



# A Study of Load Demand Forecasting Models in Electric Power System Operation and Planning

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**Abstract**— Load demand forecasting is an essential process in electric power system operation and planning. It involves the accurate prediction of both magnitudes and geographical locations of electric load over the different periods of the planning horizon. Many economic implications of power utility such as economic scheduling of generating capacity, scheduling of fuel purchases, security analysis, planning of power development, maintenance scheduling and dispatching of generation units are mainly operated based on accurate load forecasting. This paper presents the survey of electricity demand forecasting for power system management. The introductory section provides the importance of electricity demand forecasting. Subsequent sections cover recent trends of demand forecasting techniques development in energy power systems. Several models have been surveyed to identify the demand pattern and predict the future demand. These techniques would be useful to determine the powerful energy management strategy so as to meet the required load demand at minimum operating cost.

**Keywords**— Electricity demand forecasting, Energy model, Power system management, Load forecasting, Renewable energy, Sustainable development.

## 1. INTRODUCTION

Global electricity demand is projected to increase by 85% in 2040 as living standards rise, economies expand and the need for electrification of society continues [1]. Electricity demand forecasting plays an important role in load allocation and planning for future generation facilities and transmission augmentation. Load demand in a given season is subject to a range of uncertainties, including underlying population growth, climate change and economic conditions. In addition, historical data are of importance in demand forecasting.

Load forecasting can be divided into three categories: short-term forecasts, medium-term forecasts and long term forecasts. The natures of these forecasts are different as well.

Short-term forecasts are usually from one hour to one week. They play an important role in the day-to-day operations of a utility such as unit commitment, economic dispatch and load management. A short term electricity demand forecast is commonly referred to as an hourly load forecast.

Medium-term forecasts are usually from a few weeks to a few months and even up to a few years. They are necessary in planning fuel procurement, scheduling unit maintenance and energy trading and revenue assessment for the utilities. A medium-term forecast is commonly

referred to as the monthly load forecast.

Long-term electricity demand forecasting is a crucial part in the electric power system planning, tariff regulation and energy trading [2]. A long-term forecast is required to be valid from 5 to 25 years. This type of forecast is used to deciding on the system generation and transmission expansion plans. A long term forecast is generally known as an annual peak load.

This paper aims to address the survey of electricity demand forecasting for power system management. Several models have been surveyed to identify the demand pattern and predict the future demand. These techniques would be useful to determine the powerful energy management strategy so as to meet the required load demand at minimum operating cost. The factors influencing the ranges of demand forecasting, are discussed.

## 2. FACTOR AFFECTING ELECTRICITY DEMAND FORECASTING

The aims of load forecasting are to predict the load pattern. There are several factors that should be taken into consideration for load forecasting, which can be classified as time factor, economic factor, weather condition and customer factor [3-5].

### 2.1 Time factor

Time is the most important factor in load forecasting since its impact on consumer load is highest. Xue and Geng (2012) classified the load influences factor into three types, namely short-term, medium-term and long-term influencing factors [6].

For short-term load forecasting, the factors affecting often appear in certain forecasting period, and nearly have not the characteristic of time duration, for example the sudden changes of weather. For medium-term load forecasting, the influence factors often last some

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forecasting periods, and have certain characteristic of time duration, for example seasonal climate change. For long-term load forecasting, the influence factors sustain for a long time, usually many forecasting periods, and have notably the characteristic of time duration, for example the change of gross national product and the population.

Fahad and Arbab (2014) note that the observing load curve of different grid stations is periodic [7]. The periodic of load curve occurs not only in the daily load, but also in the weekly, monthly, seasonal and yearly load curves. By taking the periodic property, load forecast can be predicted effectively.

Moreover, load demand reflects the consumer's daily lifestyle. The daily load pattern based on daily activities of people, i.e. working hours, leisure hours and sleeping hours. There are specific patterns of load variations with time. The weekend and holiday load in industries and offices is lesser than week days due to less activity and works. Power load also varies as cyclic time dependency on hour of day basis, day of week basis and time of year basis.

