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Short-term load forecasting approaches: A review

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Abstract: This paper deals with a review and categorization of various short term load forecasting (STLF) approaches. Here, a comprehensivesurvey from history of load forecasting (particularly STLF) is presented. Then basic ingredients to forecast are discussed. The main focus here is to provide a review of different approaches for STLF. Different approaches for short term forecasting are discussed under three main categories: (1) Statistical or traditional approaches (2) Modern or artificial intelligence based approaches and (3) Hybrid approaches

All these approaches are often different in nature and are applied in different context for forecasting. The methodology for each category is briefly described, and the advantages and disadvantages are also discussed for each technique. At last a comparison among all approaches is presented with a conclusion like modern and hybrid approaches are far superior to classical / statistical / traditional approaches.

Keywords: Forecast ingredients, Hybrid approaches, Modern approaches, Short term load forecasting, Statistical or traditional approaches,

1. Introduction

Forecasting involves future predictions. Electric Load Forecasting is the estimation for future load by an industry or utility company. Important information is provided in advance with the help of load forecasting, so it is also useful for system security [1]. Load forecasting is one of the important factors of power systems from the point of view of economic operation [2]. Effective load forecasts can help in properly planning and improving these three fields of power systems called generation, transmission and distribution. Matthewman and Nicholson (1968) conducted an early survey of electric load forecasting techniques. Abu El-Magd and Sinha (1982), Bunn and Farmer (1985), and Gross and Galiana (1987) also reviewed load demand modelling and forecasting. A 1987 survey paper (Gross and Galiana, 1987) lists a number of publications devoted to load forecasting. According to Gross and Galiana (1987), load forecasting is also concerned with the prediction of hourly, daily, weekly and monthly values of the system load, peak system load and the system energy [3]. Moghram and Rahman (1989) surveyed electric load forecasting techniques. The electricity demand forecasting has become one of the major research fields in electrical engineering. Load forecasting acts as a central and integral process in the planning and operation of electric utilities, as it involves an accurate prediction of both the magnitudes and the geographical locations of electric load over the different periods (usually hours) of the planning horizon [3].Gross and Galiana (1987) proved that £4 million saving is possible for 1% improvement in accuracy of load forecasts for a typical British utility [4].

1.1 Factors Affecting the Power System Load

The power system load is a random non-stationary process. It is composed of several individual components broadly classified as continuous electrical loads, non-continuous electrical loads, duty-intermittent electrical loads, duty-periodic electrical loads, duty short-time electrical loads, and duty-varying electrical loads. Load is assumed to be time dependent and falls in accordance with a probabilistic law. Factors influencing the load behavior in a region are:

- Weather
- Time
- Economic factors
- Random disturbances

1.2 Time horizon based classification of load forecasting

Different forecasting horizons have different time duration to forecast the electric load. The electric load forecasting can be classified under five main classes as shown in Figure 1.

(a) Class I: Very Short Term Load Forecasting (VSTLF) which includes forecasting up to a few minutes to an hour ahead.
(b) Class II: Short Term Load Forecasting (STLF) which includes hourly forecast with a lead time up to an hour (or one day) to one week ahead.
(c) Class III: Medium Term Load Forecasting (MTLF) energy requirements include time up to a few months to one year ahead.

(d) Class IV: Long Term Load Forecasting (LTLF) includes a lead time up to 1 year to 4-5 years ahead.
(e) Class V: Very Long Term Load Forecasting (VLTLF) includes a lead time more than 5 years.

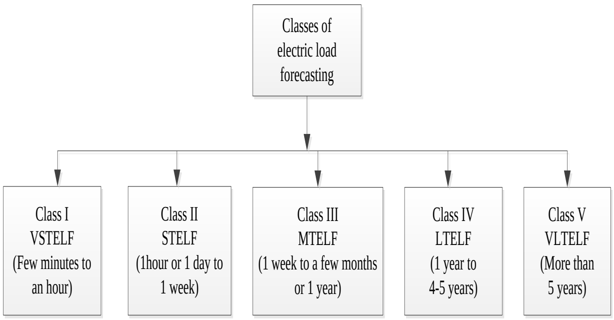

Figure 1:Classes of load forecasting

1.3 Need of Load Forecasting

It has many applications including load switching, contract evaluation, and infrastructure development. 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, national institutions, and other participants in electric energy generation, transmission, distribution, and markets [6]. For developing countries, load forecasts are extremely important. Load forecasting facilitatesto maintain a balance between electricity supply and demand [7].

