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Forecasting Methods in Electric Power Sector

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ABSTRACT

Electric power plays a vibrant role in economic growth and development of a region. There is a strong co-relation between the human development index and per capita electricity consumption. Providing adequate energy of desired quality in various forms in a sustainable manner and at a competitive price is one of the biggest challenges. To meet the fast-growing electric power demand, on a sustained basis, meticulous power system planning is required. This planning needs electrical load forecasting as it provides the primary inputs and enables financial analysis. Accurate electric load forecasts are helpful in formulating load management strategies in view of different emerging economic scenarios, which can be dovetailed with the development plan of the region. The objective of this article is to understand various long term electrical load forecasting techniques, to assess its applicability; and usefulness for long term electrical load forecasting for an isolated remote region, under different growth scenarios considering demand side management, price and income effect.

KEYWORDS

Artificial Neural Network, Electrical Energy Consumption, Electrical Energy Requirements, Long Term Electrical Load Forecasting, Parametric

INTRODUCTION

Electric power plays a fundamental role in the process of economic growth and development. Several studies conducted in developing countries indicate significant causal relationship between electricity consumption and economic growth. These studies indicate that economic growth prospect is adversely affected due to power shortage (Ebohon, 1996; Hwang & Gum, 1992; Glasure & Lee, 1997).

To meet the fast-growing power demand, on a sustainable basis, meticulous power system planning is required. This planning needs electrical load forecasting, as it provides the primary inputs and enables financial analysis. Accurate forecasts are helpful in formulating load management strategies in view of different emerging economic scenarios, which can be dovetailed with the developmental plan of the region.

For last few decades there has been a lot of research on electrical load forecasting (Fu et al., 2003; Quilumba et al., 2015). There are mainly three types of electric load fore casting short term, medium term and long term. Short term load forecasting is the prediction of electrical load demand for a period varying from the next few minutes up to a week, medium term is for a period of next few

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months to a year and long term is for a period of 2 to 15 years. A lot of other factors affect forecasting, this paper presents a list of these factors and principles. There are different methods available for different type of forecasting. Here all the methods and techniques are discussed categorically with respect to short term, mid-term and long-term forecasting.

Most of this literature relates to short term electrical load forecasting, only a few of them are related to medium term and long term electrical load forecasting (Bunn et al., 1985). Most of the long term electrical load forecasting is focused towards a large region, country or state which are well connected (Bunn, 2000). Here, an effort is made to study different types of electrical load forecasting techniques and their applicability to different geographical region. The emphasis of the study is on long term electrical load forecasting with different growth scenarios, incorporating the income, price effect on electrical load demand for an isolated remote region like Andaman & Nicober Islands, India.

The paper is organized as follows: Next section describes what is electrical load forecasting, principles and the key factors affecting load forecasting. Then it focuses on the different methods used for short term, mid-term and long term electrical load forecasting. Recently used software are discussed in a separate section. The last section presents the conclusions and future works.

ELECTRICAL LOAD FORECASTING

Definition

Load forecasting is the predicting of electrical power required to meet the short term, medium term or long-term demand. It is a central and integral process for planning periodical operations and facility expansion in the electricity sector. Demand pattern is almost very complex due to the uncertainty of energy markets. So, to find an appropriate forecasting model for any electricity network is not an easy task.

The main function of electric power system is to provide a reliable and continuous source of electricity wherever whenever required. To provide this service each of the three main components of an electric power system – generation, transmission and distribution must perform efficiently to meet the required demand.

An electric power system is a dynamic system which is a balance of supply and demand:

- The supply of electricity consists of physical devices that must be designed, constructed & operated to generate, transmit and distribute desired quantity of quality electrical power reliably;
- The demand of electricity by the consumer, which changes as a function of time on an instantaneous basis (seconds to minutes), on a short-term basis (hours to days) and on a long term basis (months to years).

Objective

Therefore, one of the main objectives of the electric power system is to keep a continuous balance between the supply and the demand of electricity (Ebohon, 1996; Hwang & Gum, 1992; Glasure & Lee, 1997). This is possible only by an accurate assessment of requirement of electrical energy and peak load demand i.e. electrical load forecasting. The assessment of requirement of electrical energy (potential demand of electrical energy) in MU (Million Unit) is carried out by making certain assumptions of GDP, population, number of households, index of industrial production, energy consumption and electricity price, while assessment of peak load demand in MW/GW (Mega/Giga Watt) is calculated using potential electrical energy demand data multiplied with coincidence factor (occurrence of peak load of different sectors) and reciprocal of load factor (Zachariadis, 2010). The primary purpose of electric load forecasting is to address the key question of when, where, why and how much electricity would be required by a region. Electric load forecasting is a vital component for electric utility industry in the deregulated economy, since electricity has become a commodity sold and bought at the market price. The electric load forecasting has many applications including energy purchase & generation, load switching, contract evaluation and infrastructure development.