## **2.2 Economic factor**

The load pattern is also function of economic factors such as industrial development, population growth, Gross Domestic Product (GDP) and cost of electricity etc. Long-term load forecasting significantly affected by economic factors, however it is also important for medium-term and short-term forecasting [8]. According to the different horizons of forecasting, the different economic factors could contribute to e.g. time-of-use for short-term forecasting, purchasing power for medium-term forecasting, and GDP for long-term forecasting etc.

- Industry development: Industrial development in a particular area will increase the power consumption.
- Population growth: High growth rate of population will increase the power consumption. Therefore there is a constructive correlation between population growth and power consumption.
- GDP: It indicates the size of economic activity and economic conditions. Economic growth and its impact on living standard is the primary impetus to stimulate the power demand.
- Cost of electricity: This is also affects the load. The amount of useless electricity consumption increases when the electricity becomes cheaper. Moreover, petroleum oil price play a significant role as variation in petroleum price will vary the cost of electricity generation and thus cost of electricity, which finally influence on load curve.
- Time of use: Time of use pricing can change the duration and the time of occurrence of peak load. Time of use pricing can also make domestic as well as industrial consumers to adjust their load and thus helps in peak shaving.

## **2.3 Weather condition**

Various weather variables could be considered for load forecasting are temperature, humidity, wind speed and cloud cover.

- Temperature: Most of activities currently involve consumption of electricity. Load and temperature are linked to some level. There is a positive correlating contribution between temperature and electric load curve especially in summer season [8]. This is because during summer change in temperature will affect the people's feeling of comfort level requirement. During summer as the temperature rises, the increased usage of cooling appliances also increases the load consumption, whereas the temperature fall in the winter season, the more usage of heating appliances would increase the load consumption.
- Humidity: Humidity affects short term load forecasting since it increases the feeling of severity of temperature during summer and rainy season. Thus, load consumption increases during summer humid day.
- Wind speed: Wind speeds effect the electricity load consumption. During the windy day human body feels the temperature far below and heating appliance is required thus increasing the load consumption.
- Cloud cover: The effects of cloud cover on the usage of electricity depend on the timings of usage. During day time the cloud cover may disturb the sunlight, results decrease in the temperature and hence lower the usage of electricity consumption.

Among these weather factors, temperature and humidity are the most commonly used load predictors to minimize the operational cost.

## **2.4 Customer factor**

The load shape may be different for different customer classes. Most electric utilities serve customers of different types as residential consumer, commercial consumer and industrial consumer. The customer factors of electricity consumption are primarily the number, type and size of the electrical equipment of the customer. While the electrical equipment and installations vary from customer to customer. There are recognized types of customers which have similar properties. The residential load curve is somewhat different from commercial and industrial customers.

## **3. SURVEY OF ELECTRICITY DEMAND FORECASTING**

A survey of work done in electricity demand forecasting for power system management during the last decade is presented in Table 1. The table presents details of the research characteristics, methodology used, objective and results obtained. Summary of survey in electricity demand forecasting can be classified according to the research characteristics as follows: giving the concept of

demand forecast as well as pros and cons, a technique for load forecasting and its application for the problem of load demand forecasting.

#### 4. MATHEMATICAL MODEL

Electricity demand forecasting techniques can be classified as follows:

- Multiple regression
- Exponential smoothing
- Iterative reweighted least-squares
- Adaptive load forecasting
- Stochastic time series
- Neural networks

The mathematical models of these techniques are discussed [9-11].

##### 4.1 Multiple regression

Multiple regression of weighted least-squares estimation. Based on this analysis, the statistical relationship between total load and weather conditions as well as the day type influences can be calculated by using equation (1). The regression coefficients are computed by a weighted least square estimation using the defined amount of historical data [10].

$$Y_t = v_t a_t + e_t \tag{1}$$

where

- $Y_t$  : Measured system total load,
- $v_t$  : Vector of adapted variables such as time, temperature, light intensity, wind speed, humidity and day type (workday or weekend),
- $a_t$  : Transposed vector of regression coefficients,
- $e_t$  : Model error at time  $t$ , and
- $t$  : Sampling time.