1.4 Applications of electric load forecasting

Different classes of electrical load forecasting have different applications and usefulness. The applications have been listed below:

VSTELF: It is useful in security assessment, economic dispatching and sensitivity analysis of electric equipment etc.

STELF: It is needed for control and scheduling of power system, for power system operation studies, losses reduction, voltage regulation, fuel allocation, unit commitment and maximizing the utility revenues in the deregulated environment. It is also useful in security analysis.

MTELF: It solves the problem of operation planning, maintenance scheduling, energy contracts, fuel management and revenue from sales, and also applied in load dispatching coordination.

LTELF: This method is used to solve the problem of capacity expansion planning and strategy planning. These are also useful to purchase generating units and for staff hiring. Besides this, it is also helpful in searching for renewable resources.

VLTELF: This is applied in scheduling construction of new generating capacity, searching for renewable resources, environmental policies planning and staff recruitment[8, 9].

The organization of the paper is as follows: Methodology for electrical load forecasting is presented in section 2; Reviewof short term load forecasting andits all approaches are described in section 3; Comparison of short term load forecasting approaches is discussed in section 4 and the conclusions are drawn in section 5.

2. Methodology for load forecasting

There are four basic forecast ingredients: function, independent variable, dependent variable and elasticity. The relationships between electricity demand (dependent variable) and the multitude of factors (independent variables) that influence or affect electricity demand are expressed in mathematical equations called functions. A model is a collection of functions. It is a description of how the dependent variable i.e. electrical load depends on independent variables (weather, time, the electricity prices, income, population, economy, and the growth rates individually and different sets i.e. combinations of these variables. Elasticities describe how much the dependent variable changes in sense to small changes in the independent variables. Elasticities are the measures for the consumer behavior [10].

3. Review and approaches of short term load forecasting

STLF studies began at early 1960s with one of the first studies done by Heinemann *et al*. in 1966 which dealt with the relationship between temperature and load [11].

Many years prior to 1960, the procedure that had been used, had the following characteristics:

- On the basis of billing records, weekly historical data on each type of order were collected. In general, these data were thought to be accurate.
- Graphs were prepared for the more important items.
- Then, the forecasts were prepared judgmentally by a man who had been doing this job for many years.

Most forecasting models and methods have already been tried out on load forecasting, with varying degrees of success. Some models of the first class suggested in recent papers are multiplicative autoregressive models (Mbamalu and El-Hawary, 1993), dynamic linear (Douglas et al., 1998a) or nonlinear (Sadownik and Barbosa, 1999) models, threshold autoregressive models (Bunn, 2000), and methods based on Kalman filtering (Infield and Hill, 1998; Park et al., 1991a; Sargunaraj et al., 1997). Some of the second classes are Box and Jenkins transfer functions (Hagan and Behr, 1987; Jenkins, 1979), ARMAX models (Yang and Huang, 1998; Yang et al., 1996), nonparametric regression (Charytoniuk et al., 1998), structural models (Harvey and Koopman, 1993), and curve-fitting procedures (Taylor and Majithia, 2000). Despite this large number of alternatives, however, the most popular causal models are still the linear regression ones (Ramanathan et al., 1997; Soliman et al., 1997; Haida and Muto, 1994; Engle et al., 1992; Papalexopoulos and Hesterberg, 1990) and the models which decompose the load, usually into basic and weather-dependent components (Fan and McDonald, 1994; Park et al., 1991a; Bunn and Farmer, 1985). Owing to the importance of load forecasting several reviews (Singh and Singh, 2002; Gross and Galiana, 1987; Hippert et al., 2001) and IEEE committee reports (1980, 1981) have been published in the past years [12, 13].

