General review of load forecasting models

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10th February of 2009

SUMMARY

A general review of electric load forecasting techniques is presented. Initially a simple classification of forecasting models is presented for different periods of the planning horizon. A brief description of important factors in load forecast are shown: economic, time, random. Formulation of load forecast model are presented in additive and multiplicative form. Medium and long-term load forecast model: econometric and end-use are described and main advantage/disadvantage are compiled in a table. Ten short-term load forecast are briefly described: multiple regression, exponential smoothing, iterative reweighted least-squares, adaptive load forecasting, stochastic time series, ARMAX models based on genetic algorithms, fuzzy logic, neural networks, expert systems and support vector machine. Each methodology is briefly described and the advantages and disadvantages discussed.

Key Words: Load forecasting, multiple regression, stochastic time series, long-term, general exponential smoothing, neural network, expert system, short-term, support vector machine.

INTRODUCTION

Load data is crucial for planning electricity distribution networks and optimal production capacity [1]. The electricity demand models are often applied to forecast the demand at the utility level. Load forecasting is a central and integral process in the planning and operation of electric utilities [2].

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 market [2].

In other hand, utilities have information about the loads but do not contain much information about its nature. Domestic electric consumption is known for utilities but this data is normally aggregated consumption of multiple households without knowledge about the events in individual households. The fluctuation of electricity consumption concerning an individual household remains unrevealed as well as the division of consumption between different types of household appliances. Nevertheless, detailed knowledge can be produced with some accuracy by simulation models.

Load forecasting is vitally important for the electric industry in the deregulated economy. It has many applications including energy purchasing and generation, load switching, contract evaluation, and infrastructure development. A large variety of mathematical methods have been developed for load forecasting. In this document we discuss various approaches to load forecasting, making a review of most important methods. In the second part of this document, we review some of most important electricity demand models suitable to be used in household consumer loads.

Load Forecasting Horizons

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 geographic allocations of electric load over the different periods of the planning horizon.

Regarding the planning horizon load forecasting can be divided into three categories: *short-term load forecasting* (STLF) which are usually from one hour to one week, *medium-term load forecasting* (STLF) which are usually from a week to a year, and *long-term load forecasting* (LTLF) 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 different as well.

Important factors in load forecasting

The system load is a random non-stationary process composed of thousands of individual components [2]. The system load behavior is influenced by a number of factors, which can be classified as: economic factors, time (day, season), weather and random effects.

Economic factors, such as the service area demographics, levels of industrial activity, changes in the farming sector, the nature and level of penetration/saturation of the appliance population, developments in the regulatory climate and, more generally, economic trends have significant impacts on the system load growth/decline trend. Typically, these economic factors operate with considerably longer time constants than one week [3]. It is important to account for these factors in long-term load forecasting, however, not are represented in the short-term load forecasting models.

Excluding economics and random factors, all remaining factors are dependent on the time. These factors are dominant just in a particular term of time and are called time factors. The time factors include the time of the year, the day of the week, and the hour of the day.

There are three principal *time factors*: *seasonal effects*, *weekly daily cycle*, and *legal and religious holidays*. These factors play an important role in influencing load pattern.

Certain changes in the load pattern occur gradually in response to seasonal variations such as the number of daylight hours and the changes in temperature. On the other hand, there are seasonal events which bring about abrupt but important structural modifications in the electricity consumption pattern [3].

Weather conditions influence the load. In fact, forecasted weather parameters are the most important factors in short-term load forecasts: temperature and humidity. In many systems, temperature is the most important weather variable in terms of its effects on the load [3]. Nerveless, other mixtures of whether parameters could be used (THI: temperature-humidity index, WCI: wind chill index) to describe the effects of weather conditions over load pattern [2].

The weekly-daily periodicity of the load is a consequence of the work-rest pattern of the service area population. There are well-defined load patterns for “typical” seasonal weeks [3]. There are important differences in load between weekdays and weekends. The load on different weekdays also can behave differently [2].

The existence of statutory and religious holiday has the general effect of significantly lowering the load values to levels well below "normal." Moreover, on days preceding or following holidays, modifications in the electric general pattern are observed duet o the tendency of creating "long weekends" [3]. Holidays are more difficult to forecast than non-holidays because of their relative infrequent occurrence [2].

