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# Forecasting the Load of Electrical Power Systems in Mid- and Long-term Horizons - A Review

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## Abstract

Load forecasting has always been an important part in the planning and operation of electric utilities, i.e., both transmission and distribution companies. With technological advancement, change in economic condition and many other factors (to be discussed in this work), load forecasting is becoming more important. The forecast affects as well as gets affected because of the load impacting factors and actions taken in different time horizons. However, due to its stochastic and uncertainty characteristics, it has been one challenging problem for electrical utilities to accurately forecast future load demand. This paper aims at reviewing the different load forecasting techniques developed for the mid- and long-term horizons of electrical power systems. Since there has never been an explicit literature study of the various forecasting techniques for mid- and long-term horizons, this paper reviews techniques for each of the forecasting horizons, citing various methodologies developed so far supported by published literature. The study is concluded with discussion on future research directions.

## Keywords:

Bibliography review, load forecasting, long-term load forecast, mid-term load forecast.

## 1. Introduction

Load forecasting is not something new, and it dates back to late 1960s when the first paper on load forecasting techniques was published [1]. Today, load forecasting has become an integral part of planning for

more than just utilities; system operators, energy suppliers, financial institutions, and participants in the generation, transmission, and distribution of electricity have a vested interest in load forecast accuracy. The long-term plan evaluates how well the short-term planning commitments fit into long-term needs. No commitment needs to be made to the elements in a long-term plan, and capacity and location are more important than timing in long-term forecast. In other words, it is more important to know what will eventually be needed than to know exactly when it will be needed. Based on time-scale, load forecast can be broadly classified into three main categories [2]:

- Short-term load forecast (STLF): The time-period of STLF lasts for few minutes, hours to one-day ahead or a week. STLF aims at economic dispatch and optimal generator unit commitment, while addressing real-time control and security assessment.
- Mid-term load forecast (MTLF): The time-period of MTLF is a month to a year or two. MTLF aims at maintenance scheduling, coordination of load dispatch and price settlement so that demand and generation is balanced.
- Long-term load forecast (LTLF): The time-period of LTLF is few years (> 1 year) to 10-20 years ahead. LTLF aims at system expansion planning, i.e., generation, transmission and distribution. In some cases, it also affects the purchase of new generating units.

Each of the three categories is equally important for the smooth operation of power system, and any error/uncertainty in forecast affects the economy and control aspect of power system. Especially in the mid- and long-term horizons, since load forecasting is highly related to the system development, attention has been paid to the impact of load forecasting on system design [3] and economics [4]. Load forecasting is usually tied to reliability analysis [5-7], and very recently in European projects (for e.g., GARPUR<sup>1</sup>). An accurate forecast leads to better maintenance plan during mid-term, and generation and expansion planning during long-term horizon. Preciseness of long-term forecast significantly affects the development of future generation systems. For example, construction of a new generation plant takes approximately 5-10 years, and involves huge amount of capital investment. In order to meet the demand and make the economic growth continuous, load forecasting is required for the related electricity utilities. Utilities do not want a huge investment going in vain. Both an overestimation as well as underestimation of forecast will result in

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<sup>1</sup> <http://www.garpur-project.eu/>

discontent among utilities and substantial investment for the construction of new generation units. So, accurate forecasting helps in assessing the needs in relation to planning, designing, environmental admitting to constructing step of power plants, and subsequent planning of transmission and distribution systems.

There are dozens of different load forecasting methods that have been used and documented during the last 50 years. Majority of them fall into the category of STLF, which is beyond the scope of this paper. MTLF and LTLF are much less popular as research topics as compared to STLF; dozens of papers on STLF are published every year for each paper on MTLF or LTLF. The answer, of course, is that forecasting for the med-term and specially for the long-term is a whole different problem from forecasting for the short term. It cannot be done by simply fitting a model (either statistical or computational) over a dataset, and then extrapolating from it. It is evident from refs. [8-9], that MTLF or LTF is usually ignored because of the complications. Ref. [10] reported the difficulty in accurate forecasting since the factors are not stable random, but rather unstable random factors like governance within a country. Ref [11] discussed the impact of long-term weather forecast and wind penetration on electrical load in Ireland. The work showcased the importance to consider the combined potential impacts of prolonged cold weather and periods of low winds under future projected generation scenarios. Makridakis et al. [12] clearly stated that long-term forecasting ‘requires a different approach’, and suggested that these forecasts should be based on (a) identifying and extrapolating mega-trends going back in time as far as necessary (as an example, they discuss the variations in the price of copper, since the year 1800); (b) analogy and (c) constructing scenarios to consider future possibilities. The influence of economic factors on load in long-term horizon becomes only visible on longer time scales or in extreme situations such as economic crisis of 2009 [13]. Effect of weather (mostly, temperature) is extensively discussed in the work also. It reported that during winter, a drop of temperature by 1°C causes an additional power request of about 1.8 GW in France. Weather forecast, itself, is difficult in longer horizon. So, it can be concluded how complicated load forecasting for mid-/long-term horizon is. [The problem of robust MTLF/LTLF can be foreseen as principal part of strategies design for substitutable development and optimal equipment renovation of energy systems under energy-saving technical progress.](#) [One of the feasible ways here is to design such strategies using integral dynamical models employment, as suggested in refs \[14-15\]. Here readers may refer to the extensive bibliography in these manuscripts on the use of integral dynamic models.](#) Hong [16] performed a study on past, current and future trends in energy

forecasting. The article showcased the trend in spatial, STLF, LTLF and energy price forecasting in a lucid manner. It quoted “*When you flick that switch, you expect the lights to go on – but the business of keeping them on is not nearly as straightforward*”. Till date, few of the prominent survey studies in load forecasting are Matthewman and Nicholson [17] in 1968, Abu El-Magd and Sinha [18] in 1982, Gross and Galiana [19] in 1987, Moghram and Rahman [20] in 1989, Srinivasan and Lee [21] in 1995, Hippert et al. [22] in 2001, Alfares and Nazeeruddin [23] in 2002, Bunoon et al. [24] in 2010 and Ghods and Kalantar [25] in 2011. Out of these review articles, either most of them are for STLF or the reviews are more than a decade old. Also, it can be seen that the review articles did not explicitly review the methodologies for MTLF and LTLF, apart from refs. [24-25]. Thus, the paper aims at quantifying the recent methodologies as well as tries to gather the concept of MTLF and LTLF into one article that can be referenced for future use.