The dominance of STLF-methods was also reflected in the survey papers (Hippert et al., 2001; Tzafestas and Tzafestas, 2001; Feinberg and Genethliou, 2005; Kyriakides and Polycarpou, 2007) [14].

In 1971, a load forecasting system was developed by Lijesen and Rosing which used statistical approach. In 1987, Hagan and Behr forecasted load using a time series model**.** Traditionally, load forecasts were made either by multivariate regression or time series transfer function modeling (see, e.g., Jabbour et al., 1988; Moghram& Rahman, 1989; Bunn 1992)[15]. Early methods also included exponential smoothing (Amjady, 2007), regression (Papalexopoulos and Hesterberg, 1990), Box-Jenkins models (Meslier, 1978), and the time-series techniques (Irisarri et al., 1982) [16].

From 1990, researchers began to implement different approaches for STLF other than statistical approach. The emphasis shifted to the application of various AI techniques for STLF**.** In 1991 Park *et al*. were among the first group of researchers who choose to use the ANN approach for STLF**.** Further improvements were made by Rahman and Hazim (1993) to incorporate a knowledge base in load forecasting, expert system techniques (Rahman and Hazim, 1993), neural networks (NN) (Hippert et al., 2001) [15, 16].

Some group of researchers used hybrid methods. The study conducted by Srinivasan *et al*. in 1995 was an example of hybrid approach which used a model that consisted of fuzzy logic and neural network**.** Another hybrid approach was fuzzy time series (Mamlook et al., 2009) **[**17]

In this paper, different approaches are discussed under three main categories.

- Statistical or traditional approaches
- Modern or artificial intelligence approaches
- Hybrid approaches

3.1 Statistical approaches

Statistical approaches require amathematical model which gives the relationship between load and several input factors [14R]. Another way to classify the statistical approach is stationary & Non-stationary techniques. Stationary techniques for forecasting stationary electric load patterns include the simple moving average and the exponential smoothing methods. Non-stationary methods used for forecasting electric loads that exhibit a trending pattern, includes the regression method and adaptive filtering [18].

Statistical approaches are as follows:

- Regression based approach
- Time series analysis
- Simple Moving Average (SMA)
- Exponential smoothing
- Adaptive Filtering (AF)
- Similar day lookup approach

3.1.1 Regression based approach

It is the one of most widely used statistical techniques. For electric load forecasting, regression methods are usually used to model the relationship between load consumption and other factors such as weather, day type, and customer class. The selection of independent variables is based on the numeric value of the correlation between them and the dependent variables [10]. The process of load forecasting using the regression approach involves:

(a) Selection of appropriate weather variables based on correlation coefficient criteria.
(b) Assuming a nonlinear mathematical relation between the dependent and independent variables with unknowns as the coefficients of the independent variables.
(c) Calculation of coefficients for the assumed non-linear mathematical relation.

This approach requires complex modelling techniques and consequently heavy computational efforts which can be considered as the main disadvantage of this technique [30].

3.1.2 Time series analysis

The time series analysis is a non-weather-sensitive approach that uses historical load data for extrapolation of future load [20]. It is based on the idea that reliable predictions can be achieved by modeling patterns in a time series plot, and then extrapolating those patterns to the future. Mostly used classical time series methods are:

ARMA and ARIMA: ARMA (autoregressive moving average) is usually used for stationary processes while ARIMA (autoregressive integrated moving average) is an extension of ARMA for non-stationary processes. They both use the time and load as the only input parameters.

ARIMAX: ARIMAX (autoregressive integrated moving average with exogenous variables) is the most natural tool for load forecasting among the classical time series models because load generally depends on the weather and time of the day [10].

The inaccuracy in predictions and numerical instability are the general problems with the time series approach. Since these models do not use weather information, they often give inaccurate results as there is a strong correlation between the behavior of load and weather variables such as temperature, humidity, cloud cover and wind speed [22].

