AN APPROACH TO ELECTRICITY LOAD FORECASTING AND TECHNIQUES: A REVIEW

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***ABSTRACT*:** *One of the primary tasks of an electric utility is to accurately predict load demand requirements at all times, especially for long term. Accurate models for electric power load forecasting are essential to the operation and planning of a utility company. Hence knowing the load behavior in advance is very important in planning, analysis and operation of power systems to maintain an uninterrupted, reliable, secure and economic energy providing. Load forecast are extremely important in electric energy generation, transmission, distribution and markets. A large variety of mathematical methods have been developed for load forecasting. In this paper we have discuss various approaches to load forecasting such as statistical and artificial intelligence techniques that have been developed for short, medium and long tern electric load forecasting.*

KEYWORDS: Load, Forecasting, Statistics, Regression, Artificial Intelligence, Genetic Algorithm, SVM, Fuzzy Logic

1. INTRODUCTION

Accurate models for electric power load forecasting are essential to the operation and planning of a utility company. Load forecasting helps an electric utility to make important decisions including decisions on purchasing and generating electric power, load switching, and infrastructure development. Load forecasts are extremely important for energy suppliers, ISOs, financial institutions, and other participants in electric energy generation, transmission, distribution and markets. Load forecasts can be divided into three types: 1) short-term forecasts which are usually from one hour to one week 2) Medium term forecasts which are usually from a week to a year 3) Long-term forecasts which are longer than a year.

The forecasts for different time horizons are important for different operations within a utility company. The natures of these forecasts are also different. For example, for a particular region, it is possible to predict the next day load with an accuracy of approximately 1-3%. However, it is impossible to predict the next year peak load with the similar accuracy since accurate long-term weather forecasts are not available. For the next year peak forecast, it is possible to provide the probability distribution of the load based on historical weather observations. Load forecasting has always been important for planning and operational decision conducted by utility companies. However, with the deregulation of the energy industries, load forecasting is even more important. With supply and demand fluctuating and the changes of weather conditions and energy prices increasing by a factor of ten or more during peak situations, load forecasting is vitally important for utilities. Short-term load forecasting can help to estimate load flows and to make decisions that can prevent overloading. Timely implementations of such decisions lead to the improvement of network reliability and to the reduced occurrences of equipment failures and blackouts. In the deregulated economy, decisions on capital expenditures based on long-term forecasting are also more important than in a non-deregulated economy when rate increases could be justified by capital expenditure projects. Most forecasting methods use statistical techniques or artificial intelligence algorithms such as regression, neural networks, fuzzy logic, and expert systems. Two methods known as end-use and econometric approach are broadly used for medium- and long-term forecasting. A variety of methods, which include the similar day approach, various regression models, time series, neural networks, statistical learning algorithms, fuzzy logic, and expert systems, have been developed for short-term forecasting. As we see, a large variety of mathematical methods and ideas have been used for load forecasting. The development and improvements of appropriate mathematical tools will lead to the development of more accurate load forecasting techniques. The accuracy of load forecasting depends not only on the load forecasting techniques, but also on the accuracy of forecasted weather scenarios.

2. IMPORTANT FACTORS FOR FORECAST

The medium and long-term forecasts take into account the historical load and weather data, the number of customers in different categories, the appliances in the area and their characteristics including age, the economic and demographic data and their forecasts, the appliance sales data, and other factors. On the other hand for short-term load forecasting several factors should be considered such as time factors, weather data and possible customer classes.

The time factors include the time of the year, the day of the week, and the hour of the day. There are important differences in load between weekdays and weekends. The load on different weekdays also can behave differently. For example, Mondays and Fridays being adjacent to weekends, may have structurally different loads than Tuesday through Thursday. This is particularly true during the summer time. Holidays are more difficult to forecast than non-holidays because of their relative infrequent occurrence. Weather conditions influence the load. In fact, forecasted weather parameters are the most important factors in short-term load forecasts. Various weather variables could be considered for load forecasting. Temperature and humidity are the most commonly used load predictors. An electric load prediction survey published in [17] indicated that of the 22 research reports considered, 13 made use of temperature only, 3 made use of temperature and humidity, 3 utilized additional weather parameters, and 3 used only load parameters. Among the weather variables listed above, two composite weather variable functions, the THI (temperature-humidity index) and WCI (wind chill index), are broadly used by utility companies. THI is a measure of summer heat discomfort and similarly WCI is cold stress in winter. Most electric utilities serve customers of different types such as residential, commercial, and industrial. The electric usage pattern is different for customers that belong to different classes but is somewhat alike for customers within each class. Therefore, most utilities distinguish load behavior on a class-by-class basis [36].

