Electricity Load Forecasting – Science and Practices

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Abstract: Electricity demand forecasting plays a central role in the process of power system planning and operation. This topic has been, and is still attracting vast research activities that are performed by researchers in the academia and power companies. This is attributed to the fact that better forecasting of power implies reaching exact plans with no over- or –under planning. It should be emphasized that the number of methods used in demand forecasting is tremendous, and the selection of the most suitable forecasting algorithm is not an easy process. Many factors and parameters must be considered in the process of load forecasting including the time frame of the forecast, the application and purpose of the forecast, weather factors, cultural and social factors, in addition to system-specific related factors, all of which will affect the forecasting process. This paper discusses the frame work of this topic, where various numbers of methodologies and models developed are demonstrated. A description of forecasting models helps in identifying the characteristics, features, and strengths of each model.

Keywords: *Load forecasting techniques, planning, load model, time frame, forecasting accuracy.*

1. Introduction

Forecasting has evolved over the years into an exact science and many models and tools are presently available commercially. The main purpose of forecasting is to meet future requirements, reduce unexpected cost and provide a potential input to decision making [1]. Energy sector received great attention from countries and individuals as it leads to comfortable life. With the advent of increased civilization and economic development energy has become a life-sustaining commodity. Due to the fact that conventional energy resources on earth are limited people started to look for new energy resources; especially environmentally benign and renewable ones. Meanwhile, researchers focused on developing better methodologies for predicting the future demand for energy to meet future supply, which will help countries to plan their development activities correctly, thus, avoiding under-or over-planning of future supply.

Electricity constitutes a major share of the total energy requirements of many societies. Moreover, electricity networks lend themselves to be utilized as sources of live or on-line information about electricity consumption. On the other hand, operating a power system has the mission of matching demand for electric energy with available supply, while meeting the expected peak demand of the power system. As such, electrical demand forecasting provides input to the planning of future resources, where the focus is on total annual consumption of electric energy which is a key factor in predicting system requirements.

Forecasting is broadly classified in the literature, in the context of time frames, as: a) long-term forecasting (1-20 years), b) medium-term (1-12 months), and c) short-term (1-4 weeks ahead), and d) very short term (1-7days ahead) [2, 3].

Long-term load forecasting is intended for applications in capacity expansion, and long-term capital investment return studies. Medium-term forecasting is utilized in preparing maintenance scheduling, and to plan for outages and major works in the

power system. Short-term forecasting is used in operation planning, unit commitment, and economic dispatching. The very-short term forecasting is devoted for load exchange and contracting with neighboring networks, and to maintain a secure power system. Because electrical energy cannot be stored appropriately, accurate load forecasting is very important for the correct investments.
It can be confidently stated that the "science" of electricity load forecasting has reached an advanced level. This field attracts the attention of the industry and academia, and is performed at higher levels of power companies and academic research. However, further collaboration between the academic and industrial fields is a must which shall imminently lead to better implementation of this science in real world and shall result in more prosperity to the societies in terms of better utilization of the scarce resources of our planet [4].
It must be emphasized that prior to the selection of a forecasting model certain factors must be studied and assessed in order to guarantee selecting a suitable model. These factors include the following:

a. State of the economy
b. Clear vision of planning
c. Type of economy
d. Status of the electric power system
e. Status of electricity market
f. Understanding of the interrelations with other energy forms
g. Integrating other demand manipulation programs in the forecasting

The maim objective of this paper is to give a quick, however, exclusive overview of the science and practices of load forecasting. The paper is organized as follows: section 2 discusses the time frames involved in load forecasting, the various methods of load forecasting are presented in section 3. The performance of the available methods are illustrated in section 4, and section 5 presents the conclusions of the paper.

2. Electrical Forecasting Time frames

In power utilities, the general practice gives the responsibility for conducting the Short-term load forecasting (STLF), and Medium-term load forecasting (MTLF) to system operation departments (e.g. Generation, Transmission, and Distribution operations). On the other hand, Long-term load forecasting (LTLF) is assigned for the planning department. However, other departments use the estimated forecasts for conducting various studies related to financial and investment planning within the utility. These categories are briefly discussed in the following.

2.1. Short-term and Very Short-term Forecasting

STLF focuses on predicting electrical hourly loads and energy demand for periods up to one week ahead taking into account that load demand is highly volatile on a day to day basis. STLF is a very crucial element in the process of power system operational planning that affects the performance of many functions. Such functions cover load flow studies, security and contingency analysis, economic dispatch , unit commitment, hydro-thermal coordination , preventive maintenance plan for the generators, transaction evaluation, reliability evaluation of the power system and trading of power in interconnected systems.