The aim of this paper is to define and classify the various load forecasting techniques developed for mid- and long-term horizons since the review published by Willis and Northcote-Green [2]. The paper reflects advancements in the last 20 years in terms of technological advancement, mathematical concepts and application. This work is organized as follows. Section 2 focuses on the different approaches developed for MTLF and LTLF. Section 3 discusses the mathematical methods developed and used for MTLF and LTLF. Sections 4 and 5 illustrates some unique work developed for each of the time-horizon, while addressing the application and bottlenecks of each forecasting horizon. Finally, the review is concluded in section 6 encompassing few challenging topics in load forecasting, and future perspectives.

## **2. Different approaches towards mid- and long-term load forecasting**

Since the 1960s, most of the load forecasting techniques developed till date is dedicated to STLF, and not many for MTLF or LTLF. Mid- and long-term load forecasting is much more complex than simply fitting a mathematical model to some data, and it requires a lot more knowledge about the “substantive” problem. Compared to STLF that uses a sort of exercise on data modeling (for e.g., fitting models to datasets and extrapolating from them, without really understanding much about the way an electrical system works), MTLF/LTLF, on the other hand, depends less on the analyst’s expertise on modeling, and more on experience with power systems, and a thorough understanding of the way the system works, and how the electricity market may be affected by the changes in a country’s economy throughout the years, or by changes in technology, etc.

The MTLF/LTLF takes into account some explicit factors like historical load and weather data, economic indicators like gross domestic product (GDP) and their forecasts, and demographic data which includes consumer data like population, appliances in use, etc. Influence of weather follows a hierarchy in MTLF/LTLF as compared to STLF where all weather variables are treated with equal importance. Ref. [26] indicated that the weather variables follow a decreasing order of importance starting with temperature, humidity, wind and precipitation being the last on the list. To tackle this large number of factors for forecasting problem, the three methods suitable for MTLF/LTLF are [27]:

1. *Time series approach*: Time series forecasting approach is based on the assumption that the data already have an internal structure, such as correlation, or trend. Hence, it is also referred to as trend analysis approach. Examples of trends can be linear trend, polynomial trend and logarithmic trend. The time series approach may not be the right choice when there is a lot of variability in the historical data. And if the time series curve does not perfectly fit the historical data, there is model error and hence the variability should be checked. Various methods to account for variability are smoothing techniques like moving average and weighted moving average, Box-Jenkins method [8], and accounting for seasonality or cyclicity [9]. Ref. [28] presented an elaborate study on trend analysis in long-term forecasting. An important concept that can be concluded from the study is that the applied forecast methods should enable the forecaster to check itself, i.e. to quantify the uncertainty in the future. The study also introduced a new time series model, called exponentially-polynomial probabilistic model.
2. *Econometric approach*: It is evident from the name itself that this approach is based on economic indicators affecting load forecast. Econometric models attempt to quantify the relationship between the parameter of interest (output variable) and a number of factors that affect the output variable. Econometric approach combines the knowledge of economic theory and statistical technique for load forecasting in longer time horizons. Both MTLF and LTLF are dependent on longer time horizons, and this approach has proved beneficial and accurate. The idea of considering socio-economic factors in addition to other variables for load forecasting in the form of “econometrics” was first discussed by Fu and Nguyen [29]. The first step in this method is estimating the

relationship between load demand and the factors affecting the load demand by using time series methods. Relationships are determined simultaneously to find the overall best fit.

3. *End-use approach*: End-use approach, as the name suggests, forecasts load depending on the statistical information gathered from end uses. The end use approach looks at individual devices (i.e., end-uses like appliances), amount of use, number of devices and all, while repeating the method for as many number of devices. One positive aspect of this approach is that it accounts for changes in efficiency levels, both for new technology and for replacement of old technology. In this way, this approach is well accepted for demand side management (DSM) programs. The downside of this approach is that it is tremendously data intensive. Compared to the previous two approaches, end-use approach is more limited to energy forecasting rather than peak load.

Literature survey suggests another classification theory of MTLF/LTLF methods based on load impacting factors taken into consideration. The methods can be classified to two methods [30]:

1. *Conditional modeling approach*: Conditional modeling approaches encompasses historical load and weather data, socio-economic indicators and energy policies. This approach not only focuses on forecasting load, but also relies heavily on weather forecasts as well as future socio-economic condition of the region. Socio-economic condition of some regions may rapidly change, and thus impact energy demands. So, additional economic indicators like GDP and/or electrical infrastructure measures (number of connections, appliance saturation measure, etc.) in addition to information on historical load data and weather related variables is required to forecast future energy demands. Conditional modeling approach can be treated as a combination of both economics and end-use approach. Refs. [31-33] used number of electrical connections at the end of each month to define load demand of a region. In other cases, the aim was to formulate linear and mixed integer programming models to minimize total production costs of power generation in a region while satisfying a set economic, physical and environmental constraints [34]. In such formulation, authors accounted for complicity in the form of non-linearity and certain assumptions were required to solve it.
2. *Autonomous approach*: As the name suggests, autonomous approach is free from large pool of load impacting variables. It is dependent on only historical load and weather data. Weather data

can include plenty of variables like temperature, humidity, wind speed, etc. and it is solely dependent on utility's weather characteristics. This approach is well suited for stable economies. Researchers have argued that autonomous approach provides better forecast results if the forecast horizon is less than or equal to 1-year.

### 3. Mathematical techniques used for mid- and long-term load forecasting

Some of the widely used MTLF and LTLF methods are described below (*This can only be treated as definition. References for MTLF and LTLF are elaborated in detail in subsequent sections*):

Traditional approach in MTLF and LTLF can be classified into two broad categories [35]:

- *Parametric methods*: The parametric methods construct a mathematical or statistical model of load by examining qualitative relationships between load and load-affecting factors. Some examples are linear regression, ARIMA, and grey dynamic models. The assumed model parameters are estimated from historical data and the adequacy of model is verified by analysis of model residuals, i.e., forecast errors. The concept of this method is to convene the non-linear relationships between the inputs (historical load and load-impacting factors) and outputs (forecasted load) by means of expressing them by explicit formula. In this manner, the method does not offer the user an intuitive understanding.