3. DIFFERENT METHODS OF FORECASTING

Over the last few decades a number of forecasting methods have been developed. Three methods, Trend Analysis, end-use and econometric approach are broadly used for medium and long-term forecasting. Different methods such as the similar day approach, various regression models, time series, neural networks, expert systems, fuzzy logic, and statistical learning algorithms, are used for short-term forecasting. The development, improvements, and investigation of the appropriate mathematical tools will lead to the development of more accurate load forecasting techniques. Statistical approaches usually require a mathematical model that represents load as function of different factors such as time, weather, and customer class. The two important categories of such mathematical models are: additive models and multiplicative models. They differ in whether the forecast load is the sum (additive) of a number of components or the product (multiplicative) of a number of factors.

For example, Chen *et al.* [4] presented an additive model that takes the form of predicting load as the function of four components:

$L = Ln + Lw + Ls + Lr,$

where L is the total load, Ln represents the "normal" part of the load, which is a set of standardized load shapes for each "type" of day that has been identified as occurring throughout the year, Lw represents the weather sensitive part of the load, Ls is a special event component that create a substantial deviation from the usual load pattern, and Lr is a completely random term, the noise.

A multiplicative model presented by Chen may be of the form

$L = Ln \cdot Fw \cdot Fs \cdot Fr,$

Where Ln is the normal (base) load and the correction factors Fw, Fs, and Fr are positive numbers that can increase or decrease the overall load. These corrections are based on current weather (Fw), special events (Fs), and random fluctuation (Fr). Factors such as electricity pricing (Fp) and load growth (Fg) can also be included. Rahman [29] presented a rule based forecast using a multiplicative model. Weather variables and the base load associated with the weather measures were included in the model

3.1 Methods for Medium and long-term load forecasting.

Parametric Methods:

The parametric methods are based on relating load demand to its affecting factors by a mathematical model. The model parameters are estimated using statistical techniques on historical data of load and it's affecting factors. The three types of well-known parametric methods are as, trend analysis, end-use modeling and econometric modeling.

The Trend Analysis, the end-use modeling, econometric modeling, and their combinations are the most often used methods for medium and long-term load forecasting. Descriptions of appliances used by customers, the sizes of the houses, the age of equipment, technology changes, customer behavior, and population dynamics are usually included in the statistical and simulation models based on the end-use approach. In addition, economic factors such as per capita incomes, employment levels, and electricity prices are included in econometric models. These models are often used in combination with the end-use approach. Long-term forecasts include the forecasts on the population changes, economic development, industrial Construction, and technology development.

3.1.1 Trend Analysis

Trend analysis extends past rates of electricity demand in to the future, using techniques that range from hand-drawn straight to complex computer produced curves. These extensions constitute the forecast. Trend analysis focuses on past changes or movements in electricity demand and uses them to predict future changes in electricity demand.

The advantage of trend analysis is that, it is simple, quick and inexpensive to perform [5]

The disadvantage of a trend forecast is that it produces only one result, future electricity demand. It does not help analyze why electricity demand behaves the way it does, and it provides no means to accurately measure how changes in energy prices or government polities influence electricity demand [5].

3.1.2 End-use models.

The end-use approach directly estimates energy consumption by using extensive information on end use and end users, such as appliances, the customer use, their age, sizes of houses, and so on. Statistical information about customers along with dynamics of change is the basis for the forecast. End-use models focus on the various uses of electricity in the residential, commercial, and industrial sector. These models are based on the principle that electricity demand is derived from customer's demand for light, cooling, heating, refrigeration, etc. Thus end-use models explain energy demand as a function of the number of appliances in the market [15]. Ideally this approach is very accurate. However, it is sensitive to the amount and quality of end-use data. For example, in this method the distribution of equipment age is important for particular types of appliances. End-use forecast requires less historical data but more information about customers and their equipment.

The disadvantage of end- use analysis is that most end use models assume a constant relationship between electricity and end-use (electricity per appliance) this might hold for over a few years, but over 10 or 20 year period, energy saving technology or energy prices will undoubtedly change, and the relationship will not remain constant [7].