##### 4.2 Exponential smoothing

Exponential smoothing is the load forecasting method based on the previous data to predict the future load. Equation (2) shows the load  $y(t)$  which is modeled using a fitting function [9].

$$y(t) = b(t)^T f(t) + e(t) \tag{2}$$

where

- $y(t)$  : The load at time  $t$ ,
- $f(t)$  : Fitting function vector of the process,
- $b(t)$  : Coefficient vector,
- $e(t)$  : White noise, and
- T : Transpose operator.

##### 4.3 Iterative reweighted least-squares

This method uses the autocorrelation function and the partial autocorrelation function of the resulting differenced past load data in identifying a sub-optimal model of the load dynamics. Equation (3) presents the parameter estimation problem involving the linear measurement [9].

$$Y = Xb + e \tag{3}$$

where

- $Y$  : The vector of observations,
- $X$  : The matrix of known coefficients based on previous load data,
- $b$  : The unknown parameters, and
- $e$  : The vector of random errors.

##### 4.4 Adaptive load forecasting

The model parameters of adaptive load forecasting method are automatically corrected to keep track of the changing load conditions. An adaptive load forecasting algorithm has the ability to predict load shapes in addition to daily peak loads. System operators are able to utilize the predicted load shapes even when the individual hourly errors are rather large. The total historical data set is analyzed to determine the state vector, not only the measured load but also the weather data. This mode of operation allows switching between multiple and adapted regression analysis. The model used is the same as the one utilized in the multiple regression as described by equation (1).

##### 4.5 Stochastic time series

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

###### (a) Autoregressive (AR) model

If the load is assumed to be a linear combination of previous loads, then the AR model can be used to model the load profile which given in equation (4).

$$\hat{L}_k = -\sum_{i=1}^m \alpha_{ik} L_{k-i} + w_k \tag{4}$$

where

- $\hat{L}_k$  : The predicted load at time  $k$ ,
- $\alpha_{ik}$  : The unknown coefficients, and
- $w_k$  : The random load disturbance.

**Table.1. Summary of the survey in electricity demand forecasting for power system management**

Research characteristics	Methodology used	Objective/Results obtained	Author name/year
* Present a concept as well as pros and cons of electricity demand forecasting in the area of electric power systems	* Discuss the techniques used in electricity demand forecasting for efficient energy management and better power system planning	* Survey and summarize the load demand forecasting techniques and its application: <ul style="list-style-type: none"> <li>• Statistical and time series based forecasting technique</li> <li>• Artificial intelligence based forecasting technique</li> </ul>	Raza, M.Q. and Khosravi, A., 2015 [12] Suganthi, L. and Samuel, A.A. 2012 [13]
* Load forecasting techniques for power system management	* Load forecasting techniques can be classified as follows: <ul style="list-style-type: none"> <li>• Multiple regression,</li> <li>• Exponential smoothing,</li> <li>• Iterative reweighted least-squares,</li> <li>• Adaptive load forecasting,</li> <li>• Stochastic time series,</li> <li>• Neural networks</li> </ul>	* Although the times series approach is still widely used, newer techniques offer a lot of promise for developing the methodology used for load forecasting * Over the last few years, the most active research area has been neural network based load forecasting	Almehaie, E. and Soltan, H., 2011 [9] Alfares, H.K. and Nazeeruddin, M., 2002 [10] Soliman, S.A. and Ahmad, M.A., 2010 [11]
* Propose a technique for short-term load forecast	* Apply seasonal adjustment method and regression model to the short-term load forecast	* Using the combined models provides high improvement in accuracy of short-term load forecast	Wu, J., Wang, J., Lu, H., Dong, Y. and Lu, X., 2013 [14] Dudek, G., 2015 [15-17]
* Medium-term load demand forecasting	* Consider the level suitability of wavelet and neural network in load prediction * Present a medium-term forecasting technique with semi-parametric model and fluctuation feature decomposition technology * Investigate the use of seasonal climate forecasts for electricity demand	* Aim to minimize the percentage error in load demand forecasting * Significant progress in understanding the relationship between temperature and electricity demand	Bunnoon, P., Chalermyanont, K. and Limsakul, C., 2012 [18] Shao, Z., Gao, F., Yang, S.L., Yu, B.G. and Zhang, Q., 2015 [19-21] De Felice, M., Alessandri, A. and Catalano, F., 2015 [22]
* Forecasting long-term electricity demand	* The proposed methodology for long-term demand forecasting has three models as follows: <ul style="list-style-type: none"> <li>• Demographic,</li> <li>• Macroeconomic,</li> <li>• Microeconomic</li> </ul>	* Integrate macroeconomic scenario, demographic projection, income distribution and the appliances ownership in the long-term forecast for the electricity consumption. * The estimated demand would be useful in designing such as decentralized electricity distribution systems	Pessanha, J.F.M. and Leon, N., 2015 [2] Yamagata, Y., Murakami, D. and Seya, H., 2015 [23] Andersen, F.M., Larsen, H.V. and Boomsma, T.K., 2013 [24]
* Apply artificial intelligent technique for forecasting the energy demand	* Develop the energy demand scenario based on gross domestic product (GDP), population, import and export data	* The proposed model is proved to be a successful energy demand forecasting tool	Phuangpornpitak, N., Tia, S., Prommee, W. and Phuangpornpitak, W., 2010 [25] Ünler, A., 2008 [26] El-Telbany, M. and El-Karmi, F., 2008 [27]

