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An Overview of Electricity Demand Forecasting Techniques

Arunesh Kumar Singh*, Ibraheem, S. Khatoon, Md. Muazzam ,
Department of Electrical Engineering, Jamia Millia Islamia, New Delhi-110025, India
Tel: 011-26982651, E-mail: aru_dei@yahoo.com*
D. K. Chaturvedi
Department of Electrical Engineering, Dayalbagh Educational Institute, Agra-282010, India
Tel: 0562-22801224, E-mail: dkc_foe@rediffmail.com

Abstract
Load forecasts are extremely important for energy suppliers and other participants in electric energy generation, transmission, distribution and markets. Accurate models for electric power load forecasting are essential to the operation and planning of a utility company. Load forecasts are extremely important for energy suppliers and other participants in electric energy generation, transmission, distribution and markets. This paper presents a review of electricity demand forecasting techniques. The various types of methodologies and models are included in the literature. Load forecasting can be broadly divided into three categories: short-term forecasts which are usually from one hour to one week, medium forecasts which are usually from a week to a year, and long-term forecasts which are longer than a year. Based on the various types of studies presented in these papers, the load forecasting techniques may be presented in three major groups: Traditional Forecasting technique, Modified Traditional Technique and Soft Computing Technique.
Keywords: Electricity Demand, Forecasting Techniques, Soft Computing, Regression method, SVM

1. Introduction

Load forecasting helps an electric utility to make important decisions including decisions on purchasing and generating electric power, load switching, and infrastructure development. The subject of load forecasting has been in existence for decades to forecast the future demand. This involves the accurate prediction of both the magnitudes and geographical locations of electric load over the different periods of the planning horizon. Electricity demand forecasting is considered as one of the critical factors for economic operation of power systems, Bunn and Farmer [1] infers that accurate load forecasting holds a great saving potential for electric utility corporations. The maximum savings can be achieved when load forecasting is used to control operations and decisions like economic dispatch/ unit commitment and fuel allocation /on -line network analysis. According to Haida and Muto [2], the operating cost is increased due to the forecasting errors (either positive or negative).
This part of the research work is necessary to establish the statistical relevance of the proposed research work, establish a generalized research question, analyzing existing methods, and explore areas of possible improvements. This chapter covers the analysis of various existing load forecasting techniques which provides up-to-date brief mathematical descriptions of each category. A comparative study of reviewed literature, findings and remarks are discussed here.

2. Classification of Demand Forecasting Techniques

There have been many studies relating demand forecasting methodology since its inception. Various types of classifications based on duration of forecasting and forecasting methods are proposed in literature over a period of time. Demand forecasting methods can be also classified in terms of their degrees of mathematical analysis used in the forecasting model. These are presented into two basic types, namely: quantitative and qualitative methods. In most cases historical data are insufficient or not available at all. The qualitative forecasting methods are generally used by planners to forecast accurately, these methods are Delphi method, Curve fitting and technological comparisons including other methods. Other forecasting techniques such as decomposition methods, regression analysis, exponential smoothing, and the Box-Jenkins approach are quantitative methods [3]. Based on the various types of studies presented in these papers, the load forecasting techniques may be grouped broadly in three major groups: 1.Traditional Forecasting technique, 2.Modified Traditional Technique and 3.Soft Computing Technique.

2.1 Traditional Forecasting Techniques

One of the most important topics for the planners of the nation is to predict future load demands for planning the infrastructure, development trends and index of overall development of the country etc. In early days, these predictions or forecasts were carried out using traditional/conventional mathematical techniques. With the development of advanced tools, these techniques have been augmented with the finding of researches for more effective forecasting in various fields of study. The traditional foresting techniques are as following: regression, multiple regression, exponential smoothing and Iterative reweighted least-squares technique.