Under *random factor* classification are include a variety of random events causing variations in the load pattern that cannot be explained in terms of economic, time, or seasonal factors. Load is continuously subject to random disturbances reflecting the fact that the system load is a composite of a large number of diverse individual demands. In addition total large number of very small disturbances, there are large loads whose operation can cause large variations in electricity usage [3]. Since the hours of operation of these large devices are usually unknown to utility they represent large unpredictable disturbances.

For *short-term load forecasting* several factors should be considered, such as time factors, weather data, and possible customers' classes.

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.

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.

Load forecasting methods

The electricity demand models are often applied to forecast the demand at the utility level. Rigorous studies on the topic were conducted already in the 1970s and 1980s, resulting in a large number of forecasting methods [1].

The development, improvements, and investigation of the appropriate mathematical tools will lead to the development of more accurate load forecasting techniques.

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.

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.

Additive Model

Traditionally, system load at any given time L is assumed to be a combination of any separate components. In [4], H. Chen presented an additive model that takes the form of predicting load as the function of four components:

$$L = L_n + L_w + L_s + L_r \tag{1}$$

Where: L_n 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; L_w corresponds to the weather-sensitive part of the load, which is tightly coupled to the season of the year; L_s stands for the special event part, which is the occurrence of an unusual or special event leading to a significant deviation from the typical load behavior; L_r corresponds to a random part, which is an "unexplained" component usually represented as zero mean white noise.

In the present competitive electricity market system load may also be significantly affected by prices. In this additive model [4] electricity pricing could be an additional term that can be included in the model. Naturally, price decreases/increases affect electricity consumption. Large cost sensitive industrial and institutional loads can have a significant effect on loads.

Multiplicative Model

A multiplicative model may be of the form:

$$L = L_n F_w F_s F_r \tag{2}$$

where L_n is the "normal" (base) load and the correction factors F_w, F_s, and F_r are positive numbers that can increase or decrease the overall load. These corrections are based on current weather (F_w), special events (F_s), and random fluctuation (F_r).

Factors such as electricity pricing (F_p) and load growth (F_g) can also be included. An example of multiplicative model for forecast can be found in [5], [6].

Medium- and long-term load forecasting methods

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 so-called *end-use approach*. [9]

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 [9].

Long-term forecasts include the forecasts on the population changes, economic development, industrial construction, and technology development.

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 [7].

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.

Econometric models

The econometric approach combines economic theory and statistical techniques for forecasting electricity demand. The econometric approach estimates the relationships between energy consumption (*dependent variables*) and factors influencing consumption.

Econometric load forecasts of demand are based on a model whose parameters are estimated from historical data. A *linear* or *log-linear model* is usually postulated. In the linear model, the variable to be forecasted, the endogenous variable, is a linear function of the exogenous variables; the exogenous variables being the "input" variables. In the log-linear model, a linear relationship is assumed between the logarithm of the endogenous variable and logarithms of the exogenous variables. Log-linear models are the ones most commonly used for modeling the demand for electric energy. The model coefficients are estimated using historical data [8].

The relationships energy consumption and factors influencing consumption 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, commercial, 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.

Comparison of end-use and econometric model

The end-use and econometric methods require a large amount of information relevant to appliances, customers, economics, etc. Their application is complicated and requires human participation. In addition such information is often not available regarding particular customers and a utility keeps and supports a profile of an “average” customer or average customers for different type of customers.

The problem arises if the utility wants to conduct next-year forecasts for sub-areas, which are often called *load pockets*. In this case, the amount of the work that should be performed increases proportionally with the number of load pockets. In addition, end-use profiles and econometric data for different load pockets are typically different. The characteristics for particular areas may be different from the average characteristics for the utility and may not be available.

Table 1. Comparative matrix between end-use and econometric models for medium and long term load forecast

Model	*Advantage*	*Drawback*
End-Use	• Very accurate. • Require less historical data than econometrics	• Sensitive to the amount and quality of end-use data. • Require more information about consumer and their equipments. • Problems to conduct next-year forecasts for sub-areas.
Econometric	• Combines economic theory and statistical techniques. • Simple methods could be used: least-squares method or time series methods.	• Require great amount of historical data. • Problems to conduct next-year forecasts for sub-areas. • Not exact for because only a finite number of data points, and thus because of the random component. • Model is not structurally perfect. There are additional exogenous variables which have influence on demand but are not included in the model.

Short-term load forecasting methods

The short-term load forecasting (STLF) imply predictions of the order of hours. The time boundaries are from the next hour, or possibly half-hour up to168 h.