3.1.3 Simple moving average (S.M.A.)

This technique considers the use of recently observed values' average specified by the user and using this value to forecast for the coming time period specified by the user. The term moving average is used because as each new observation becomes available, a new average is calculated and used as a forecast. Mathematically, the S.M.A. method can be represented as follows:

$$Y_{t+1} = \frac{1}{N}\sum_{i=t-N+1}^{t} X_i \qquad (1.1)$$

where, Y_{t+1} is the forecast value at time t+1, X_i is the observation at time i and N is the number of terms included in the average.

This method can be used for forecasting up to one, two, or three time periods but it is generally used for forecasting only one time period in advance because with increase in time period of every iteration, forecast error increases [18]. Though S.M.A. can be implemented very easily, it is manifested with the drawback of large space requirement for storing 'N' observed values as represented in Equation (1.1).

3.1.4 Exponential smoothing method

This method operates in a manner similar to the S.M.A. method by smoothing historical observations to eliminate randomness. So it is regarded as more sophisticated than moving average approach [12, 18]. The mathematical smoothing procedure differs from that used in SMA as follows:

$$Y_{t+1} = \alpha X_t + (1-\alpha) Y_t \qquad (1.2)$$

Where Y_{t+1} is the forecast value at time t+1, Y_t is the forecast value at time t, $X_t$is the actual value at time t and. The most recent observation is given a weight of αwhereas the most recent forecast is given a weight of (1-α). $\alpha = 1/N$, where N is the number of terms included in the average.

From Equation (1.2) it can be observed that the forecast at time $(t+1)^{th}$ instant depends on the actual value at time 't' and forecasted value at time 't'. Thus, the exponential smoothing method uses previous observations and requires less computer storage and hence less expensive.

3.1.5 Adaptive Filtering (AF)

This is an approach to determine the appropriate set of weights for a given data set. The technique is described by Equation (1.3).

$$Y_{t+1} = \sum_{i=1}^{N} w_i X_{t-i+1} \qquad (1.3)$$

Where w_i is the weight assigned to i^{th}observationswhich is updated by calculating the difference between the value of actual observation and its forecast, such that:

$$w_i' = w_i + 2M(X_{t+1} - Y_{t+1})X_{t-i+1} \qquad (1.4)$$

Where, Mis a constant, Y_{t+1} is the forecast value at time t+1, X_{t+1} is the actual observation at time t+1, Y_{t+1} is the forecast observation for this actual value.

The procedure represented by Equations (1.3) and (1.4) are repeated until the observations are given the most appropriate set of weights. The AF method can only be used to forecast one time-period ahead because the updating process of the weights depend upon the availability of new observations. Good forecasting results may be obtained if, and only if, a given load data trend is purely linear.

3.1.6 Similar Day Lookup Approach

Similar days are those which have approximately the same attributes (i.e. similar weather conditions) as that of the forecast day. These can be found using the Euclidean norm method. This is explained by Equation (1.5).

$$D = \sqrt{\hat{w}_1(\Delta L_l)^2 + \hat{w}_2(\Delta H_h)^2 + \hat{w}_3(\Delta T_t)^2} \qquad (1.5)$$

where, ΔL_l is the load deviation between load on forecast day and load on historical days, ΔT_t is the deviation of temperature between forecast day and historical days and ΔH_h is the deviation of humidity between forecast day and historical days. $\hat{w}_i$ (i = 1, 2, 3,..) is the weighted factor, which is determined by the least square method based on regression model that is constructed using historical temperature and load data. Therefore, a selection of similar days that consider a trend of load, humidity and temperature is performed.

In this method, weighted factors are used to measure the similarity between the forecast days and searched previous days. Similar days are based on the same season. The past 65 days from the day before a forecast day, and past 65 days before and after the forecast day in the previous year are considered for the selection of similar days. If the forecast day is changed, similar days are selected in the same manner.

