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Khuntia, Swasti R.; Rueda, José L.; van der Meijden, Mart A.M.M.

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

Swasti. R. Khuntia[a], José L. Rueda[a], and Mart A. M. M. van der Meijden[a,b]

[a]:Department of Electrical Sustainable Energy, Delft University of Technology, The Netherlands
[b]:TenneT TSO B.V., The Netherlands

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[1]). 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 need 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

[1] 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 cyclicality [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 complicacy 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 is 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 evolvement 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 distributers. 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. MLTF 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

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

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