Some of the widely used time series methods are autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA), autoregressive moving average with exogenous variables (ARMAX), and autoregressive integrated moving average with exogenous variables (ARIMAX). Their use in MTLF and LTLF are reported in refs. [36-39]. Ref. [40] discussed that moving average models are not efficient in load forecasting, while integration of moving average with autoregressive models are efficient in load forecasting. In addition, the time horizon and data availability are two important factors in deciding if it beneficial to choose univariate (ARMA) or multivariate (ARMAX) models.

Grey dynamic models are based on grey system theory proposed by Ju-Long [41]. It is based on the theory that there are three types of systems: white system in which all required information is available, black system in which no information is available and grey system in which partial information is available. Based on this, it is used for modeling and decision making processes for



the future that contains uncertain information. The method takes the uncertain systems of “small samples and incomplete information” with “partial known information and partial unknown information” as the research object. This theory extracts valuable information mainly by generating and developing the “partial” known information. Subsequently, the accurate demonstration of the system running behavior and the evolution rule is done and effective monitoring is achieved. It has attracted researchers for studying MTLF and LTLF [42-44].

- *Artificial intelligence (AI) methods:* Artificial intelligence (AI) methods mostly include fuzzy logic, artificial neural network (ANN) and support vector regression (SVR). It can be considered as non-traditional or modern methodology in load forecasting problems. The use of fuzzy logic with linear regression and ANN for MTLF and LTLF are reported in refs. [45-46]. The most popular ANN architecture used in load forecasting is multilayer feed-forward architecture. Hippert et al. [22] performed a detailed review of ANN application in STLF. The use of ANN in a hybrid manner with fuzzy and regression methods to give more flexible relations between load and load impacting variables. And, till today ANN is accepted for MTLF and LTLF [47]. Support vector regression (SVR) is the most common application form of support vector machine (SVM). An overview of the basic ideas underlying SVM for regression and function estimation has been given in [48], and its use in load forecasting is reported in literatures [49-53].

At the same time, the downsides of AI-based methods cannot be unseen. Fuzzy logic is difficult to inherit the knowledge of the previous mathematical models, and it is poor at solving the logic problems. ANN is considered as black-box since it does not explicitly clarifies the relationship between input and output variables. The traditional architecture of a feed forward back propagation ANN consists of an input layer, one or more hidden layers and an output layer. The choice of architecture is problem dependent and it often undergoes experimentation before the final architecture is selected. Ref. [30] proposed a dynamic ANN, called DAN2, which is based on the principle of self-learning at each layer till the desired network performance criteria is reached, and thereby deciding the architecture of neural network.

- *Other hybrid methods:* Recently, emerging heuristic optimization algorithms have been applied to optimize the design and effectiveness of AI-based predictors/forecasters and have been reported in

literatures. Examples are genetic algorithm [54-56], expert system [57-60], and evolutionary computation algorithms [61].

#### **4. Mid-term load forecasting overview**

Mid-term load forecasting (MTLF) emerged as an important tool in the past decade in countries when electric utilities started operating in deregulated environment. In addition, MTLF has gained importance in last decades because of reliability aspect, as the primary aim of MTLF is maintenance scheduling and economic operation of power system that bears a direct relation to reliability. The fact that MTLF is squeezed between STLF and LTLF is the reason that it has not gained much popularity because researchers have been working on other two load forecasting horizons explicitly. The time-horizon of MTLF is from few months to a year or two. In this time-frame, MTLF also contributes towards allocation of available resources and development of other infrastructure elements that is feasible during mid-term horizon [62]. An example is improving the congestion management in transmission grids, thereby improving overall system efficiency and cost of energy for consumer [30]. Added advantage with accurate MTLF is that deregulated firms can utilise the required information to guide the improvement of their transmission grid as well as distribution system. Economic impact of MTLF has been assessed in regulated and deregulated market since last two decades [32]. When energy is traded, accurate MTLF for monthly or yearly time-frame can help in better negotiations or purchase of energy, development of medium-term generation, transmission and distribution contracts [63]. Also, it affects the contract vendors of generators, energy transmitters and distributors. Ref. [32] discussed the impact of inaccurate MTLF on the economic aspect of electric utility. Inaccurate forecasts may result in either inadequate supply that could negatively impact the economic growth of a developing region, or oversupply that would result in utility cost overruns that might ultimately be transferred to consumers. Thus, it can be concluded that accurate MTLF results in a more economically viable system. Other uses of MTLF being hydro-thermal coordination and development of cost efficient fuel purchasing strategies in the mid-term horizon [4, 64-65]. In the current scenario, MTLF can be used to optimize maintenance scheduling for generation and transmission utilities, while contributing towards system reliability [66].

Literature study reveals that different authors have different approach in considering time-horizon for MTLF. Ref. [67] considered the horizon of MTLF, as few years ahead with a forecast step of one year, and it

is more LTLF than MTLF. Refs. [68-70] modelled MTLF in monthly forecast step, and refs. [21, 71-72] considered a horizon of 12 months or 1 year for their study. Many of the MTLF modelling methods were discussed in each of the sections discussing on various approaches for MTLF/LTLF. It would be important to highlight some of the works dedicated to MTLF, which are modelled either on any one or combination of the approaches studied in previous section. The effect of weather variables on load forecasting in mid-term horizon is extensively studied in refs. [73-75]. Autonomous approach has been widely accepted in MTLF modelling, where the historical load and weather data are the main load impacting variables. Ref. [76] proposed a MTLF model based on autonomous approach to forecast monthly load for Jeddah area. The authors compared the results of statistical approach (ARIMA) with AI-based (ANN and fuzzy-NN) results, and concluded that AI-based method was superior. It was also observed that the load profile was not stationary and statistical pre-processing (autocorrelation and partial autocorrelation analysis) was needed for further analysis. In ref. [69], the authors propose a ANN model that outperforms statistical approach methods (regression models). Historical temperature data was used to predict monthly load demand for 1-year period. A dynamic ANN-based MTLF model (DAN2) proposed by [30] compared their model with statistical approach (ARIMA), and concluded that the forecasted values were more accurate as measured by MAPE values. An added advantage of this model is that the authors did not rely on weather forecasts, which can be inaccurate or maybe unavailable. The model developed seasonal models that did not require weather information. Ref. [77] also proposed a MTLF model based on trend approach and neural networks without any weather information. In other words, it follows an autonomous approach and the load modeling is based on load seasonality factor. In this work, daily peak load is forecasted for the next month.

