Adaptive online load forecasting via time series modeling. *Electric Power Systems Research*, **32**, 219–225.

Padmakumari, K., Mohandas, K. P., and Theruvengadam, S., 1999, Long term distribution demand forecasting using neuro fuzzy computations. *Electrical Power and Energy Systems Research*, **21**, 315–322.

Papadakis, S. E., Theocharis, J. B., Kiartzis, S. J., and Bakirtzis, A. G., 1998, Novel approach to short-term load forecasting using fuzzy neural networks. *IEEE Transactions on Power Systems*, **13**, 480–489.

Papalexopoulos, A. D., Hao, S., and Peng, T.-M., 1994, An implementation of a neural network based load forecasting model for the EMS. *IEEE Transactions on Power Systems*, **9**, 1956–1962.

Papalexopulos, A. D., and Hesterberg, T. C., 1990, A regression-based approach to short-term load forecasting. *IEEE Transactions on Power Systems*, **5**, 1214–1221.

Park, D. C., El-Sharkawi, M. A., Marks, R. J., Atlas, L. E., and Damborg, M. J., 1991a, Electric load forecasting using an Artificial Neural Network. *IEEE Transactions on Power Systems*, **6**, 442–449.

Park, D. C., and Osama, M., 1991, Artificial neural network based peak load forecasting. *IEEE Proceedings of the SOUTHEASTCON '91*, **1**, pp. 225–228.

Park, J. H., Park, Y. M., and Lee, K. Y., 1991b, Composite modeling for adaptive short-term load forecasting. *IEEE Transactions on Power Systems*, **6**, 450–456.

Peng, T. M., Hubele, N. F., and Karady, G. G., 1990, An conceptual approach to the application of neural networks for short term load forecasting. *Proceedings of the IEEE International Symposium on Circuits and Systems*, New Orleans, LA, pp. 2942–2945.

Peng, T. M., Hubele, N. F., and Karady, G. G., 1992, Advancement in the application of neural networks for short-term load forecasting. *IEEE Transactions on Power Systems*, **7**, 250–257.

Peng, T. M., Hubele, N. F., and Karady, G. G., 1993, An adaptive Neural Network approach to one-week ahead load forecasting. *IEEE Transactions on Power Systems*, **8**, 1195–1203.

RAHMAN, S., 1990, Formulation and analysis of a rule based short term load forecasting algorithm. *Proceedings of IEEE*, **78**, 805–816.

RAHMAN, S., 1993, Generalized knowledge-based short-term load forecasting technique. *IEEE Transactions on Power Systems*, **8**, 508–514.

RAHMAN, S., and HAZIM, O., 1993, A generalized knowledge-based short term load forecasting technique. *IEEE Transactions on Power Systems*, **8**, 509–514.

RAHMAN, S., and HAZIM, O., 1996, Load forecasting for multiple sites: development of an expert system-based technique. *Electric Power Systems Research*, **39**, 161–169.

RAHMAN, S., and SHRESHTA, G., 1991, A priority vector based technique for load forecasting. *IEEE Transactions on Power Systems*, **6**, 1459–1465.

RAMIREZ-ROSADO, I. J., and DOMINGUEZ-NAVARRO, J. A., 1996, Distribution planning of electric energy using fuzzy models. *International Journal of Power and Energy Systems*, **16**, 49–55.

SENJYU, T., HIGA, S., and UEZATO, K., 1998, Future load curve shaping based on similarity using fuzzy logic approach. *IEE Proceedings: Generation, Transmission and Distribution*, **145**, 375–380.

SINHA, A. K., and MANDAL, J. K., 1999, Hierarchical dynamic state estimator using ANN-based dynamic load prediction. *IEE Proceedings: Generation, Transmission and Distribution*, **146**, 541–549.

SRINIVASAN, D., CHANG, C. S., and LIEW, A. C., 1992, Demand forecasting using fuzzy neural computation, with special emphasis on weekend and public holiday forecasting. *IEEE Transactions on Power Systems*, **8**, 343–348.

SRINIVASAN, D., and LEE, M. A., 1995, Survey of hybrid fuzzy neural approaches to electric load forecasting. *Proceedings of the IEEE International Conference on Systems, Man and Cybernetics, Part 5*, Vancouver, BC, pp. 4004–4008.

SRINIVASAN, D., LIEW, A. C., and CHEN, S. P. J., 1991, A novel approach to electric load forecasting based on neural networks. *IEEE International Joint Conference on Neural Networks*, Singapore, 18–21 November, pp. 1172–1177.

SRINIVASAN, D., TAN, S. S., CHANG, C. S., and CHAN, E. K., 1999, Parallel neural network-fuzzy expert system for short-term load forecasting: system implementation and performance evaluation. *IEEE Transactions on Power Systems*, **14**, 1100–1106.

VARADAN, S., and MAKRAM, E. B., 1996, Harmonic load identification and determination of load composition using a least squares method. *Electric Power Systems Research*, **37**, 203–208.

VERMAAK, J., and BOTHA, E. C., 1998, Recurrent neural networks for short-term load forecasting. *IEEE Transactions on Power Systems*, **13**, 126–132.

WILLIS, H. L., FINLEY, L. A., and BURI, M. J., 1995, Forecasting electric demand of distribution system planning in rural and sparsely populated regions. *IEEE Transactions on Power Systems*, **10**, 2008–2013.

WILLIS, H. L., and NORTHCOTE-GREEN, J. E. D., 1984, Comparison of fourteen distribution load forecasting methods. *IEEE Transactions on Power Apparatus and Systems*, **PAS-103**, 1190–1197.

WU, H.-C., and LU, C., 1999, Automatic fuzzy model identification for short-term load forecast. *Generation, Transmission and Distribution, IEE Proceedings*, **146**, 477–482.

YANG, H.-T., and HUANG, C.-M., 1998, New short term load-forecasting approach using self-organizing fuzzy ARMAX models. *IEEE Transactions on Power Systems*, **13**, 217–225.

YANG, H.-T., HUANG, C.-M., and HUANG, C.-L., 1996, Identification of ARMAX model for short term load forecasting: an evolutionary programming approach. *IEEE Transactions on Power Systems*, **11**, 403–408.

YOO, H., and PIMMEL, R. L., 1999, Short term load forecasting using self-supervised adaptive neural network. *IEEE Transactions on Power Systems*, **14**, 779–784.

ZHAO, H., REN, Z., and HUANG, W., 1997, Short-term load forecasting considering weekly period based on periodical auto regression. *Proceedings of the Chinese Society of Electrical Engineers*, **17**, pp. 211–213.

ZHENG, T., GIRGIS, A. A., and MAKRAM, E. B., 2000, A hybrid wavelet–Kalman filter method for load forecasting. *Electric Power Systems Research*, **54**, 11–17.