The basic quantity of interest in short-tem load forecasting, typically, the hourly integrated total system load. In addition to the prediction of the hourly use of the system load, a short-term load forecasting is also concerned with the forecasting of [3]:

- Daily peak system load
- Values of system load at certain times of the day
- Hourly or half-hourly values of system energy
- Daily and weekly system energy.

The technical literature displays a wide range of methodologies and models for short-term load forecasting. A simple classification could be done regarding type of load model used. The classification considers two basic models: *peak load* and *load shape models* [3].

The peak load models are basically of a single type, but load shape models are grouped into two basic classes with each subtype, namely [3]:

- Time of day
    - Summation of explicit time functions models
    - Spectral decomposition models.
- Dynamic
    - ARMA models
    - State-space models.

In comparison with those earlier literature reviews, this survey not only covers newer papers, but also includes new categories that reflect recent research trends.

The *peak load models* only determinate the daily or weekly day peak load is modeled as a function of the weather. Time does not play a role in such models which are typically of the form:

peak load = base load + weather dependent component

$$L_{peak} = L_n + F_w \tag{3}$$

where the base load L_n, is an average weather insensitive load component to which the weather dependent component $F_w = F(W)$ is added. The weather variables W can include the temperature at the peak load time or a combination of predicted and historical temperatures. Humidity, light intensity, wind speed, and precipitation have also been considered in such models.

Table 2. Main characteristics of peak load models

Model	*Advantage*	*Disadvantage*
Peak load	• Its structural simplicity • Its relatively low data requirements to initialize and to update. • The parameters of the model are estimated through linear or nonlinear regression.	• Do not define the time at which the peak occurs. • Do not provide any information about the shape of the load curve. • These models are essentially static, dynamic phenomena such as correlation across the periods cannot be forecast.

Load shape models describe the load as a discrete time series (process) over the forecast interval. The load sampling time interval is typically one hour or one-half hour (one-quarter hour), while the quantity measured is generally the energy consumed over the sampling interval (MWh or kWh).

Focusing on Gross and Galina (1987) paper [3], there exist two types of load shape models [3]: *time of day* and *dynamic* models. Combinations of these two basic types are also possible.

The time-of-day model defines the load $L(t)$ at each discrete sampling time t of the forecast period of duration T by a time series:

$$\{L(t), t = 1,2,\ldots,T\} \tag{4}$$

A more common *time-of-day model* takes the form [3]:

$$L(t) = \sum_{i=1}^{N} \alpha_i f_i(t) + v(t), \qquad t \in \tau \tag{5}$$

where the load at time t, $L(t)$, is considered to be the sum of a finite number of explicit time functions $f(t)$, usually sinusoids with a period depending on the forecasting lead time.

The coefficients a_i are treated as slowly time-varying constants, while $v(t)$ represents the modeling error, assumed to be white random noise. The model is assumed to be valid over a range of time interval covering the recent past, the present, and a future time period covering the maximum lead time (τ).

The time of day models based on *spectral decomposition* has basically the form shown (4). In this models the time functions $f(t)$ represent the eigenfunctions corresponding to the autocorrelation function of the load time series (after removal of trends and periodicities).

Dynamic load models recognize the fact that the load is not only a function of the time of day, but also its most recent behavior, as well as that of weather and random inputs [3]. Dynamic models are: *autoregressive moving average or ARMA models* and *state space models.*

A more recent review and classification of the forecasting methods has been given by Alfares and Nazeeruddin (2002) [2]. Load forecasting techniques are classified into ten categories. 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;
- Knowledge-based expert systems and,
- Support vector machine.

Multiple regression

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 [9].

Multiple regression analysis for load forecasting uses the technique of weighted least-squares estimation [2]. 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.

In the *multiple linear regression* (MLR) method, the load is found in terms of explanatory variables such as weather and non-weather variables which influence the electrical load The load model using this method is expressed in the form as [6]:

$$Y_t = v_t a_t + \varepsilon_t \tag{5}$$

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., at a_t transposed vector of regression coefficients, and ε_t model error at time t.

The explanatory variables of this model are identified on the basis of correlation analysis on each of these (independent) variables with the load (dependent) variable.

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 [2].