2.1.1 *Regression Methods*

Regression is one of the most widely used statistical techniques and it is often easy to be implemented. The regression methods are usually employed to model the relationship of load consumption and other factors such as weather conditions, day types and customer classes. This method assumes that the load can be divided in a standard load trend and a trend linearly dependent on some factors influencing the load. The mathematical model can be written as:

$$L(t) = Ln(t) + \Sigma\, ai\, xi(t) + e(t) \tag{1}$$

Where, Ln(t) is the normal or standard load at time t, ai is the estimated slowly varying coefficients, xi(t) are the independent influencing factors such as weather effect, e (t) is a white noise component, n is the number of observations, usually 24 or 168.

The method accuracy relies on the adequate representation of possible future conditions by historical data but a measure to detect any unreliable forecast can be easily constructed. The proposed procedure requires few parameters that can be easily calculated from historical data by applying the cross-validation technique. In order to forecast the load precisely throughout a year, one should consider seasonal load change, annual load growth and the latest daily load change. To deal with these characteristics in the load forecasting, a transformation technique is presented. This technique consists of a transformation function with translation and reflection methods. The transformation function is estimated with the previous year's data points, in order that the function converts the data points into a set of new data points with preservation of the shape of temperature-load relationships in the previous year [4, 5-7].

2.1.2 *Multiple Regression*

Multiple Regressions is the most popular method and often used to forecast the load affected by a number of factors ranging from meteorological effects, per capital growth, electricity prices, economic growth etc. Multiple Regression analysis for load forecasting uses the technique of least-square estimation. Mbamalu and El-Hawary used the following load model for applying this analysis [8]:

$$Y(t) = V_t\, a_t + e_t \tag{2}$$

Where , t is sampling time, Yt is total measured load system, Vt is vector of adapted variables such as time, temperature, light intensity, wind speed, humidity, day type (workday, weekend), etc., at is transposed vector of regression coefficients and et is model error at time t.

The Polynomial degree of influence of the variables from 1 to 5 can be selected by the data analysis program. In most cases, linear dependency gives the best results. Moghram and Rahman compared it with other models for a 24-h load forecast [9]. Barakat evaluated the regression model to fit data and check seasonal variations [10]. Papalexopulos and Hesterberg developed a model that produces an initial daily peak forecast and then uses this initial peak forecast to produce initial hourly forecasts [11]. In subsequent 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. Trend estimation evaluates growth by the variable transformation technique, while Trend cancellation removes annual growth by subtraction or division. A least-squares approach was used by Varadan and Makram to identify and quantify the different types of load at power lines and substations [12]. To predict load demand for Irish electricity in 1997 Hyde and Hodnett developed a weather-load model based on regression analysis of historical load and weather data. Lately they modified the developed model as an adaptable regression model for 1-day-ahead forecasts, which identifies weather-insensitive and sensitive load components. They used linear regression of past data to estimate the parameters of the two components Broadwater (1997) introduced a new regression-based method, Nonlinear Load Research Estimator (NLRE) [13-14, 15].

2.1.3 *Exponential Smoothing*

Exponential smoothing is one of the approaches used for load forecasting. In this method, first load is model based on previous data, then to use this model to predict the future load. In Moghram and Rahman's exponential smoothing model, the load at time t, y(t), is modeled using a fitting function and is expressed in the form [9]:

$$y(t) = \beta(t)T\; f(t) + e(t), \tag{3}$$

Where, $f(t)$-Fiting function vector of the process, β(t)-Coefficient of vector, e(t) White noise and T-Transpose operator.

The Winter's method is one of existing exponential smoothing methods having capacity to analyze seasonal time series directly. It is based on three smoothing constants for stationary, trend and seasonality. Barakat [14] analyzed the result of the model and conclude that unique pattern of energy and demand pertaining to fast growing areas was difficult to analyze and predict by direct application of the Winter's method. Exponential smoothing was augmented with power spectrum analysis and adaptive autoregressive modeling in El-Keib [16] hybrid approach. Infield and Hill [17] optimal smoothing based trend removal technique has been shown to compare favorably with conventional methods of load forecasting.