3.1.3 Econometric models.

The econometric approach combines economic theory and statistical techniques for forecasting electricity demand. The approach estimates the relationships between energy consumption (dependent variables) and factors influencing consumption. The relationships are estimated by the least-squares method or time series methods. One of the options in this framework is to aggregate the econometric approach, when consumption in different sectors (residential, comer cial, industrial, etc.) is calculated as a function of weather, economic and other variables, and then estimates are assembled using recent historical data. Integration of the econometric approach into the end-use approach introduces behavioral components into the end-use equations.[5]

The advantage of econometrics are that it provides detail information on future levels of electricity demand, why future electricity demand increases, and how electricity demand is affected by all the various factors. [7], [8], [30].

3.1.4 Statistical Model based learning.

In order to simplify the medium-term forecasts, make them more accurate, and avoid the use of the unavailable information, Feinberg *et al.* ([11], [12]) developed a statistical model that learns the load model parameters from the historical data. Feinberg *et al.*[11], [12] studied load data sets provided by a utility company in Northeastern US. The focus of the study was the summer data. Author compared several load models and came to the conclusion that the following multiplicative model is the most accurate

$L(t) = F(d(t), h(t)) \cdot f(w(t)) + R(t),$

where $L(t)$ is the actual load at time t, $d(t)$ is the day of the week, $h(t)$ is the hour of the day, $F(d, h)$ is the daily and hourly component, $w(t)$ is the weather data that include the temperature and humidity, $f(w)$ is the weather factor, and $R(t)$ is a random error. In fact, $w(t)$ is a vector that consists of the current and lagged weather variables. This reflects the fact that electric load depends not only on the current weather conditions but also on the weather during the previous hours and days. In particular, the well-known effect of the heat waves is that the use of air conditioners increases when the hot weather continues for several days. To estimate the weather factor $f(w)$, we used the regression model

$f(w) = \beta_0 + \sum \beta j + Xj$

Where Xj are explanatory variables which are nonlinear functions of Current and past weather parameters and β_0, βj are the regression coefficients. The parameters of the model can be calculated iteratively. We start with $F = 1$. Then we use the above regression model to estimate f. Then we estimate F, and so on. The described algorithm demonstrated rapid convergence on historical hourly load and weather data [7].

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3.2 Short-term load forecasting methods

A large variety of statistical and artificial intelligence techniques have been developed for short-term load forecasting.

3.2.1 Similar-day approach.

This approach is based on searching historical data for days within one, two, or three years with similar characteristics to the forecast day. Similar characteristics include weather, day of the week, and the date. The load of a similar day is considered as a forecast. Instead of a single similar day load, the forecast can be a linear combination or regression procedure that can include several similar days. The trend coefficients can be used for similar days in the previous years.

3.2.2 Regression methods.

Regression is the one of most widely used statistical techniques. For electric load forecasting regression methods are usually used to model the relationship of load consumption and other factors such as weather, day type, and customer class. Engle *et al.* [9] presented several regression models for the next day peak forecasting. Their models incorporate deterministic influences such as holidays, stochastic influences such as average loads, and exogenous influences such as weather. References [19], [31], [16], [3] describe other applications of regression models to loads forecasting.

3.2.3 Stochastic Time series.

Time series methods are based on the assumption that the data have an internal structure, such as autocorrelation, trend, or seasonal variation. Time series forecasting methods detect and explore such a structure. Time series have been used for decades in such fields as economics, digital signal processing, as well as electric load forecasting. Following are the most often used classical time series methods.

3.2.3.1 *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.* [10] as

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

where ^ *Lk* is the predicted load at time *k* (min), w_k is a random load disturbance, a_i , i = 1 ……..m are unknown coefficients, and (1) is the AR model of order *m*. The Unknown coefficients in equation (1) can be tuned on-line using the well-known least mean square (LMS) algorithm of Mbamalu and El-Hawary [13]. The algorithm presented by El-Keib *et al.* [14] includes an adaptive autoregressive modelling technique enhanced with partial autocorrelation analysis. Huang [18] proposed an autoregressive model with optimum threshold stratification algorithm. This algorithm determines the minimum number of parameters required to represent the random component, removing subject judgement, and improving forecast accuracy. Zhao et. al. [33] developed two periodical autoregressive (PAR) models for hourly load forecasting.