Several factors affect STLF including: 1) trend effects, 2) seasonal effects, 3) special effects, 4) weather effects, 5) random effects such as: human activities, load management, pricing strategy, and electricity tariff structures. Moreover, sudden changes in system demand or system outages represent another type of uncertainty associated with load forecasting process. All of the above adds to the complexity of getting an accurate STLF for electrical loads, and press to focus on the different factors involved in this process and in the continuous development of new methodologies to minimize the errors encountered.

2.2. Medium-term Forecasting

MTLF is suitable for power companies for maintenance planning. The forecast period is from several weeks to 12 months ahead. This type of forecast depends mainly on growth factors, i.e. factors that influence demand such as main events, addition of new loads, demand patterns of large facilities, and maintenance requirements of large consumers. This type of forecast is not concerned with hourly loads like short term forecast, but rather predicts the peak load of days or for the weeks ahead. With this information it can be decided to whether take certain facilities/plants for maintenance or not during a given period of time. The methods used for this type of forecast are similar to the short term forecast except that there is less need for accuracy [5].

2.3. Long-term Forecasting

As the name implies LTLF is used to plan the expansion of the power system, i.e. what type of generation or transmission plant(s) are needed, when, where, and what size. Usually generation system planning is done separately from transmission system planning [5]. The study period of this forecast is from 1 year to 15-20 years ahead. The output of this forecast is usually the peak load and annual energy requirement of the system. That is to say that the peak load and energy requirement for the coming years of the study period are determined by the forecasting method. Usually econometric or regression analysis methods are widely used in this type of forecast. However, end-use and expert system methods are also used [6].

3. Forecasting Methods

The forecasting methods are generally classified into: 1) statistical-based methods, and 2) artificial intelligence-based methods. There is no clear preference of one group of methods over the other. It all depends on the application on hand. However, due to advents in computer technology in the hardware and software areas, the artificial intelligence-based methods have recently overtaken the statistical-based methods and are being adopted by more users at the present time.

A short discussion of the different scopes and techniques and models representing these methods are presented in the following.

3.1 Statistical-based methods

Statistical-based methods are widely used in many branches of forecasting. For electricity demand forecasting, these methods run well under normal conditions, however, their performance worsens during abrupt changes in environmental or sociological variables that affect load patterns. Moreover, those techniques require a large number of complex relationships, accompanied by long computational times, and may result in numerical instabilities. These methods include:

Regression methods

In regression methods, the load data is assumed to fit a pre-defined function or model tat has unknown parameters. The regression method is used to find out the optimum set of these unknown parameters, that makes the known data and the forecasted data result in the minimum sum of squared errors. Many models exist including:

A- Linear

Here, the model is described as:

$$\hat{L}_k = a_1 t_k + a_0 \qquad (1)$$

Where,

- $\hat{L}_k$: is the k[th] estimated load based on the selected model
- t_k : is the time of the load (can be hour, day,… etc)
- a_0, a_1 : are the model unknowns to be estimated
- k: is the index of data =1,2, …, N

The unknowns are found using:

$$\begin{pmatrix} a_0 \\ a_1 \end{pmatrix} = \begin{pmatrix} N & \sum_{k=1}^{N} t_k \\ \sum_{k=1}^{N} t_k & \sum_{k=1}^{N} t_k^2 \end{pmatrix}^{-1} \begin{pmatrix} \sum_{k=1}^{N} L_k \\ \sum_{k=1}^{N} L_k t_k \end{pmatrix} \qquad (2)$$

B- Polynomial

The model is described as:

$$\hat{L}_k = \sum_{m=0}^{p} a_m t_k^m \qquad (3)$$

The unknown parameters are estimated using:

$$\begin{pmatrix} a_0 \\ a_1 \\ \vdots \\ a_p \end{pmatrix} = \begin{pmatrix} N & \sum_{k=1}^{N} t_k \cdots & \sum_{k=1}^{N} t_k^p \\ \sum_{k=1}^{N} t_k & \sum_{k=1}^{N} t_k^2 \cdots & \sum_{k=1}^{N} t_k^{p+1} \\ \vdots & \vdots & \vdots \\ \sum_{k=1}^{N} t_k^p & \sum_{k=1}^{N} t_k^{p+1} & \sum_{k=1}^{N} t_k^{2p} \end{pmatrix}^{-1} \begin{pmatrix} \sum_{k=1}^{N} L_k \\ \sum_{k=1}^{N} L_k t_k \\ \vdots \\ \sum_{k=1}^{N} L_k t_k^p \end{pmatrix} \qquad (4)$$

C- Selected-model function

The model function can be chosen to be any reasonable function e.g. exponential, logarithmic, …etc, and the optimization is done based on minimizing the sum of squared errors between original and predicted loads.