2.1.4 Iterative Reweighted Least-Squares

Mbamalu and El-Hawary [8] used iteratively reweighted least-squares procedure to identify the model order and parameters. The method uses an operator that controls one variable at a time and determines optimal starting point. Autocorrelation function and the partial autocorrelation function of the resulting differenced past load data is utilized to identify a suboptimal model of the load dynamics. A three-way decision variable is formed by the weighting function, the tuning constants and the weighted sum of the squared residuals in identifying an optimal model and the subsequent parameter estimates. Consider the parameter estimation problem involving the linear measurement equation:

$$Y = X\beta + e, \tag{4}$$

Where, Y is an n x 1 vector of observations, X is an n x p matrix of known coefficients (based on previous load data), β is a p x 1 vector of the unknown parameters and e is an n x 1 vector of random errors.

Results are more accurate when the errors are not Gaussian. Iterative methods are used to find β. Newton method /alternatively Beaton-Turkey iterative reweighted least-square's algorithm (IRLS) can be applied if β is known. Mbamalu, El- Hawary [8] enhanced this work by introducing an interactive approach employing least-squares and the IRLS procedure for estimating the parameters of a seasonal multiplicative autoregressive model.

2.2 Modified Traditional Techniques

The traditional forecasting techniques have been modified so that they are able to automatically correct the parameters of forecasting model under changing environmental conditions. Some of the techniques which are the modified version of these traditional techniques are adaptive load forecasting, stochastic time series and support vector machine based techniques.

2.2.1 Adaptive Demand Forecasting

Demand forecasting model parameters are automatically corrected to keep track of the changing load conditions. Hence Demand forecasting is adaptive in nature and can also be used as an on-line software package in the utilities control system. Next state vector is estimated using current prediction error and the current weather data acquisition programs. State vector is determined by total historical data set analysis. Switching between multiple and adaptive regression analysis is possible in this mode. The same model as in the multiple regression section, by equation given below is used in this model [4].

$$Y(t) = Xt\ at + et, \tag{5}$$

Where, t-sampling time, Y(t)- measured system total load, Xt -vector of adapted variables such as time, temperature, light intensity, wind speed, humidity, day type (workday, weekend), etc., at -transposed vector of regression coefficients and et-Model error at time t.

Lu [18] developed an adaptive Hammerstein model with an orthogonal escalator structure as well as a lattice structure for joint processes. This model used a joint Hammerstein non-linear time-varying functional relationship between load and temperature. This algorithm performed better than the commonly used RLS (Recursive Least-square) algorithm. Grady [19] enhanced and applied the algorithm developed by Lu. An improvement was obtained in the ability to forecast total system hourly load as far as 5 days McDonald [20], presented an adaptive-time series model and simulated the effects of a direct load control strategy. A composite model for load prediction composed of three components (nominal load, type load and residual load) was developed by Park in [7]. To use Kalman's filter nominal load is modeled accordingly and the parameters of the model are adapted by the exponentially weighted recursive least-squares method. Paarmann and Najar's [21] introduced an adaptive online load forecasting approach which 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 & in addition to updating model parameters, the structure and order of the time series is adaptable to new conditions. Zheng [22] used Wavelet transform Kalman filter method for load forecasting. The Wavelet coefficients are modelled and solved by the recursive Kalman filter algorithm.

2.2.2 Stochastic Time Series

The Time series methods appear to be among the most popular approaches that applied to STLF. Time series methods are based on the assumption that the data have an internal structure, such as autocorrelation, trend or seasonal variation. The first impetus of the approach is to accurately assemble a pattern matching available data and then obtain the forecasted value with respect to time using the established model. The next subsection discusses some of the time series models used for load forecasting.