In the exponential smoothing models the load at time t, $y(t)$, is modeled using a fitting function and is expressed in the form:

$$y(t) = \beta(t)^T f(t) + \varepsilon_t \tag{6}$$

Where, $f(t)$ is the fitting function vector of the process, $\beta(t)$ is the coefficient vector, $\varepsilon(t)$ is the white noise, and T is the transpose operator. The estimates of the coefficients are found using weighted or discounted mean square error for the recent N sampled intervals

Iterative reweighted least-squares

This method uses iteratively reweighted least-squares to identify the model order and parameters [2], [10]. An operator is used to control 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 suboptimal model of the load dynamics.

The weighting function, 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 [10]. Consider the parameter estimation problem involving the linear measurement equation:

$$Y = X\beta + \varepsilon \tag{7}$$

where Y is the vector of observations, X is a matrix of known coefficients (based on previous load data), β is a vector of the unknown parameters and ε is an vector of random errors. Results are more accurate can be obtained by iterative methods when the errors are not Gaussian.

Adaptive load forecasting

The adaptive load forecasting model is adaptive in the sense that the model parameters are automatically corrected to keep track of the changing load conditions. This method can be used as an on-line software package in the utilities control system [2].

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 analyzed 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 [2].

Stochastic time series

Stochastic time series is one of the most popular approaches that has been applied and is still being applied to short-term load forecasting in the electric power industry. The theory of stochastic time series is discussed in many text books, and many load forecasting papers using this approach have been published [10].

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 [9]. It has been observed that unique patterns of energy and demand pertaining to fast-growing areas are difficult to analyze and predict by direct application of time-series methods. [2].

Using the time-series approach, a model is first developed based on the previous data, and then future load is predicted based on this model.

Time series have been used for decades in short-term load forecasting and present a number of variations with different names [3].

In particular, ARMA (autoregressive moving average), ARIMA (autoregressive integrated moving average), ARMAX (autoregressive moving average with exogenous variables), and ARIMAX (autoregressive integrated moving average with exogenous variables) are the most often used classical time series methods [9].

ARMA models are usually used for stationary processes while ARIMA is an extension of ARMA to non-stationary processes [9].

ARMA and ARIMA use the time and load as the only input parameters. Since load generally depends on the weather and time of the day, ARIMAX is the most natural tool for load forecasting among the classical time series models [9].

Autoregressive (AR) model

In the autoregressive process, the current value of the time series $y(t)$ is expressed linearly in terms of its previous values ($y(t\text{-}1)$, $y(t\text{-}2)$. ..) and a random noise $a(t)$ that simulate the random load disturbance. The order of this process depends on the oldest previous value at which $y(t)$ is regressed on [10].

For an autoregressive process of order p, this model can be written as [10]:

$$y(t) = a(t) + \phi_1 y(t-1) + \phi_2 y(t-2) + \ldots + +\phi_p y(t-p)$$

$$y(t) = \sum_{j=1}^{p} \phi_j y(t-j) + a(t) \tag{8}$$

Where $y(t)$ is the load predicted at time t.

By introducing the backshift operator B that defines $y(t\text{-}1) = By(t)$, and consequently $y(t - m) = B^m y(t)$,equation (8) can be written in the form [10]:

$$\phi(B) y(t) = a(t) \tag{9}$$

where:

$$\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p$$

$$\phi(B) = 1 - \sum_{j=1}^{p} \phi_j B^j \tag{10}$$

Moving-Average (MA) model

In the moving-average model, the current value of the time series $y(t)$ is expressed linearly in terms of current and previous values of a white noise series $a(t)$, $a(t\text{-}1)$. … . This noise series is constructed from the forecast errors or residuals when load observations become available [10].

The order of this process depends on the oldest noise value at which $y(t)$ is regressed on. For a moving average of order q, this model can be written as [10]:

$$y(t) = a(t) - \theta_1 a(t-1) - \theta_2 a(t-2) - \ldots - \theta_q a(t-q)$$
$$y(t) = -\sum_{j=0}^{q} \theta_j a(t-j) \tag{11}$$

where $\theta_0 = -1$.

The unknown coefficients in (11) can be tuned on-line using the well-known least mean square (LMS) algorithm of Mbamalu and El-Hawary [11].