3.2.3.2 *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) . . . . .] and 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:

$$y(t) = \phi_1\, y(t-1) + \ldots + \phi_p\, y(t-p) + a(t) - \Theta_1 a(t-1) \_ \ldots \_ \; \Theta q\,(t-q) \qquad (2)$$

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.* [34] 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 [37] used the WRLS (Weighted Recursive Least-Squares) algorithm to update the parameters of their adaptive ARMA model. Chen *et al.* [38] 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.

3.2.3.3 *Autoregressive Integrated Moving-Average (ARIMA)*

If the process is non-stationary or dynamic, 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 $\blacktriangledown$ operator, the series 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:

$$\phi(B)\, \blacktriangledown^{d}\, y(t) = \Theta\,(B)\, a(t) \qquad (3)$$

The procedure proposed by Elrazaz and Mazi [40]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.* [39] used a seasonal ARIMA model on historical data to predict the load with seasonal variations. Juberias *et al.* [41] developed a real time load forecasting ARIMA model that includes the meteorological influence as an explanatory variable.

4. NEURAL NETWORKS

The use of artificial neural networks (ANN or simply NN) has been a widely studied electric load forecasting technique since 1990 [28] Neural networks are essentially non-linear circuits that have the demonstrated capability to do non-linear curve fitting. The outputs of an artificial neural

network are some linear or nonlinear mathematical function of its inputs. The inputs may be the outputs of other network elements as well as actual network inputs. .
In practice network elements are arranged in a relatively small number of connected layers of elements between network inputs and outputs. Feedback paths are sometimes used. In applying a neural network to electric load forecasting, one must select one of the architectures (e.g. Hopfield, back propagation, Boltzmann machine, Adaline, Madline, Perceptron multilayer,), the number and connectivity of layers and elements, use of bi-directional or uni-directional links, and the number format (e.g. binary or continuous) to be used by inputs and outputs, and internally. The most popular artificial neural network architecture for electric load forecasting is back propagation. Back propagation neural networks use continuously valued functions and supervised learning. That is, under supervised learning, the actual numerical weights assigned to element inputs are determined by matching historical data (such as time and weather) to desired outputs (such as historical electric loads) in a pre-operational "training session". Artificial neural networks with unsupervised learning do not require pre-operational training. Bakirtzis *et al.* [1] developed an ANN based short-term load forecasting model for the Energy Control Center of the Greek Public Power Corporation. In the development they used a fully connected three-layer feed forward ANN and back propagation algorithm was used for training. Input variables include historical hourly load data, temperature, and the day of the week. The model can forecast load profiles from one to seven days. 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*. [10]), 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.
Also Papalexopoulos *et al.* [27] developed and implemented a multi-layered feed forward ANN for short-term system load forecasting. In the model three types of variables are used as inputs to the neural network: season related inputs, weather related inputs, and historical loads. Khotanzad *et al.* [20] described a load forecasting system known as ANNSTLF. ANNSTLF is based on multiple ANN strategies that capture various trends in the data. In the development they used a multilayer perceptron trained with the error back propagation algorithm. ANNSTLF can consider the effect of temperature and relative humidity on the load. It also contains forecasters that can generate the hourly temperature and relative humidity forecasts needed by the system. An improvement of the above system was described in [21]. In the new generation, ANNSTLF includes two ANN forecasters, one predicts the base load and the other forecasts the change in load. The final forecast is computed by an adaptive combination of these forecasts. The effects of humidity and wind speed are considered through a linear transformation of temperature. As reported in [21], ANNSTLF was being used by 35 utilities across the USA and Canada. Chen *et al.* [4] developed a three layer fully connected feed forward neural network and the back propagation algorithm was used as the training method. Their ANN though considers the electricity price as one of the main characteristics of the system load. Many published studies use artificial neural networks in conjunction with other forecasting techniques (such as with regression trees [26], time series [7] or fuzzy logic [32]). ANN has been integrated with several other techniques to improve their accuracy. Chow and Leung [42] 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*. [43] used weighted least-squares procedure in the training phase of developing an ANN for load forecasting. 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 [44] and Czernichow *et al* [45] surveyed methods and applications of electrical load forecasting with ANNs.

5 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.