**(b) Autoregressive moving-average (ARMA) model**

In the ARMA model the current value of  $y(t)$  is expressed linearly in terms of its values at previous periods and in terms of previous values of white noise. Equation (5) presents The ARMA model [10].

$$y(t) = f_1 y(t-1) + \dots + f_p y(t-p) + a(t) - q_1 a(t-1) + \dots + q_q a(t-q) \quad (5)$$

where

- $y(t)$  : The current value of the time series,
- $a(t)$  : The white noise,
- $p$  : The order of AR component, and
- $q$  : The order of MA component.

**(c) Autoregressive integrated moving-average (ARIMA) model.**

The ARIMA model includes the meteorological data to predict the load. Equation (6) presents The ARIMA model [10].

$$f(B)\nabla^d y(t) = \theta(B)a(t) \quad (6)$$

Equation (7) shows the expression of operator  $\nabla$ .

$$\nabla y(t) = (1 - \beta)y(t) \quad (7)$$

where

- $\nabla$  : The operator,
- $B$  : The parameter of autoregressive,
- $p$  : The order of AR component,
- $q$  : The order of MA component, and
- $d$  : The differenced time.

**4.6 Neural networks**

Neural networks (NN) have been widely applied since its ability to learn the process. The advantage of this intelligent technique have been applied in electrical demand forecasting with a success level [12].

The network is specified as equation (8) and (9).

$$o_{pj} = f_j(\text{net}_{pj}) \quad (8)$$

$$\text{net}_{pj} = \sum_k w_{jk} o_{pk} \quad (9)$$

where

- $f_j$  : The difference and nondecreasing function,

$w_{jk}$  : The weight to be adjusted.

**5. CONCLUSION**

Accurate load forecasting is very important for electric utilities. In this paper we review some statistical and artificial intelligence techniques that are used for electric load forecasting. We also discussed factors that affect the accuracy of the forecasts such as weather data, time factors, customer classes, as well as economic factors. Load forecasting methods use advanced mathematical modeling. Additional progress in load forecasting and its use in industrial applications can be achieved by providing short-term load forecasts in the form of probability distributions rather than the forecasted numbers; for example the so-called ensemble approach can be used. The progress in load forecasting will be achieved in two directions: (i) basic research in statistics and artificial intelligence and (ii) better understanding of the load dynamics and its statistical properties to implement appropriate models. A review of survey in load demand forecasting techniques for power system management in recent years indicates the promising potential of such research characteristics in the future.

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