3.2 AI based approaches for STLF

As statistical approaches were not able to forecast highly non-linear load, some modern or soft computing approaches were suggested. These approaches are categorized as:

- Fuzzy Logic
- Support Vector Machines (SVM)
- Knowledge-based expert systems
- Artificial Neural Network (ANN)
- Genetic Algorithm (GA)

3.2.1 Fuzzy Logic

Fuzzy sets are able to represent and manipulate electrical load pattern which possesses non-statistical uncertainty.Fuzzy logic is based on the usual Boolean Logic that is used for digital circuit design. With their help, we can deduce outputs from inputs logically. In this sense, the fuzzy facilitate for mapping between inputs and outputs like curve fitting. Fuzzy sets are a generalization of conventional set theory in the sense that they introduce vagueness in the data with the help of “linguistic variables”. The three main steps of fuzzy logic are:

Fuzzification: The real world input data is transformed into linguistic variables. This process is called *Fuzzification*.

Fuzzy inference: The next step involves the evaluation of the input information according to *IF…THEN* rules created by the user during the fuzzy control system programming and design stages.

Defuzzification: The terminating step involves the transformation of the results from the rule-processing stage and revert it back to its real world form. This process is called the *Defuzzification*.

The main advantage of fuzzy logic is that there is no need of mathematical models for mapping inputs and outputs and also there is no need of precise or even noise free inputs. The *IF…THEN* rules are easy to understand as the rules are linguistic in nature. Still there are some disadvantages of fuzzy logic. Fuzzy rules and membership function designing requires thorough knowledge of the system, which in most real world systems is a challenge. Fuzzy output can be interpreted in a number of ways making analysis difficult. Slow response due to serial data processing [10, 29].

3.2.2 Support Vector Machines (SVM)

The SVM is an elegant and highly principled learning method for the design of a feedforward network with a single hidden layer of nonlinear units. These are the most powerful techniques for data classification and regression problems. SVM use the nonlinear mapping of the data into high dimensional features by using the *kernel* functions mostly. The RBF kernel is used in most cases of load forecasting. But simple linear functions may also be used to create linear decision boundaries in the new space [10, 14].

3.2.3 Knowledge-based expert systems

The main objective of these approaches was to imitate the knowledge, experience and analytical thinking of experimental system operators. Expert-system based methods capture the expert knowledge into a comprehensive database which is then used for forecasting the load. These models are discrete as well as logical in nature, and use the knowledge of a human expert to develop rules for forecasting the load [37]. An Expert Systemmay be addressed as a computer program, which has the ability to act as an expert i.e. this computer program can reason, explain, and have its knowledge base expanded as new information becomes available to it. Basic characteristic of any expert system is that it must have the capability to trace its reasoning if asked by the user. Still the disadvantage of this method lies in the fact that it is often a very difficult task to transform an expert knowledge to a set of mathematical rules.

3.2.4 Artificial Neural Network

ANN’s were proposed early in 1960’s, but they received little attention until mid-80’s [19R]. The first article on artificial neural networks (ANN) modeling was published by McCulloch and Pitts (1943).The first reports on ANN application to the load forecasting problem were published in the late 1980’s and early 1990’s [38]. In 1992, Peng et al. [39] presented a search procedure for selecting the training cases for ANNs to recognize the relationship between weather changes and load shape, while Ho et al. [40] implemented a multilayer neural network with an adaptive learning algorithm. In the years 2000 and 2001, several researchers dealt with the application of ANN to the STLF problem, with varying success [41-44]. Neural networks are very frequently applied for load forecasting (see e.g. Hippert et al. (2001) for a survey). As stated in Hippert et al. (2005), in 1998 a software based on neural networks technology was used by over 30 US electric utilities [14].

An artificial neural network is an efficient information processing system to perform non-linear modeling and adaptation. It is based on training the system with past and current load data as input and output respectively. The ANN learns from experience and generalizes from previous examples to new ones [29].

Advantage of ANN is that no complex mathematical formulation or quantitative correlation between inputs and outputs is required. Another advantage of ANNover statistical models lies in its ability to model a multivariate problem without making complex dependency assumptions among input variables [45-49]. Furthermore, the ANN extracts the implicit non-linear relationship among input variables by learning from training data [30].