2.2.2.1 Autoregressive (AR) Model

Auto-Regressive (AR) model can be used to model the load profile, If the load is assumed to be a linear combination of previous loads, which is given by Liu [23] as:

$$Lk = \sum_{i=1}^{m} \alpha ik\, Lk\text{-}i + ek \tag{6}$$

Where, Lk is the predicted load at time k (min), ek is a random load disturbance, αi , i =1…m are unknown coefficients and above given equation is the auto regressive model of order m. The unknown coefficients in equation can be tuned on-line using the well-known least mean square (LMS) algorithm of Mbamalu and El-Hawary [8]. Huang [24] and Zhao [25] proposed an autoregressive model with an optimum threshold stratification algorithm and two periodical autoregressive (PAR) models for hourly load forecasting respectively.

2.2.2.2 Autoregressive Moving-Average (ARMA) Model

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

$$y(t) = \varphi 1y(t-1)+\ldots+ \varphi py(t-p)+a(t)- \varphi 1a(t-1)-\ldots- \varphi q(t-q). \tag{7}$$

A recursive scheme is used to identify the parameters, or using a maximum-likelihood approach. Barakat [26] 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 [12] used the WRLS (Weighted Recursive Least Squares) algorithm to update the parameters of their adaptive ARMA model. Chen [27] 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.

2.2.2.3 Autoregressive Integrated Moving-Average (ARIMA) Model

If the process is dynamic/non-stationary, then transformation of the series to the stationary form has to be done first. This transformation can be done by the differencing process. By introducing the ▼ operator, the series ▼X(t) = (1-B)X(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

$$\Phi(B)\blacktriangledown d\; X(t) = \theta(B) * a(t) \tag{8}$$

That is proposed by Elrazaz and Mazi [28] 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 [10] used a seasonal ARIMA model on historical data to predict the load with seasonal variations. Juberias [29] developed a real time load forecasting ARIMA model that includes the meteorological influence as an explanatory variable.

2.2.3 Support Vector Machine based Techniques

Vapnik was the first to introduce SVM; it is a novel powerful machine learning method based on statistical learning theory (SLT), which analyzes data and recognizes patterns, used for classification and regression analysis. They combine generalization control with a technique to address the curse of dimensionality [30]. B.J.Chen et.al proved that temperature and other climate information is not much useful for mid-term load forecasting and introduction of time series forecasting may improve the results [31]. F. E. H. Tay and L. J. Cao [32] modified risk function of conventional support vector machines by penalizing insensitive errors more heavily than the distant insensitive errors, they named this method as C-ascending support vector machine. They conclude by a test that the C-ascending support vector machines with the actually ordered sample data consistently forecast better than the standard support vector machines.

X. Tao et.al proposed a SVM based strategy to rand individual components according to their influence on the load forecasting by limiting the number of features that cuts down the model capacity [33]. To estimate the relations between input and output variables Lee & Song further modified the Support Vector Machine (SVM) by using an empirical inference model. This method was derived by modifying the risk function of the standard SVM by using the concept of Locally Weighted Regression. The proposed method proves useful to be in the field of process monitoring, optimization and quality control [34]. G. S. Hu et.al presented a new short-term load forecasting method by conjunctive use of fuzzy C-mean clustering algorithm and weighted support vector machines (WSVMs). They clustered input samples according to the similarity degree [35]. Ying-Chun Guo showed that SVM based model provides a promising arithmetic to forecasting electricity load than artificial neural network. The model overcomes the disadvantages of general artificial neural network (ANN), such as it is not easy to converge, liable to trap in partial minimum and unable to optimize globally, and the generalization of the model is not good, etc [36]. Jingmin Wang et.al proposed a new optimal model which is based on Stimulated Annealing Particle Swarm Optimization Algorithm (SAPSO) that combines the advantages of PSO algorithm and SA algorithm. The new algorithm is employed to choose the parameters of a SVM model. The model is proved to be able to enhance the accuracy and improved the convergence ability and reduced operation time by numerical experiment [37].