Ref. [71] proposed a MTLF methodology for 1-year period with monthly load demand based on time series and statistical approach. The method was tested for the Greek power system. An observation from [76] was autocorrelation in load profile, which was tackled in this regression method. According to ref [12], if the errors are serially correlated then the most-common *F*- and *t*-tests (variance and mean tests) and *confidence intervals* are invalid, and hence the coefficients of forecast model are unstable. Thus, the proposed model was modified by introduction of an autoregressive structure. Another important finding from this work is the impact of heteroskedasticity on the model. The existence of heteroskedasticity violates the ‘constant

variance' assumption in regression analysis, and it was evident from the demand data. The final model was a logarithmic one as proposed by [12] to combat heteroskedasticity.

Ref. [72] proposed a semi-parametric additive model for both STLF and MTLF for the French distribution grid. The model was tested with historical data to forecast load for more than 2200 substations without any human intervention. For the mid-term horizon, monthly peak demand is aggregation of daily peak load, and it is forecasted for 1-year period. The authors in ref. [78] have included macroeconomic indicators, such as the consumer price index, the average salary earning and the currency exchange rate in their MTLF analysis.

From the above analysis, it can be concluded that inclusion of weather or economic indicators for MTLF, authors have used statistical measure (e.g., autocorrelation or partial autocorrelation analysis) and personal experience and intuition to assess the validity, effectiveness and contribution of such variables to load forecasting. Other works on regression-based method were reported in refs. [77, 79-81]. AI-based methods have been widely used for MTLF, mostly ANN [30, 32, 71, 78, 82-84].

## **5. Long-term load forecasting overview**

Long-term load forecasting (LTLF) plays an important role in power systems for system planning, scheduling expansion of generation units by construction and procurement of generation units. It spans from a few years (> 1 year) to 10-20 years [62]. Because it takes several years and requires a huge investment for construction of power generation and transmission facilities, accurate and error-free forecasting is necessary for an electric utility. Accuracy of LTLF has a direct impact on development of future generation and transmission planning, and hence it is a crucial instrument for planning and forecasting future conditions of the electricity network. Based on the forecast, electric utilities coordinate their resources to meet the forecasted demand using a least-cost plan. In general, LTLF is subjected to a large number of uncertainties and ample amount of research indicates that load predication in presence of uncertainties is required for future capacity resource needs and operation of existing generation resources. Ref. [85] described the difficulties in long-term load forecast in a lucid and clear way. The various reasons for inaccuracy are:

- Peak demand is very much dependent on temperature
- Some of the necessary data for LTLF including weather data and economic data (vital ones) are not available

- It is very difficult to store electric power with the present available technology
- It takes several years and requires a great amount of investment to construct new power generation stations and transmission facilities

Till today not much amount of work has been done in the area of LTLF as compared to STLF. The reason is the same as for MTLF, i.e., uncertainty, complexity and difficulty in collecting as well as processing of data. And it can be accounted for the various factors, like, weather, economic and social factors. Economic indicators, such as GDP, population growth, and economic development, are the bottlenecks for long-term load forecasting as compared to weather variables. The various factors that add to the non-linearity and complexity are daily/weekly/seasonal weather, economic growth, and social factors. Low resolution and missing data points for weather has been addressed in ref. [86]. The authors used multiple linear regression model for LTLF while normalizing the load hourly.

During the last three decades, many techniques have been developed to improve the long-term load forecast. As discussed in MTLF, the load model for regression and time series based methods has a complex and non-linear behaviour. Various regression based models have been developed for LTLF and it includes linear [28], multiple linear regression [86], linear-log regression [87], autoregressive [31], moving average [31], autoregressive moving average (ARMA) [31], fuzzy linear regression [88], and hybrid regression model based on Bayesian approach [89]. In 1987, ref. [28] used regression-based load model to forecast load for Yugoslav till year 2000.

ANN has also found application in LTLF. Kermanshahi and Iwamiya [85] extended the ANN technique to forecast load for long-term. Their article published in 2002 tried to forecast load for the years 2010, 2015 and 2020. Similarly, Hamzacebi [90] used ANN to forecast load in Turkey until 2020 in the year 2007. Before that, Kermanshahi [91] in 1998 used ANN forecast load for 10 years, Ekonomou [92] used ANN to forecast load in Greece. Other commendable work in LTLF using ANN is reported in literatures [93-100].

Jia et al. [101-102] developed a dynamic simulation approach for LTLF a decade ago called General Simulations theory (GSIM) based on the limitations of both parametric and AI-methods in context to interaction between load and load-impacting factors. The technique was implemented in Tokyo area while comparing the results with traditional regression-based method. In GSIM, load demand correlations are divided into functional and impact relations, and then GSIM learns the inter-dependencies between two

relations simultaneously. Ref. [35] proposed a parametric regression method for both MTLF and LTLF based on short-term load correlation. In this method, 24-hour load predication using regression is averaged to capture the load prediction for longer time-horizons. Correlation of daily load behavior with annual growth has accounted for low mean absolute error of 3.8%.

In long-term horizon, some authors preferred to forecast annual energy demand and then derive the annual peak load forecast from it. Annual energy demand can be modeled by any of the three approaches defined in previous section: trend, econometric or end-use. Ref. [103] proposed a hybrid fuzzy-neural approach to forecast annual energy consumption. However, the authors also cite disadvantages of such an approach which are same as for end-use approach. It is data extensive and fuzzy rules are complicated owing to large amount of data. The short-comings are addressed by authors using principal component analysis and neural network in ref. [104].