A similar application of the backshift operator on the white noise series would allow equation (11) to be written as [10]:

$$y(t) = \theta(B)a(t) \tag{12}$$

where:

$$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q$$
$$\theta(B) = 1 - \sum_{j=1}^{q} \theta_j B^j \tag{13}$$

Autoregressive Moving-Average (ARMA) model

In the autoregressive moving average process, the current value of the time series $y(t)$ is expressed linearly in terms of its values at previous periods ($y(t\text{-}1)$, $y(t\text{-}2)$, ...) and in terms of current and previous values of a white noise ($a(t)$, $a(t\text{-}1)$, $a(t\text{-}2)$. ...).

The order of the ARMA model is selected by both the oldest previous value of the series and the oldest white noise value at which $y(t)$ is regressed on. For an autoregressive moving-average process of order p, and q, the model is written as [10]:

$$y(t) = \phi_1 y(t-1) + \ldots + +\phi_p y(t-p) + a(t) - \theta_1 a(t-1) - \ldots - \theta_q a(t-q)$$
$$y(t) = \sum_{j=1}^{p} \phi_j y(t-j) + a(t) - \sum_{j=0}^{q} \theta_j a(t-j) \tag{14}$$

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 [2]. By using the backshift operator defined earlier, equation (14) can be written in the following form:

$$\phi(B)y(t) = \theta(B)a(t) \tag{15}$$

where $\theta(B)$ and $\phi(B)$ have been defined earlier in (10) y (13).

Autoregressive integrated moving-average (ARIMA) model

The time series defined previously as an autoregressive, moving-average, or as an ARMA process is called a stationary process. This means that the mean of the series of any of these processes and the covariance among its observations do not change with time [10].

If the process is non-stationary, transformation of the series to a stationary process has to be performed first. This can be achieved, for the time series that are non-stationary in the mean, by a differencing process [2], [10].

By introducing the ∇ operator, a differenced time series of order 1 can be written as:

$$\nabla y(t) = \mathrm{y}(t) - \mathrm{y}(t - 1) = (1-B)y(t) \tag{16}$$

Consequently, an order *d* differenced time series is written as:

$$\nabla^{d} y(t) = (1-B)^{\mathrm{d}} y(t) \tag{17}$$

The differenced stationary series can be modeled as an AR, MA, or an ARMA to yield an ARI, IMA, ARIMA time series processes.

For a series that needs to be differenced *d* times and has orders *p* and *q* for the AR and MA components, the model is written as [10]:

$$\phi(B)\nabla^{d} y(t) = \theta(B)a(t) \tag{18}$$

where $\phi(B)$, $\theta(B)$ and ∇^{d}, and have been defined in (10), (13) and (17) respectively.

ARIMA is an extension of ARMA to non-stationary processes as the non-weather cyclic component of the weekly peak load or historical data to predict the load with seasonal variations.

Since load generally depends on the weather and time of the day, ARIMAX (autoregressive integrated moving average with exogenous variables) is the most natural tool for load forecasting among the classical time series models [9].

ARMAX Model based on genetic algorithms

ARMAX (autoregressive moving average with exogenous variables) is one of the most often used classical time series methods. In this new version of the classical method genetic algorithm (GA) or evolutionary programming (EP) approach is used to identify the ARMAX model for load demand forecasts.

GA simulate the natural evolutionary process, the algorithm offers the capability of converging towards the global extremum of a complex error surface. 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 [2].

A well known and used ARMAX model based in GA is presented in [12], this consider a system load described in the following ARMAX form:

$$\varphi(B)y(t) = \delta(B)u(t)\lambda(B)e(t) \tag{18}$$

where: $y(t)$ is the load at time t, $u(t)$ is the exogenous temperature input at time t, $e(t)$ is the white noise at time t, B is back-shift operator. $\varphi(B)$, $\delta(B)$, and $\lambda(B)$ are parameters of the autoregressive (AR), exogenous (X), and moving average (MA) parts, respectively [2], [12].

$$\begin{gathered}\varphi(B) = 1 + \varphi_1 B^{-1} - \varphi_2 B^{-2} + \ldots + \varphi_q B^{-n} \\ \delta(B) = \delta_1 + \delta_2 B^{-1} + \ldots + \delta_q B^{-m+1} \\ \lambda(B) = 1 + \lambda_1 B^{-1} + \ldots + \lambda_r B^{-r}\end{gathered} \tag{19}$$

Having selected the model type, we should then determine the appropriate model orders of *n*, *m* and *r* as described above. Traditionally, the information on the sample autocorrelation function (ACF), the sample partial autocorrelation function (PACF), and the cross correlation function (CCF) is used as reference to guess the appropriate model order [12].