Jingmin Wang et al., presented A short-term load forecasting model based on SVM with Adaptive Quantum-behaved Particle Swarm Optimization Algorithm (AQPSO) .They introduced a diversity-guided model into the Quantum-behaved Particle Swarm Optimization (QPSO), the AQPSO algorithm is employed to determine the free parameters of SVM model automatically. The model is proved to be able to enhance the accuracy and improve global convergence ability and reduce operation time [38]. Ehab E. Elattar et.al presented a modified version of the support vector regression (SVR) to solve the load forecasting problem. They derived the model by modifying the risk function of the SVR algorithm with the use of locally weighted regression (LWR) while keeping the regularization term in its original form. [39].

2.3 Soft Computing Techniques

It is a fact that every system is pervasively imprecise, uncertain and hard to be modelled precisely. A flexible approach called Soft Computing technique has emerged to deal such models effectively and most efficiently on research scenario. It has been very widely in use over the last few decades. Soft computing is an emerging approach which parallels the remarkable ability of the human mind to reason and learn in an environment of uncertainty and imprecision. It is fast emerging as a tool to help computer-based intelligent systems mimic the ability of the human mind to employ modes of reasoning that are approximate rather than exact. The basic theme of soft computing is that precision and certainty carry a cost and that intelligent systems should exploit, wherever possible, the tolerance for imprecision and uncertainty. Soft computing constitutes a collection of disciplines which include fuzzy logic (FL), neural networks (NNs), evolutionary algorithms (EAs) like genetic algorithms (GAs) etc. Natural intelligence is the product of millions of years of biological evolution. Simulating complex biological evolutionary processes may lead us to discover, how evolution propels living systems toward higher-level of intelligence. One of the newer and relatively simple optimization approaches is the GA which is based on the evolutionary principle of natural selection. Perhaps one of the most attractive qualities of GA is that it is a derivative free optimization tool. The demand/ load forecasting techniques are also developed based on the following soft computing/ intelligent techniques. The Knowledge-based expert systems have been utilized for this purpose also.

2.3.1 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 extreme 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 uni-modal, 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 Genetic Algorithm 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 Pi, i = 1, 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 described the system load model in the following ARMAX form: [40]

$$A(q) * y(t) = B(q) * u(t) + C(q) * e(t) \tag{9}$$

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 [41] 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 [40] presented a fuzzy autoregressive moving average with exogenous variable (FARMAX) model for load demand forecasts. The model is formulated as a combinatorial optimization problem, and then solved by a combination of heuristics and evolutionary programming. Ma [42] used a genetic algorithm with a newly developed knowledge augmented mutation-like operator called the forced mutation. Lee [43] used genetic algorithms for long-term load forecasting, assuming different functional forms and comparing results with regression. To maximize the efficiency of GAs, the three inherent parameters of GAs are to be optimized, the mutation probability (Pm) crossover probability (Pc), and the population size (POPSIZE). For parameter optimization of GAs several results have been obtained over the last few years. De Jong and Schuster proposed heuristics for an optimal setting of the mutation probability Pm. Fogarty and booker investigated time dependencies of the mutation and the crossover probability respectively.

Greffenstette and schaffer found optimal settings for all three parameters of the GAs by experiment; Goldberg and Ros estimated optimal population size theoretically [44-47].

2.3.2 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 [23] observed that a fuzzy logic system has great capability in drawing similarities from huge data. The similarities in input data (L-i -L0) can be identified by different first order differences (Vk) and second-order differences (Ak), which are defined as:

$$Vk = (Lk - Lk\text{-}1)/T, \qquad Ak = (Vk - Vk\text{-}1)/T \tag{10}$$

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 [48] 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 [49] formulated a fuzzy linear programming model of the electric generation scheduling problem, representing uncertainties in forecast and input data using fuzzy set notation. The hybrid fuzzy-neural technique to forecasting load was later enhanced by Dash [50]. This hybrid approach can accurately forecast on weekdays, public holidays, and days before and after public holidays.