For long-term forecasting, economic indicators play an important role when compared to weather as seen in mid-term forecasting. It is evident from the discussion in previous paragraphs, and few more works that support the fact about economic indicators playing an important role [105-107]. Authors also emphasize in predicting load demand for a large region or say country when they prefer to forecast in long-term horizon. This is supported by the fact that long-term horizon planning refers to system development and expansion planning, which in most cases takes place for a large region. Refs. [90, 92, 103] are few examples described in the previous section.

## **6. Conclusion and discussion**

Forecasting, by nature, is a stochastic problem. Since exact prediction of the future is impossible, it can be assumed that forecasting for mid- and long-term horizons can only be wrong. One way to counter this assumption is scenario analysis that looks into selected scenario in future. Due to the uncertainty in weather and economic forecasts, forecasters are encouraged to provide multiple forecasts based on different scenarios. Other ways to counter the assumption are predictive modeling, weather normalization, and probabilistic forecasting. Today, most utilities are still developing and using point forecasts instead of probabilistic forecasts. Given the uncertainty surrounding long-term forecasts, it is not advisable to follow one single forecast but rather multi-scenario load forecasting. MTLF and LTLF are the best examples of multi-scenario load forecasting in which the multi-scenario or *what-if load forecast* comes into picture to

study the various possibilities in future. Different outcomes require different plans or approaches for which no average plan can be built. Due to the poor predictability of weather and economic indicators, which is a main driver of electricity demand, it is unrealistic and unfair to judge a long term forecaster by comparing a few years of point forecasts with the corresponding actual values.

As studied in few works, load profiling in load forecasting can be a solution in long run. Load profiling is a process in which the classification of customers according to type or class (i.e., residential, commercial, industrial, etc.) is carried out based upon the data (measurements, henceforth to be called load profile) received at transmission and distribution utilities. It is important in the future to foresee the future load forecasting model as a data mining-based model that incorporates influencing factors like historical data, seasonal data, economic data, maintenance schedule of the main industrial consumers, etc. This aims at the following advantages:

- Tackling spatio-temporal correlations. Some consumers are influenced by season/temperature and therefore will consume more in winter, some others (e.g., industries) not much.
- Load profiling helps in targeting the variation of the Value of Lost Load (VoLL) depending on the customer class and time of the year. Estimates of the VoLL provides critical information to support customer-focused, value-based planning. It is useful to determine the economically efficient level of investment in utility plant (i.e., generation, transmission, and distribution). VoLL can also be used to evaluate the payoff for investments in mid-term decision making process, i.e., improve reliability and provide service quality.

An important observation from this study is that with future demand and interest, new mathematical tools and algorithms evolve, and accordingly new forecasting techniques will develop. It is vital to closely monitor technological trends in future such as the future effects of electrification loads, e.g. electrical vehicle loads. In order to improve the accuracy of forecasting process, monitoring trends in forecasting approaches and tracking developments that may affect the load forecasts is recommended. The load forecast model should be dynamic in nature so as to adjust itself if new information on load impacting variables becomes available. Other unwanted events like economic crises, wars and revolutions, strikes, and trade disputes in commodity markets impact electricity demand. Combining the stochasticity nature of load and uncertainty,

use of stochastic models like geometric Brownian motion and Monte Carlo models with high and low uncertainty bands are recommended in the current scenario.

To conclude this review, a concise overview of different mathematical methods is presented in Table 1:

**Table 1: Different mathematical methods for MTLF and LTLF in nutshell**

| <b>Time-horizons</b>           | <b>MTLF</b>   | <b>LTLF</b>  |
|--------------------------------|---|--|
| <b>Mathematical methods</b>    |   |  |
| <b>Parametric</b>              | Regression-based (refs. 35,71,72,77,79-81)  | Regression-based (refs. 28,31,35,86-89)  |
| <b>Artificial intelligence</b> | Fuzzy (refs. 45, 46)<br>ANN (refs. 30,32,47,69,71,78,82-84)<br>SVM (refs. 49, 51-53,68) | Fuzzy (refs. 45, 46)<br>ANN (refs. 85,90-94,97,99-100)<br>Nuero-fuzzy (refs. 95,98,103-104)<br>GSIM (refs. 101-102)<br>SVM (ref. 50) |
| <b>Other methods</b>           | DAN2 (ref. 30)<br>GA (ref. 55)<br>Expert system (refs. 57,58,60)                        | GA (refs. 54,56)<br>Expert system (ref. 59)<br>PSO (ref. 61)   |

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## 8. References

- [1] Heinemann G, Nordman D, Plant E. The relationship between summer weather and summer loads: A regression analysis. *IEEE Trans. Power App. Syst.* 1966; **PAS-85**(11): 1144-1154.
- [2] Willis HL, Northcote-Green JE. Spatial electric load forecasting: a tutorial review. *Proc. IEEE* 1983; **71**(2): 232-253.
- [3] Willis HL. Load forecasting for distribution planning-error and impact on design. *IEEE Trans. Power App. Syst.* 1983; **PAS-102**(3): 675-686.
- [4] Ranaweera DK, Karady GG, Farmer RG. Economic impact analysis of load forecasting. *IEEE Trans. Power Syst.* 1997; **12**(3): 1388-1392.
- [5] Billinton R, Huang D. Effects of load forecast uncertainty on bulk electric system reliability evaluation. *IEEE Trans. Power Syst.* 2008; **23**(2): 418-425.