The load forecasting of electricity has become one of the major research fields in electrical engineering. The supply industry requires forecast with a lead time that ranges from short term (a few minutes, hours or day ahead) to long term (up to 20 years ahead). The short-term forecast, in particular, has become more important, since the rise of competitive energy markets. Many countries including India, of late, have privatized and de-regulated their power systems and electricity is sold and bought at market prices (Weron et al., 2004). Since, the load forecasts play a crucial role in the composition of these prices; they have become vital for the supply industry.

Constraints

Electrical load forecasting is, however, a difficult task. Firstly, because electric load is complex and exhibits several levels of seasonality: the load at a given hour is dependent not only on the load at the previous hour, but also on the load at the same hour on the previous day, and on the load at the same hour on the day in the previous week and so on. Secondly, because there are many important exogenous variables like temperature, humidity, increase in population, income, GDP/SDP and tariff that must be considered, while carrying out the electrical load forecasting. It is relatively easy to get forecasts with about a 10% mean absolute percent error (MAPE); however, the costs of the error are so high, the research that could help reducing it to a few percent points is amply justified. Often quoted estimate in (Fu et al., 2003) suggests that an increase of 1% in the forecasting error would imply (in 1984) a £10 million (719 million INR) increase in operating costs per year, for a country like Australia. Forecasting loads and prices in the wholesale markets are mutually intertwined activities and the fundamental approach to this is to look for the intersections of the demand and supply functions at each time period in the market (Bunn, 2000).

Principles of Forecasting

An accurate model for electric load forecasting is essential for the operation and planning of a utility company as it helps them to make important decisions on purchase and generation of electric power. In (*Expansion Planning for Electrical Generating Systems*: *A Guidebook*. 1984), it is suggested that the points discussed below should be kept in mind while carrying out electrical load forecasting. By following them, the forecasting process can be more accurate and provides more useful information to the policy makers.

Identify Causality

The cause and effect relationship is to be identified for carrying out a proper forecasting. The basic reason for change in electrical load can be identified. Economic activities create commercial and industrial demand. Number of households connected to the grid and their access to electrical appliances, shape domestic demand. Beyond this level of generality, the search for causal relationship can take different forms in terms of its effect on the load, depending on the characteristics of utility system in question (Bruhns et al., 2005).

Reproducible

If predictions are reproducible then independent researchers are able to obtain the same results as the original study using the same data and the same methods. Reproducibility is a first step towards replication and so, if it cannot be achieved, the generalization of findings is likely to be in doubt and perfect reproduction of results may not be possible. An inability to reproduce results implies that the methods have been insufficiently specified (Boylan et al., 2015; Tawfiq et al., 1999).

Functional

The forecast is to be carried out, such that it can be used by the policy maker in decision making process, without much change. If the decision concerns the scheduling of maintenance of existing plants, the forecast time frame can be one year, divided into months (perhaps in weekly increments). If the decision relates to construction of central generating station, the forecast should focus on annual increments of demand considering the lead time for constructing the plant (probably for a decade or more). However, in both short-term and long-term planning, the pattern of daily variations in load is to be considered (Reddy et al., 1991).

Test Sensitivity

A sensitivity analysis is a technique used to determine how different values of an independent variable impact a particular dependent variable under a given set of assumptions. This technique is used within specific boundaries that depend on one or more input variables, such as the effect that changes in population have on electric load.

The forecasts are carried out by making assumptions of the future growth rate, population, tariff and scope for new business development. It is difficult to make accurate assumptions of the above variables. One of the significant ways to do this is to prepare alternative forecasts, often called *scenarios,* which contain different assumptions about variables shaping the forecast (Reddy et al., 1991). Scenario analysis provides a process to estimate the changes in forecast value, based on the occurrence of different situations, referred to as scenarios, following the principles of "what if".

Simplicity

Modelling means specifying clearly and unambiguously the relationship that governs the physical and social activity. The real-world activities are more complex than those that can be described in a model. The principle of simplicity dictates that there is a need to include only as much information in the model, as it is necessary for accurate prediction.

Types of Load Forecasting

The different types of load forecasting are classified according to the forecast period (Metaxiotis et al., 2003):

- Short term load forecasting;
- Medium term load forecasting;
- Long term electrical load forecasting.

In each of the types of load forecasting period of time, forecasted values and purpose of forecasting are noticeably different and are as illustrated in Table 1.

Factors Affecting Load Forecasting

For short term electrical load forecasting, several factors are considered, such as time factors, weather data and possible customers' class. The medium and long-term forecasts take into account the historical load and weather data, the number of customers in different categories, the appliances in the area and their characteristics including appliance age, the economic and demographic data and their forecasts, the appliance sales data and other factors like GDP, tariff and disposable income.