Mori and Kobayashi [51] 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 [52] 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 [53] 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 [54] 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 [55] applied a fuzzy, multi-objective model to spatial load forecasting. The fuzzy logic approach proposed by Senjyu [56] 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 [57] 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 [58] proposed an alternative to the traditional trial and error method for determining of fuzzy membership functions. Automatic model identification is used, that utilizes analysis of variance, cluster estimation, and recursive least-squares. Mastorocostas. [59] applied a two-phase STLF methodology that also uses orthogonal least-squares (OSL) in fuzzy model identify cation. Padmakumari [60] combined fuzzy logic with neural networks in a technique that reduces both errors and computational time. Srinivasan [61] combined three techniques fuzzy logic, neural networks and expert systems in a highly automated hybrid STLF approach with unsupervised learning.

2.3.3 Neural Networks

Neural networks (NN) or artificial neural networks (ANN) have very wide applications because of their ability to learn. According to Damborg [62], 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 ωi and are added to a threshold θ to form an inner product number called the net function. The net function NET used by Ho [63], 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 [23], 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 [64] surveyed hybrid fuzzy neural approaches to load forecasting.

Djukanovic [65] 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 hrs. Papalexopoulos [29] 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 [63] extended the three-layered feed forward adaptive neural networks to multilayer. Dillon [66] proposed a multilayer feed forward neural network, using a learning algorithm for adaptive training of neural networks. Srinivasan [3] used an ANN based on back propagation for forecasting, and showed its superiority to traditional methods. Liu [23] 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 [67].

Azzam-ul-Asar and McDonald [68] 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. Dash [50] also used fuzzy logic in combination with neural networks for load forecasting. Their work has been discussed in the previous section. Chen [69] 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 [70] incorporated temperature and humidity effects in an ANN approach for STLF in Kuwait. Vermaak and Botha [71] 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. S.K. Sheikh et al. [72] has been carried out a short term laod forecasting in their campus at Ahmadnagar, by using ANN. It was hourly based forecasting, by using this technique fure demand can be predicted.

2.3.4 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 affect 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 [31, 73] and Ho [63]. The algorithms of Rahman and Hazim [73] combine features from knowledge-based and statistical techniques, using the pairwise comparison technique to prioritize categorical variables. Brown [74] 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 [75] combined fuzzy logic with expert systems. Kim [76] 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. Mohammad [77] applied a combination of expert systems and NN for hourly load forecasting in Egypt. Chiu [78] determined that a combined expert system- NN approach is faster and more accurate than either one of the two methods alone. Chandrasekhar [79] applied a combined expert system-NN procedure divided into three modules: location planning, forecasting and expansion planning.

3. Comparative Study of Techniques

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 [80], who performed comparison tests on 14 load forecasting methods. Dash [50] and Papadaocis et.al [15] also compared several fuzzy neural network based methods. On the basis of a simulation study, Liu [23] 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 [8] compared their interactive autoregressive model to the Box-Jenkins method. Willis [81] compared their simulation-based method to two other simulation methods. 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. Different techniques of electric load forecasting are compared using short term load forecasting based on statistical robust method [82].

4. Conclusions

Different techniques namely; regression, multiple regression, exponential smoothing, iterative reweighted least-squares, adaptive load forecasting, stochastic time series- autoregressive, ARMA model, ARIMA model, support vector machine based, soft computing based models- genetic algorithms, fuzzy logic, neural networks and knowledge based expert systems etc. have been applied to load forecasting. The merits and demerits of these techniques are presented technique wise. From the works reported so far, it can be inferred that demand forecasting techniques based on soft computing methods are gaining major advantages for their effective use. There is also a clear move towards hybrid methods, which combine two or more of these techniques. The research has been shifting and replacing old approaches with newer and more efficient ones.

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