- [6] Wu L, Shahidehpour M, Li T. Stochastic security-constrained unit commitment. *IEEE Trans. Power Syst.* 2007; **22**(2): 800-811.
- [7] Wu L, Shahidehpour M, Li T. Cost of reliability analysis based on stochastic unit commitment. *IEEE Trans. Power Syst.* 2008; **23**(3): 1364- 1374.
- [8] Box GE, Jenkins GM, Reinsel GC. *Time series analysis: forecasting and control*. Wiley, Hoboken, 2008.
- [9] Chatfield C. *Time-series forecasting*. Chapman & Hall, New York, 2001.
- [10] Xia C, Wang J, McMenemy K. Short, medium and long term load forecasting model and virtual load forecaster based on radial basis function neural networks. *Electr. Power Energy Syst.* 2010; **32**(7): 743-750.
- [11] Leahy PG, Foley AM. Wind generation output during cold weather-driven electricity demand peaks in Ireland. *Energy*. 2012; **39**(1): 48-53.
- [12] Makridakis S. *Forecasting: Methods and applications*. / Makridakis S, Wheelwright SC, Hyndman RJ, New York: John Wiley & Sons, 1998.
- [13] Troccoli A. *Management of weather and climate risk in the energy industry*. Springer, 2009.
- [14] Hritonenko N, Yatsenko Y. Energy substitutability and modernization of energy-consuming technologies. *Energy Economics*. 2012; **34**(5): 1548-1556.
- [15] Sidorov D. *Integral dynamical models: Singularities, signals and control*. World Scientific Series on Nonlinear Science Series A: Volume 87, World Scientific Publ., Singapore, 2015.
- [16] Hong T. Energy forecasting: Past, present, and future. *Foresight: The International Journal of Appl. Forecast.* 2014; **32**: 43-48.
- [17] Matthewman PD, Nicholson H. Techniques for load prediction in electricity supply industry. *Proc. IEEE* 1968; **115**: 1451-1457.
- [18] Abu El-Magd MA, Sinha NK. Short-term load demand modeling and forecasting. *IEEE Trans. Syst. Man Cyber.* 1982; **12**(3): 370-382.
- [19] Gross G, Galian FD. Short term load forecasting. *Proc. IEEE* 1987; **75**(12): 1558-1573.
- [20] Moghram IS, Rahman S. Analysis and evaluation of five short-term load forecasting techniques. *IEEE Trans. Power Syst.* 1989; **4**(4): 1484-1491.

- [21] Srinivasan D, Lee MA. Survey of hybrid fuzzy neural approaches to electric load forecasting. Proc. IEEE Int. Conf. Syst. Man Cyber., 1995.
- [22] Hippert HS, Pedreira CE, Souza RC. Neural networks for short-term load forecasting: A review and evaluation. *IEEE Trans. Power Syst.* 2001; **16**(1): 44-55.
- [23] Alfares HK, Nazeeruddin M. Electric load forecasting: literature survey and classification of methods. *Int. J. Syst. Science* 2002; **33**: 23–34.
- [24] Bunnoon P, Chalermyanont K, Limsakul C. A computing model of artificial intelligent approaches to mid-term load forecasting: a state-of-the-art survey for the researcher. *Int. J. Eng. Techn.* 2010; **2**(1): 94-100.
- [25] Ghods L, Kalantar M. Different methods of long-term electric load demand forecasting; a comprehensive review. *Iranian J. Electr. Electronic Eng.* 2011; **7**(4): 249-259.
- [26] Robinson P. Modeling utility load and temperature relationships for use with long-lead forecasts. *J. Appl. Meteorol.* 1997; **36**:591–598.
- [27] Feinberg EA, Genethliou D. *Load forecasting. In Applied mathematics for power systems: Optimization, control, and computational intelligence* 2005, eds. J. H. Chow, F. F. Wu, and J. A. Momoh, 269-285. New York: Springer.
- [28] Vlahović VM, Vujošević IM. Long-term forecasting: a critical review of direct-trend extrapolation methods. *Electr. Power Energy Syst.* 1987; **9**(1): 2-8.
- [29] Fu CW, Nguyen TT. Models for long-term energy forecasting. Proc. IEEE Power Eng. Society General Meeting, 2003.
- [30] Ghiassi MD, Zimbra DK, Saidane H. Medium term system load forecasting with a dynamic artificial neural network model. *Electr. Power Syst. Res.* 2006; **76**(5): 302-316.
- [31] Barakat EH, Al-Rashed SA. Long range peak demand forecasting under conditions of high growth. *IEEE Trans. Power Syst.* 1992; **7**(4): 1483-1486.
- [32] Islam SM, Al-Alawi SM, Ellithy KA. Forecasting monthly electric load and energy for a fast growing utility using an artificial neural network. *Electr. Power Syst. Res.* 1995; **34**(1): 1-9.
- [33] Kandil MS, El-Debeiky SM, Hasanien NE. Long-term load forecasting for fast developing utility using a knowledge-based expert system. *IEEE Trans. Power Syst.* 2002; **17**(2): 491-496.

- [34] Bart A, Benahmed M, Cherkaoui R, Pitteloud G, Germond A. Long-term energy management optimization according to different types of transactions. *IEEE Trans. Power Syst.* 1998; **13**(3): 804-809.
- [35] Al-Hamadi HM, Soliman, SA. Long-term/mid-term electric load forecasting based on short-term correlation and annual growth. *Electr. Power Syst. Res.* 2005; **74**(3): 353-361.
- [36] Willis HL, Tram HN. Load forecasting for transmission planning. *IEEE Trans. Power App. Syst.* 1984; **PER-4**(3): 561-568.
- [37] Abdel-Aal RE, Al-Garni AZ. Forecasting monthly electric energy consumption in eastern Saudi Arabia using univariate time-series analysis. *Energy* 1997; **22**(11): 1059-1069.
- [38] Barakat EH. Modeling of nonstationary time-series data. Part II. Dynamic periodic trends. *Electr. Power Energy Syst.* 2001; **23**(1): 63-68.
- [39] Filik ÜB, Gerek ÖN, Kurban M. A novel modeling approach for hourly forecasting of long-term electric energy demand. *Energy Conv. Manag.* 2011; **52**(1): 199-211.
- [40] Weron R. *Modeling and forecasting electricity loads and prices: A statistical approach*. Chichester: John Wiley and Sons, 2006.
- [41] Ju-Long D. Control problems of grey systems. *Syst. Cont. Letters* 1982; **1**(5): 288-294.
- [42] Tamura Y, Deping Z, Umeda N, Sakashita K. Load forecasting using grey dynamic model. *J. Grey Syst.* 1992; **4**(1): 49-58.
- [43] Morita H, Zhang DP, Tamura Y. Long-term load forecasting using grey system theory. *Electr. Eng. Japan* 1995; **115**(2): 11-20.
- [44] Kang J, Zhao H. Application of improved grey model in long-term load forecasting of power engineering. *Syst. Eng. Procedia* 2012; **3**: 85-91.
- [45] You SH, Cheng HZ, Xie H. Mid-and long-term load forecast based on fuzzy linear regression model. *Electr. Power Automation Equipment* 2006; **26**(3): 51-53.
- [46] Yue L, Zhang Y, Xie H, *et al.* The fuzzy logic clustering neural network approach for middle and long term load forecasting. Proc. IEEE Grey Syst. Intel. Serv., 2007.
- [47] Lee WJ, Hong J. A hybrid dynamic and fuzzy time series model for mid-term power load forecasting. *Electr. Power Energy Syst.* 2015; **64**: 1057-1062.