Several hybrid methods combine expert systems with other load-forecasting approaches. Dash *et al.* [46] [47] combined fuzzy logic with expert systems. Kim *et al.* [48] used a two-step approach in forecasting load for Korea Electric Power Corporation. First, an ANN is trained to obtain an initial load prediction, and then a fuzzy expert system modifies the forecast to accommodate temperature changes and holidays. Mohamad *et al.* [49] applied a combination of expert systems and NN for hourly load forecasting in Egypt. Bataineh *et al.* [51] used neural networks and fuzzy logic for data representation and manipulation to construct the expert system's rule base.

6. FUZZY LOGIC

Fuzzy logic is one of a number of techniques for mapping inputs to outputs (i.e. curve fitting). Among the advantages of fuzzy logic are the absence of a need for a mathematical model mapping inputs to outputs and the absence of a need for precise (or even noise free) inputs. With such generic conditioning rules, properly designed fuzzy logic systems can be very robust when used for forecasting. Of course in many situations an exact output (e.g. the precise 12PM load) is needed. After the logical processing of fuzzy inputs, a "defuzzification" process can be used to produce such precise outputs.

One of the applications of the fuzzy rules is to combine them with neural network to train ANN and have a better load demand forecasting. The training patterns for the ANN models were collected from the historical load data. The number of training cycles has been determined through a trial process, to avoid overtraining [52].

References [22], [24], [32] describe applications of fuzzy logic to electric load forecasting.

7. GENETIC ALGORITHMS

To manage electrical energy supply is a complex task. The most important part of electric utility resource planning is forecasting of the future load demand in the regional or national service area. This is usually achieved by constructing models on relative information, such as climate and previous load demand data. Genetic programming approach is proposed to forecast long term electrical power consumption. The empirical results demonstrate successful load forecast with a low error rate [2]

Genetic Algorithms (GAs) have recently received more attention as robust stochastic search algorithms for various problems. This class of method is based on the mechanism of natural selection and natural genetics, which combines the notion of survival of the fittest, random and yet structured, search and parallel evaluation to the points in the search space. GAs have been successfully applied in various areas such as , load low problems, fault detection, stability analysis, economic dispatch, power system control and load demand forecasting.[53]

Genetic algorithms are a numerical optimization technique. More specifically, they are parameter search procedures based upon the mechanics of natural genetics. This technique has gained popularity in recent years as a robust optimization tool or a variety of problems in engineering, science, economics, finance, etc. GAs accommodate all the facts of soft computing, namely uncertainty, imprecision, non-linearity, and robustness.

From the literature survey it is found that forecasting results using GA were found to be the best. This indicates that the GA approaches is quite promising and deserves serious attention due to its robustness and suitability or parallel implementation. [53]

8. SUPPORT VECTOR MACHINES.

Support Vector Machines (SVMs) are a more recent powerful technique for solving classification and regression problems. This approach was originated from Vapnik's [35] statistical learning theory. Unlike neural networks, which try to define complex functions of the input feature space, support vector machines perform a nonlinear mapping (by using so-called kernel functions) of the data into a high dimensional (feature) space. Then support vector machines use simple linear functions to create linear decision boundaries in the new space. The problem of choosing architecture for a neural network is replaced here by the problem of choosing a suitable kernel for the support vector machine [6]. Mohandas [25] applied the method of support vector machines for short-term electrical load forecasting. The author compares its performance with the autoregressive method. The results indicate that SVMs compare favorably against the autoregressive method. Chen *et al.* [2] proposed a SVM model to predict daily load demand of a month. Li and Fang [23] also used a SVM model for short-term load forecasting.

Thus the study of different load forecasting techniques revels that accurate load forecasting is very important for electric utilities in a competitive environment created by the electric industry deregulation.

9. CONCLUSION

In this paper we have discussed several statistical and artificial intelligence techniques that have been developed for short, medium and long-term electric load forecasting. Several statistical models and algorithms that have been developed though are operating ad hoc. We also discussed factors that affect the accuracy of the forecasts such as weather data, time factors, customer classes, as well as economic and end use factors. Load forecasting methods use advanced mathematical modeling. . The accuracy of the forecasts could be improved, if one would study these statistical models and develop mathematical theory that explains the convergence of these algorithms. Researchers should also investigate the boundaries of applicability of the developed models and algorithms.

After surveying all these approaches, we can observe a clear trend toward new, stochastic, and dynamic forecasting techniques. 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. 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 and different transform based load forecasting.

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