The time factors include time of the year, day of the week and hour of the day pertaining to the area for which forecast is to be carried out. There are important differences in load between weekdays and weekends. The load on different weekdays can also behave differently. For example, Mondays and Fridays being adjacent to weekends, may have different load pattern compared to Tuesday to

Table 1. Types of load forecasting

Forecast Problem	Short Term	Medium Term	Long Term
Time horizon	¼ - 24 h	1 day – few weeks	Few months – years
Forecasted value	Load curves	Load curves	Energy required
Accuracy	Exact load curves	Error << Capacity	Exact energy
Time step	¼ - 1 h	1 h	1 h
Operation	Economic dispatch	Unit commitment	Reserve planning
Planning	Unit commitment	Reserve planning	Capacity expansion

Thursday. Holidays are more difficult to forecast compared to working days, because of their relative infrequent occurrence.

Weather conditions influence the load. In fact, forecasted weather parameters are the most important factors in short term load forecasts. Various weather variables could be considered for load forecasting. Temperature and humidity are the most commonly used load predictors.

The variables listed against long term electrical load forecasting in Table 2 are taken to forecast the peak electrical load of Japan up to the year 2020 using Artificial Neural Network (ANN) (Kermanshahi et al., 2002).

Table 2. Factors involved in load forecasting

Sl. No	Types of Load Forecasting	Input Variables
1.	Short term load forecasting	• Historical load • Temperature • Humidity • Rainfall • Wind speed • Season • Weekday: Working day • Weekend: Non-working day • Special day
2.	Medium term load forecasting	• Historical load • Temperature • Gross Domestic Product • Current Price Index • Housing • Population • Humidity • Wind speed • Rainfall
3.	Long term load forecasting	• Gross National Product (GNP) • Gross Domestic Product (GDP) • Population • Number of households • Number of air conditioners • Amount of CO_2 pollution • Index of industrial production • Oil price • Energy consumption • Electricity Price

METHODS USED FOR ELECTRICAL LOAD FORECASTING

The methods used for load forecasting may be broadly classified into two categories viz. artificial intelligence based techniques and classical or statistical approaches (Weron et al., 2004). The former includes expert systems, fuzzy inference, fuzzy neural models and in particular artificial neural network (ANN). The statistical methods differ from the previous approach, in that they forecast the current value of a variable by using an explicit mathematical combination of the previous values of that variable and, possibly, previous values of exogenous factors (especially weather and social variables). Models that have been applied recently include autoregressive (AR) models, linear regression models, dynamic, threshold AR models, methods based on Kalman filtering, optimization techniques and curve fitting procedures (Weron et al., 2004). The statistical models are attractive because some physical interpretation may be attached to its components, allowing engineers and system operators to understand their behaviour.

Short Term Electrical Load Forecasting Methods

A large variety of statistical and artificial computational intelligence techniques are developed for short term electrical load forecasting and are discussed in (Feinberg et al., 2005, Hernandez et al., 2014):

- **Similar Day Approach:** This approach is based on searching historical data for days within one, two or three years with similar characteristics to the forecast day. Similar characteristics include weather and day of the week. The load of a similar day is considered as a forecast. Instead of a single similar day lead, the forecast can be a linear combination or regression procedure that can include several similar days. The trend coefficient can be used for similar days in the previous years (Chen et al., 2008);
- **Regression Methods:** Regression is one of the most widely used statistical techniques. For electric load forecasting regression methods are usually used to model the relationship of load consumption and other factors such as weather, day type and customer class. Several relational models are presented in research articles for next day peak load forecasting. These models incorporate deterministic influence such as holidays, stochastic influence such as average load and exogenous influence such as weather (Papalexopoulus et al., 1990);
- **Time Series:** 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. Time series have been used for decades in the fields such as economics, digital signal processing as well as electric load forecasting (Chaouch, 2014). In particular, ARMA (autoregressive moving average), ARMAX (autoregressive moving average with exogenous variables) and ARIMAX (autoregressive integrated moving average with exogenous variables) are the most often used classical time series methods. ARMA models are usually used for stationery processes, while ARIMA is an extension of ARMA to non-stationary processes. ARMA and ARIMA use the time and load as the only input parameters. Since load generally depends on the weather and time of the day, ARIMAX is the most natural tool for load forecasting among the classical time series models (Deng et al., 2010);
- **Neural Networks:** The use of artificial neural network (ANN or simply NN) has been a widely studied electric load forecasting technique since 1990 (Bansal, 2006; Quan et al. 2014; Ekici, 2016). NNs are essentially non-linear circuits that have the demonstrated capability to do non-linear curve fitting.