- [48] Smola AJ, Schölkopf B. A tutorial on support vector regression. *Statistics and computing* 2004; **14**(3): 199-222.
- [49] Hong WC, et al. SVR with hybrid chaotic immune algorithm for seasonal load demand forecasting. *Energies* 2011; **4**(6): 960-977.
- [50] Zhang Z, Ye S. Long term load forecasting and recommendations for china based on support vector regression. Proc. IEEE Information Management, Innovation Management and Industrial Engineering, 2011.
- [51] Wang J, et al. An annual load forecasting model based on support vector regression with differential evolution algorithm. *Applied Energy* 2012; **94**: 65-70.
- [52] Hong WC, et al. Cyclic electric load forecasting by seasonal SVR with chaotic genetic algorithm. *Electr. Power Energy Syst.* 2013; **44**(1): 604-614.
- [53] Hu Z, et al. Mid-term interval load forecasting using multi-output support vector regression with a memetic algorithm for feature selection. *Energy* 2015; **84**: 419-431.
- [54] Lee DG, Lee BW, Chang SH. Genetic programming model for long-term forecasting of electric power demand. *Electr. Power Syst. Res.* 1997; **40**(1): 17-22.
- [55] De Aquino RR, Neto ON, Lira M, et al. Development of an artificial neural network by genetic algorithm to mid-term load forecasting. Proc. IEEE Int. Joint Conf. Neural Networks, 2007.
- [56] Karabulut K, Alkan A, Yilmaz AS. Long term energy consumption forecasting using genetic programming. *Math. Comp. Appl.* 2008; **13**(2): 71-80.
- [57] Mohamad EA, Mansour MM, El-Debeiky S, et al. Results of Egyptian unified grid hourly load forecasting using an artificial neural network with expert system interface. *Electr. Power Syst. Res.* 1996; **39**(3): 171-177.
- [58] Chandrashekara AS, Ananthapadmanabha T, Kulkarni AD. A neuro-expert system for planning and load forecasting of distribution systems. *Electr. Power Energy Syst.* 1999; **21**(5): 309-314.
- [59] Kandil MS, El-Debeiky SM, Hasanien, NE. The implementation of long-term forecasting strategies using a knowledge-based expert system: part-II. *Electr. Power Syst. Res.* 2001; **58**(1): 19-25.

- [60] Li HZ, Guo S, Li CJ, *et al.* A hybrid annual power load forecasting model based on generalized regression neural network with fruit fly optimization algorithm. *Knowledge-Based Syst.* 2013; **37**: 378-387.
- [61] AlRashidi MR, El-Naggar KM. Long term electric load forecasting based on particle swarm optimization. *Appl. Energy* 2010; **87**(1): 320-326.
- [62] Khuntia SR, Tuinema BW, Rueda JL, van der Meijden MAMM. Time-horizons in the planning and operation of transmission networks: an overview. *IET Gen. Trans. Distr.* 2016; **10**(4): 841-848.
- [63] Oliveira FS, Ruiz C, Conejo AJ. Contract design and supply chain coordination in the electricity industry. *Europ. J. Operat. Res.* 2013; **227**(3): 527-537.
- [64] Gonzalez-Romera E, Jaramillo-Moran MA, Carmona-Fernandez D. Monthly electric energy demand forecasting based on trend extraction. *IEEE Trans. Power Syst.* 2006; **21**(4): 1946-1953.
- [65] Amjady N, Farrokhzad D, Modarres M. Optimal reliable operation of hydrothermal power systems with random unit outages. *IEEE Trans. Power Syst.* 2003; **18**(1): 279-287.
- [66] GARPUR consortium. *How to upgrade reliability management for asset management decision making.* 2016 [Online: <http://www.garpur-project.eu/deliverables>]
- [67] Tsekouras GJ, Hatziargyriou, ND, Dialynas EN. An optimized adaptive neural network for annual midterm energy forecasting. *IEEE Trans. Power Syst.* 2006; **21**(1): 385-391.
- [68] Chen BJ, Chang MW, Lin CJ. Load forecasting using support vector machines: A study on EUNITE competition 2001. *IEEE Trans. Power Syst.* 2004; **19**(4): 1821-1830.
- [69] Doveh E, Feigin P, Greig D, *et al.* Experience with FNN models for medium term power demand predictions. *IEEE Trans. Power Syst.* 1999; **14**(2): 538-546.
- [70] Yalcinoz T, Eminoglu U. Short term and medium term power distribution load forecasting by neural networks. *Energy Conv. Manag.* 2005; **46**(9): 1393-1405.
- [71] Mirasgedis S, *et al.* Models for mid-term electricity demand forecasting incorporating weather influences. *Energy* 2006; **31**(2): 208-227.
- [72] Goude Y, Nedellec R, Kong N. Local short and middle term electricity load forecasting with semi-parametric additive models. *IEEE Trans. Smart Grid* 2014; **5**(1): 440-446.