3.2.5 Genetic Algorithms (GAs)

Genetic algorithms (GAs) represent a powerful and robust approach for developing heuristics for large-scale combinatorial optimization problems. In the field of STELF, few GA based load forecasting methods have been reported, but encouraging results have appeared [50-52]. Srinivasan used a GA to evolve the optimum neural network structure and connecting weights for the one day ahead electric load forecasting problem [36, 53].

3.3 Hybrid approaches

Generally, these approaches combine two or more different approaches in order to overcome some drawbacks of the original methods [14]. Various hybrid intelligent techniques used in load forecasting problems include fuzzy neural network, neural network fuzzy expert system, neural expert systems, fuzzy expert, neural-genetic algorithm, etc. [13].

Park et al. made a further step by using fuzzy logic in an expert system for a STLF problem [54]. In 1995, Kim et al. [55] implemented a hybrid short term load forecaster by using ANNs and a fuzzy expert system, while later, Mori and Kobayashi [56] presented an optimal fuzzy inference approach for the STLF problem. Ranaweera et al. [57] proposed a fuzzy logic expert system model for the STLF problem, which used fuzzy rules to incorporate historical weather and load data. These fuzzy rules were obtained from historical data using a learning type algorithm. A back propagation neural network with the output provided by a rule based expert system was designed by Chiu et al. for the STELF problem [58]. Later, in 2000, Tamimi and Egbert [59] made a similar work, presenting how a fuzzy logic expert system can be integrated with ANNs for a more accurate short term load forecast. Recently, Liang and Cheng [60] proposed an approach based on an ANN combined with a fuzzy system for STELF. Frequently, genetic algorithms or other evolutionary algorithms are applied in combination with artificial neural networks (de Aquino et al., 2007; El Desouky et al., 2001; Liao and Tsao, 2006). In Huo et al. (2007) genetic programming (see e.g. Eiben and Smith, 2003) was used directly for load forecasting [14R].

4. Comparison of STLF techniques

A number of researchers have attempted to compare some of the methods used in load forecasting. One of the most comprehensive comparisons is made by Willis and Northcote-Green (1984), who performed comparison tests on 14 load forecasting methods. Atlas *et al*. (1989) compared the performance of different structures of neural networks with regression models. Dash *et al*. (1995a) also compared several fuzzy neural network based methods. Another comparison between neural networks and econometric models of forecasting electricity consumption was performed by Liu *et al*. (1991). Girgis*et al*. (1995) used actual load data to compare estimation errors of one-hour ahead and one-day ahead forecasts associated with three self-learning forecasting techniques [3]. Wu and Lu (1999) compared their fuzzy modelling method to Box - Jenkins transfer functions and ANN. Srinivasan *et al*. (1999) compared their NN-fuzzy expert system methodology to a regression-based model, showing significant improvement in forecasting accuracy.

Some of the conventional forecasting methods have major drawbacks especially their inability to map the non-linear characteristic of the load, thus a substitute of classical methods with intelligent system based models is to a great extent essential [2].

5. Conclusion

Electricity load forecasting is thus an important topic, since accurate forecasts can avoid wasting energy and prevent system failure. As we know that power system load is affected by many load factors such as weather, economic and social activities and different load components. By the analysis of only historical load data, it is not easy to make the accurate forecast.

All approaches are discussed with their classification. After surveying all these approaches, we can observe a clear trend towards new, stochastic, and dynamic forecasting techniques. Different methods have their own advantages, disadvantages & area of application. Over the years research direction has been shifted, replacing older methods i.e. some of the statistical methods like Kalman filter modelling & adaptive load forecasting. Although, time series approach is still used.While comparing all the methods, we can conclude that modern approaches are far superior to statistical approaches. There is also a clear move towards hybrid approaches.The use of these intelligent methods like fuzzy logic, expert systems and ANN provide advantage on other conventional methods. Especially ANN methods are particularly more attractive in STLF, as they have the ability to handle the nonlinear relationships between load and the factors affecting it directly from historical data. So over last few years, ANN based load forecasting has been the most active research area.

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