When the structure of the tentative model is selected, parameters of the model are then estimated by using the gradient based efficient estimation method. Parameters are estimated so as to have zero gradient of mean square sum of forecasting or fitting errors to the historical load data [12].

Once the parameters of the tentative model have been estimated, the adequacy of the tentative model is tested: t-ratio test, sample ACF and PACF of residuals, Q-statistics test.

The evolutionary programming simulates natural evolutionary process to reach the fittest individuals after repeated mutation, competition and selection procedure [12].

A fuzzy autoregressive moving average with exogenous variable (FARMAX) model for load demand forecasts was presented in [13]. The proposed a fuzzy ARMAX is called FARMAX and used for one day ahead hourly load forecasts.

Fuzzy logic

Fuzzy logic is a generalization of the usual Boolean logic used for digital circuit design. An input under Boolean logic takes on a truth value of "0" or "1". Under fuzzy logic an input has associated with it a certain qualitative ranges [2]. Fuzzy logic allows one to (logically) deduce outputs from fuzzy inputs. In this sense fuzzy logic is one of a number of techniques for mapping inputs to outputs (i.e. curve fitting).

The possibility of using fuzzy logic approach in this research is based on the following observations:

- The *very* short-term load forecasting problem can be treated as a multiple-input-multiple-output unknown dynamic system. It is well known that a fuzzy logic system with centroid defuzziffication can identify and approximate any unknown load on the compact set to arbitrary accuracy [2], [14].
- It is known that there is sort of periodic change in weekly load trends and there exist similarities in load trends between weekdays and weekdays, weekends and weekends, months and months, seasons and seasons, and so on. The fuzzy logic systems have been proved to have great capabilities in drawing similarities from a huge of data. Therefore, as long as enough historical input-output data pairs are available, the similarities exiting in load trends are able to be identified [14].

However, how to implement fuzzy logic forecast, or in other words, how to identify the similarities or unknown dynamics, is still a question.

The fuzzy logic-based forecaster works in two stages: (i) training and (ii) 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 [2].

Several techniques have been developed to represent load models by fuzzy conditional statements.

Some hybrid fuzzy-neural technique has been used to forecast load. This technique combines the neural network modeling and techniques from fuzzy logic and fuzzy set theory.

Neural networks

Neural networks (NN) or artificial neural networks (ANN) have very wide applications because of their ability to learn [2].

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 [9].

Numerous researchers have explored ways in which artificial neural networks may apply to the electric power industry [15]. The use of artificial neural networks has been a widely studied electric load forecasting technique since1990 [9]. Neural networks offer the potential to overcome the reliance on a functional form of a forecasting model [15].

There are many types of neural networks: multilayer perception network, self-organizing network, etc [9].

In applying a neural network to electric load forecasting, one must select one of a number of *architectures* (e.g. Hopfield, back propagation, Boltzmann machine), 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 [9].

Knowledge-based expert systems

Expert systems are new techniques that have emerged as a result of advances in the field of artificial intelligence [2]. Rule based forecasting makes use of rules, which are often heuristic in nature, to do accurate forecasting. Expert systems, incorporates rules and procedures used by human experts in the field of interest into software that is then able to automatically make forecasts without human assistance [10].

Expert systems work best when a human expert is available to work with software developers for a considerable amount of time in imparting the expert's knowledge to the expert system software. Also, an expert's knowledge must be appropriate for codification into software rules (i.e. the expert must be able to explain his/her decision process to programmers). An expert system may codify up to hundreds or thousands of production rules [10].

To build the load forecast 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 [2].

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 [2].

Support vector machine

Support Vector Machines (SVMs) are a relatively recent powerful technique for solving classification and regression problems. This approach was originated from Vapnik's [16] 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 [10].

One application of the method of support vector machines for short-term electrical load forecasting was developed by Mohandes [17]. A simple comparison between SVM and the autoregressive method indicate the favorable results of SVM against the autoregressive method.

The SVM models have been used to predict daily load demand of a month [18] and for short-term load forecasting [19].

Comparison of short-term load forecasting methods

The problem with *statistical techniques*, however, is their computational requirements, as these methods need to be updated with changing conditions. In fact, whole new statistical models need to be developed whenever the load conditions change sufficiently. On the other hand, *expert systems* are more responsive to changing conditions. However, it is not always easy to express the available expertise in clear quantitative terms. This often leads to inconsistent rules.