- [73] Apadula F, Bassini A, Elli A, *et al.* Relationships between meteorological variables and monthly electricity demand. *Appl. Energy* 2012; **98**: 346-356.
- [74] OrtizBeviá MJ, RuizdeElvira A, Alvarez-García FJ. The influence of meteorological variability on the mid-term evolution of the electricity load. *Energy* 2014; **76**: 850-856.
- [75] De Felice M, Alessandri A, Catalano F. Seasonal climate forecasts for medium-term electricity demand forecasting. *Appl. Energy* 2015; **137**: 435-444.
- [76] Elkateb MM, Solaiman K, Al-Turki Y. A comparative study of medium-weather-dependent load forecasting using enhanced artificial/fuzzy neural network and statistical techniques. *Neurocomputing* 1998; **23**(1): 3-13.
- [77] Amjady N, Keynia F. Mid-term load forecasting of power systems by a new prediction method. *Energy Conv. Manag.* 2008; **49**(10): 2678-2687.
- [78] Gavrilas M, Ciutea I, Tanasa C. Medium-term load forecasting with artificial neural network models. Proc. 16th Int. Conf. Exhibition Electricity Distribution, 2001.
- [79] Tsekouras G J, Dialynas EN, Hatziaargyriou ND, *et al.* A non-linear multivariable regression model for midterm energy forecasting of power systems. *Electr. Power Syst. Res.* 2007; **77**(12): 1560-1568.
- [80] Moreno-Chaparro C, Salcedo-Lagos J, Trujillo ER, *et al.* A method for the monthly electricity demand forecasting in Colombia based on wavelet analysis and a nonlinear autoregressive model. *Ingeniería* 2011; **16**(2): 94-106.
- [81] Vu DH, Muttaqi KM, Agalgaonkar AP. A variance inflation factor and backward elimination based robust regression model for forecasting monthly electricity demand using climatic variables. *Appl. Energy* 2015; **140**: 385-394.
- [82] Pan X, Lee B. A comparison of support vector machines and artificial neural networks for mid-term load forecasting. Proc. IEEE Int. Conf. Indust. Tech., 2012.
- [83] Abdel-Aal RE. Univariate modeling and forecasting of monthly energy demand time series using abductive and neural networks. *Comp. Indust. Eng.* 2008; **54**(4): 903-917.
- [84] Jaramillo-Morán MA, González-Romera E, Carmona-Fernández D. Monthly electric demand forecasting with neural filters. *Electr. Power Energy Syst.* 2013; **49**: 253-263.

- [85] Kermanshahi B, Iwamiya H. Up to year 2020 load forecasting using neural nets. *Electr. Power Energy Syst.* 2002; **24**(9): 789-797.
- [86] Hong T, Wilson J, Xie J. Long term probabilistic load forecasting and normalization with hourly information. *IEEE Trans. Smart Grid* 2014; **5**(1): 456-462.
- [87] Tripathy SC. Demand forecasting in a power system. *Energy Conv. Manag.* 1997; **38**(14): 1475-1481.
- [88] Al-Hamadi HM. Long-term electric power load forecasting using fuzzy linear regression technique. Proc. IEEE Power Eng. Automation Conf., 2011.
- [89] Niu L, Zhao J, Liu M. Application of relevance vector regression model based on sparse bayesian learning to long-term electricity demand forecasting. Proc. IEEE Int. Conf. Mechatronics Automation, 2009.
- [90] Hamzaçebi C. Forecasting of Turkey's net electricity energy consumption on sectoral bases. *Energy Policy* 2007; **35**(3): 2009-2016.
- [91] Kermanshahi B. Recurrent neural network for forecasting next 10 years loads of nine Japanese utilities. *Neurocomputing* 1998; **23**(1): 125-133.
- [92] Ekonomou L. Greek long-term energy consumption prediction using artificial neural networks. *Energy* 2010; **35**(2): 512-517.
- [93] Nagasaka K, Al Mamun M. Long-term peak demand prediction of 9 Japanese power utilities using radial basis function networks. Proc. IEEE Power Eng. Society General Meeting, 2004.
- [94] Mamun MA, Nagasaka K. Artificial neural networks applied to long-term electricity demand forecasting. Proc. IEEE Int. Conf. Hybrid Intel. Syst., 2004.
- [95] Dalvand MM, Azami SBZ, Tarimoradi H. Long-term load forecasting of Iranian power grid using fuzzy and artificial neural networks. Proc. IEEE Univ. Power Eng. Conf., 2008.
- [96] Alsayegh O, Almatar O, Fairouz F, *et al.* Prediction of the long-term electric power demand under the influence of A/C systems. *Proc. Inst. Mech. Eng., Part A: J. Power Energy* 2007; **221**(1): 67-75.
- [97] Carpinteiro OA, Leme RC, de Souza AC, *et al.* Long-term load forecasting via a hierarchical neural model with time integrators. *Electr. Power Syst. Res.* 2007; **77**(3): 371-378.

- [98] Maraloo MN, Koushki AR, Lucas C, *et al.* Long term electrical load forecasting via a neuro-fuzzy model. Proc. IEEE Int. Computer Conf., 2009.
- [99] Çunkaş M, Altun AA. Long term electricity demand forecasting in Turkey using artificial neural networks. *Energy Sources, Part B: Econ. Planning Policy* 2010; **5**(3): 279-289.
- [100] Kumaran J, Ravi G. Long-term sector-wise electrical energy forecasting using artificial neural network and biogeography-based optimization. *Electr. Power Comp. Syst.* 2015; **43**(11), 1225-1235.
- [101] Jia NX, Yokoyama R, Zhou YC. A novel approach to long term load forecasting where functional relations and impact relations coexist. Proc. IEEE PowerTech, 1999.
- [102] Jia NX, Yokoyama R, Zhou YC, *et al.* A flexible long-term load forecasting approach based on new dynamic simulation theory—GSIM. *Electr. Power Energy Syst.* 2001; **23**(7): 549-556.
- [103] Chen T. A collaborative fuzzy-neural approach for long-term load forecasting in Taiwan. *Comp. Indust. Eng.* 2012; **63**(3): 663-670.
- [104] Chen T, Wang YC. Long-term load forecasting by a collaborative fuzzy-neural approach. *Electr. Power Energy Syst.* 2012; **43**(1): 454-464.
- [105] Hyndman RJ, Fan S. Density forecasting for long-term peak electricity demand. *IEEE Trans. Power Syst.* 2010; **25**(2): 1142-1153.
- [106] Tan Z, Zhang J, Wu L, *et al.* A model integrating econometric approach with system dynamics for long-term load forecasting. *Power Syst. Tech.* 2011; **1**: 186-190.
- [107] Sanstad AH, McMenamin S, Sukenik A, *et al.* Modeling an aggressive energy-efficiency scenario in long-range load forecasting for electric power transmission planning. *Appl. Energy* 2014; **128**: 265-276.