D- Multi-variable

The model is assumed to be given y:

$$\hat{L}_k = b_0 + b_1 X_1 + b_2 X_2 + \cdots + b_p X_p \qquad (5)$$

Where,

$\hat{L}_k$: is the k[th] estimated load based on the selected model

X_i : are the independent variables, i=1, 2, … , p

and the *b*'s are termed the "regression coefficients" to be estimated.

3.2. Time series methods

Time series methods are based on the assumption that the data have an internal structure, such as autocorrelation, trend, or seasonal variation. Time series forecasting methods detect and explore such a structure [5, 7]. The objective is to assess the best model and hence extrapolate future forecasts. The structural components of the time series model can be integrated to lead to the forecast. Two inter-relationships can be formed as shown in the following equations:

$$\hat{L}_k = L_{kT} + L_{kc} + L_{kS} + L_{kI} \qquad (8)$$

or,

$$\hat{L}_k = L_{kT} \times L_{kc} \times L_{kS} \times L_{kI} \qquad (9)$$

Where, the components notations are L : load, k=time index, T=trend, C=cyclic , S=seasonal, I =irregular , and the hat indicates the forecast.

Different models are implemented, all of which seek to filter out, separate, the assumed components. Some of these methods are discussed below.

A- **ARMA (**autoregressive moving average) which is used assuming a stationary processes. Other variations include **ARIMA** (the acronym of autoregressive integrated moving average, also known as Box-Jenkins model), **ARMAX,** and **ARIMAX** (autoregressive integrated moving average with exogenous variables), and **FARMAX** (fuzzy autoregressive moving average with exogenous input variables) are used assuming a non-stationary processes. The mathematical formulation of these models is well formulated and is available in the literature [4, 8].

B- Exponential Smoothing is used when the variable to be predicted is not stable. This smoothing will filter out such variations to get the underlying trend. A simple smoothing formula is given as:

$$\hat{L}_k = \sum_{i=1}^{P} a(1-a)^{i-1} L_{k-i} \qquad (10)$$

Where,

$\hat{L}_k$: is the k[th] smoothed load.

a: is a smoothing factor with 0<a<1.

C- The Principal component Analysis (PCA)

PCA aims to separate the basic structure or pattern of the load from the disturbance or random component (filtering process more or less). In other words PCA is used for reducing the dimension of multivariate data sets, where variables are highly correlated, to a smaller set of variables. This in turn, reduces the number of variables affecting the load and leads to a better forecast. The main drawback of the PCA is that it requires a long computational time, and the difficulty of selecting the optimum order of the principal components [9, 10].

D- **Similar-day approach**

Historical loads are searched to find the loads with similar characteristics within one, two, or three years to perform the forecast day. Similar characteristics include weather, day of the week, and the date. The load of a similar day is considered as a forecast. Linear combination or regression procedure that can include several similar days can be implemented. Moreover, the trend coefficients can be used for similar days in the previous years [11].

Other methods that lie in this category include the Econometric or causal method, and the Simulation or End-Use Methods

3.3. Artificial Intelligence (AI) - based methods

The majority of the AI-based techniques focus on STLF which is necessary for operation planning. The rationale behind it being that the randomness introduced to loads in STLF is small and the predictions will be more accurate. In contrast, LTLF has a large degree of uncertainty due to the larger time frame that makes the AI-based methodologies less efficient and result in large forecasting errors when compared to traditional methods. Different AI-based techniques are discussed in the following.

A- Neural networks.

The artificial neural networks (ANN or simply NN) methods have been widely used as an electric load forecasting technique in Short-term load forecasting (STLF) since 1990. ANN methods are usually applied to perform non-linear curve fitting. The literature has a variety of ANN publications in the power system Load forecasting [12-15]. Figure (1) shows a typical block diagram of ANN scheme.