The *artificial neural* short-term load forecasting models are not easily updatable to changing conditions over the course of a season. This requires the re-training of neural networks, which can be expensive. Moreover, operators have little or no opportunity to confirm the forecast. Generally, the neural network is a "black box" for the operator that he has to either accept or reject.

In general, *accuracy is directly proportional to the complexity of the forecasting algorithm*.

In the case of neural networks, the need for accurate forecasts requires that a whole different neural network be developed for each different hour of the day, and for each different day of the week. Such complexity increases the risk of a total failure of the forecast. This is true for special cases, such as extreme weather conditions, or a special event on the target day, etc.

In Table 3 is shown a brief summary of advantages and disadvantages of each short-term load forecasting.

Table 3. Comparative matrix between short-term load forecasting methods

Model	*Advantage*	*Disadvantage*
Regression	• One of most widely used statistical techniques. • It is structurally quite simple • The model parameters can be updated very simply through linear regression or linear exponential smoothing • Model use recursive algorithms requiring a relatively low computational effort.	• Do not accurately represent the stochastically correlated nature of the load process, or its relation to weather variables. • Accuracy problems for longer lead time predictions (when weather pattern change rapidly).
Exponential smoothing	• It is one of the classical methods used for load forecasting. • Approach regressive. • Analyze seasonal time series directly.	• Same problems as regression methods.
Iterative reweighted least-squares	• The method uses an operator that controls one variable at a time. • This method utilizes the autocorrelation function and the partial autocorrelation function of the resulting differenced past load data in identifying a suboptimal model of the load dynamics.	• Method is susceptible problem of autocorrelation, trend, or seasonal variation.
Adaptive load forecasting	• It is an on-line software package in the utilities control system. • Regression analysis based on the Kalman filter theory is used.	
Stochastic time series	• Based on the assumption that the data have an internal structure.	• Method is susceptible problem of autocorrelation, trend, or seasonal variation.
ARIMA	• More robust model that incorporates dynamic, weather, and random effects. • The long run less parameter tuning is required and better forecasting performance is obtained. • The parameter identification for a general ARMA model can be done by a recursive scheme. • The updating of model parameters is not a very computationally demanding task, even in cases which require an iterative solution of a nonlinear estimation problem.	• A nonlinear parameter estimation scheme must be used to identify the model parameters. • Do not satisfactory during rapidly changing climatic conditions. • The identification of the parameters of an ARMA model is generally more computationally intensive than those of the time-of day models.
ARMAX+GA	• The algorithm to search the optimal model structure and the related parameters of the ARMAX model to overcome numerous local optima and achieve the global or near global extremum of the complex error surface. • Good performance in load data for one day and one week ahead hourly load forecasting. • EP based identification method was verified to be superior to that of the traditional gradient search based approach. • Evolutionary programming is a method for simulating evolution and constitutes a stochastic optimization algorithm.	
Fuzzy	• 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. • After the logical processing of fuzzy inputs, a "defuzzification" process can be used to produce such precise outputs.	• Process of "defuzzification" can takes a lot of time.
Neural Network	• The main advantage here is that most of the forecasting methods seen in the literature do not require a load model	• Training usually takes a lot of time. • Problems to choose an architecture for a neural network.
Knowledge-based expert system	• To build the model, the `knowledge engineer' extracts load forecasting knowledge from an expert in the field.	• The load model, the rules, and the parameters could be designed using a specific knowledge about any

		particular site.
Support vector machine	• It is perform a nonlinear mapping (by using so-called kernel functions) of the data into a high dimensional (feature) space.	• Require choosing a suitable kernel for the support vector machine.

Conclusions

A general review of electric load forecasting techniques is presented. A wide range of methodologies and models for forecasting are given in the literature, here is classified in term of different periods of the planning horizon.

For medium or long-term load forecasting end-use and econometric model are presented. For short-term load forecasting several strategies has been developed. Some methods consider the load as a time series and extrapolate it in the future. Other methods investigate the dependence of the electrical load on the temperature, humidity, wind speed and solar radiation, in this case forecasting is implemented through modeling this relationship. Further methods combine the previous two methods together to reach a better load forecasting. It seems a lot of current research effort is focused on four methods: fuzzy logic, expert systems and particularly neural networks and support vector machine. There is also a clear move towards hybrid methods, which combine two or more of these techniques.

A comparative summary of advantages and disadvantage is presented to give the reader an understanding of each of these techniques.

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