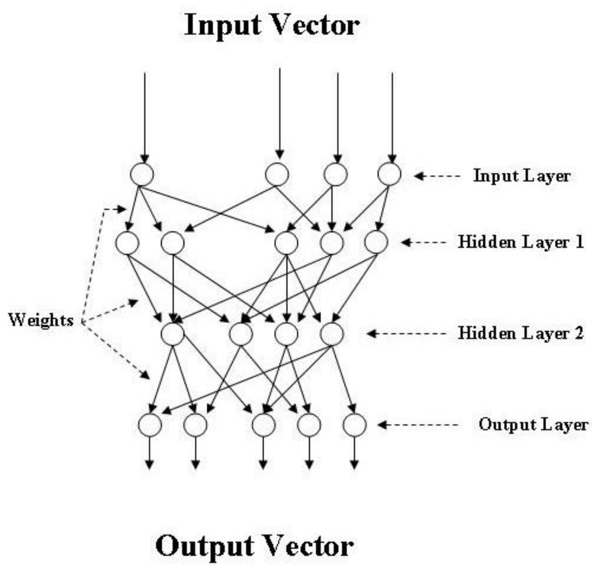

Figure (1) – ANN with Back Propagation architecture

It should be noted that for load forecasting problem, the input vector (which feeds the input layer) may include different parameters affecting the load such as temperature, humidity, and previous hourly, daily, monthly, and yearly loads, …etc. The output vector for the case of load forecasting can be the estimated loads at the required time level.

The input variables can be classified into the following classes: historical loads, historical and future temperatures, hour of day index, day of week index, wind-speed, sky-cover, rainfall, and wet or dry day.

For normal load prediction, ANN outperforms conventional methods. However, ANN treats abnormal data (e.g. sudden change of load) as bad-readings, which are typically neglected. Some research has been performed to improve the ANN performance in such cases by incorporating a transient detector that is utilized to increase the accuracy of load prediction in transient state. The combination of multi-resolution techniques (the wavelet transform) in conjunction with ANN resulted in decreasing prediction error in STLF at the expense of extra computational time [16].

B- **Expert systems**

The use of expert systems-based techniques began in the 1960's, and they work best when a human expert is available to work with software developers for a considerable amount of time in imparting the expert's knowledge to the expert system software. Also, an expert's knowledge must be appropriate for codification into software rules (i.e. the expert must be able to explain his/her decision process to programmers). An expert system may codify up to hundreds or thousands of production rules [17, 18]. In the forecasting field, historical operator's knowledge and the hourly observations, weather parameters, and any important factors related to forecasting must be incorporated and shared between the parties contributing to the building up of the expert system. In general terms the developed algorithms perform better compared to the conventional statistical methods. The more incorporation of the actual experience of system operators at different sites will serve in improving the performance of the forecast.

C- Fuzzy logic systems

In the sense of load forecasting, fuzzy logic does not need precise models relating inputs and outputs and disturbance. The proper selection of rules and related logic of this method becomes robust when used for forecasting [17].

Once the fuzzy inputs are logically processed, an inverse process called the "de-fuzzification" can be used to produce the outputs. Fuzzy logic systems can be applied for SLTF as well as for LTLF. For example: an ANFIS (Adaptive Network based on Fuzzy Inference System) was used for LTLF and it showed more accurate demand forecasting using minimum econometric or end-user information [14]. Another example presents the DMS (Distribution Management Systems) model which was used successfully to predict loads at both substation and feeder levels [19,20].

D- Support vector machines (SVM)

SVMs and its least squares version [21, 22] represent a more recent and powerful learning technique that is used for solving data classification and regression problems. Both methods represent a learning SVM that perform nonlinear mapping of the data into a high dimension (referred to as mapping the kernel functions to features).

SVCMs use simple linear functions to create linear decision boundaries in the new space. The main problem is that of choosing a suitable kernel for the SVMs [21-23]. The method was applied to STLF and produces competitive results compared to that of the statistical methods.

E- The Particle Swarm Optimization (PSO) algorithm

The PSO is a new adaptive algorithm based on a social-psychological metaphor that may be used to find optimal (or near optimal) solutions to numerical and qualitative problems. Most particle swarms are based on two socio-metric principles. The principle is based on the fact that particles fly through the solution space, and are influenced by both the best particle (called global best) in the particle population and the best solution that a current particle has discovered so far. The best position that has been visited by the current particle is donated by (local best). The (global best) individual conceptually connects all members of the population to one another. The particle swarm optimization makes use of a velocity vector to update the current position of each particle in the swarm. The position of each particle is updated based on the social behavior that a population of individuals adapts to its environment by returning to promising regions that were previously discovered [24].

4. Performance

5. Conclusions

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