The outputs of an ANN are either linear or non-linear mathematical function of its inputs. The inputs may be the outputs of other network elements as well as actual network inputs. In practice network elements are arranged in a relatively small number of connected layers of elements between network inputs and outputs. Feedback paths are sometimes used (Hippert et al., 2001). A typical artificial neuron with all its components is shown in Figure 1.

The most popular ANN architecture for electric load forecasting is back propagation. Back propagation NNs use continuously valued functions and supervised learning. In other words, under supervised learning, the actual numerical weights assigned to element inputs are determined by matching historical data (such as time and weather) to desired outputs (such as historical electric loads) in a pre-operational "training session". ANN with unsupervised learning does not require pre-operational training (Rajasekaran et al., 2003).

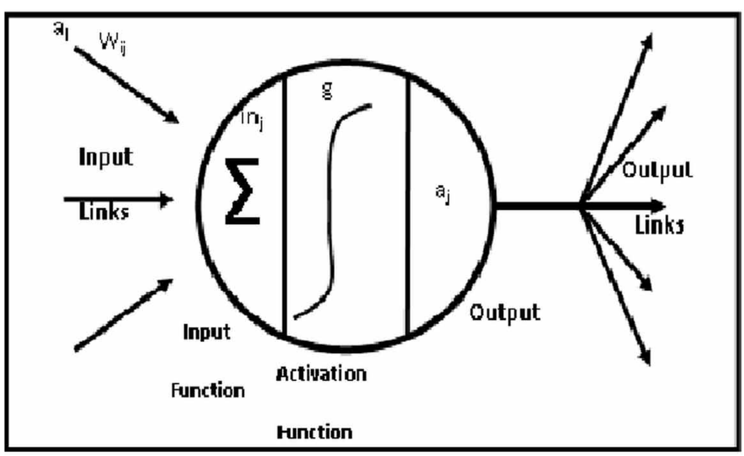
In (Folly et al., 2007) ANN based short term electrical load forecasting model is developed for Cape Town Control Centre. The three-layered ANN architecture with feed forward algorithm is used to develop the model.

- **Expert Systems:** Rule based forecasting makes use of rules, which are often heuristic in nature, to do accurate forecasting. Expert systems incorporate rules and procedures used by human experts in the field of interest into software that is then able to automatically make forecast without human assistance (Feinberg et al., 2005).

Expert systems 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 setting up software rules (i.e. the expert must be able to explain the decision process to programmers). A knowledge based expert system for the short term load forecasting of the Taiwan power system was developed using operator's knowledge and hourly observations of system load over the past five years. Weather parameters were also considered, the developed algorithm performed better compared to the conventional Box – Jenkins method (Feinberg et al., 2005; Kandil, 2002).

- **Fuzzy Logic:** Fuzzy logic is a generalization of the usual Boolean logic used for digital circuit design. An input under Boolean logic takes on a true value of "0" or "1". Under fuzzy logic an input is associated with a certain qualitative range. For instance, a transformer load may be "low", "medium" or "high". Fuzzy logic allows one to (logically) deduce outputs from fuzzy inputs. In this sense fuzzy logic is one of a number of techniques for mapping inputs to outputs (i.e. curve fitting) (Rajsekaran et al., 2003; Hong, &Wang, 2014).

Figure 1. Artificial neuron and its components. Source: Hipper et al., 2001.



Among the advantages of fuzzy logic are the absence of a need for a mathematical model mapping inputs to outputs and the absence of a need for precise (or even noise free) inputs. In (Pandian, 2006) short term electrical load forecasting is carried out using fuzzy logic algorithm with time and temperature as input data. The input variable 'time' is divided into eight triangular membership functions. The membership functions are Mid Night, Dawn, Morning, Fore Noon, After Noon, Evening, Dusk and Night. Another input variable 'temperature' is divided into four triangular membership functions. They are Below Normal, Normal, Above Normal and High. The 'forecast load' as output is divided into eight triangular membership functions. They are Very Low, Low, Sub Normal, Moderate Normal, Normal, Above Normal, High and Very High.

- **Support Vector Machines:** Support Vector Machines (SVMs) are more recent powerful techniques for solving classification and regression problems. This approach originated from Vapnik's (Vapnik, 1995) statistical learning theory. Unlike NNs, which try to define complex functions of the input feature space, support vector machines perform a non-linear mapping (by using so called kernel functions) of the data into a high or multi-dimensional (feature) space. Then support vector machines use simple linear functions to create linear decision boundaries in the new space (Kavousi-Fard et al., 2014). The problem of choosing architecture for a NN is replaced here by the problem of choosing a suitable kernel for the SVM (Christiani et al., 2000).

A hybrid technique using support vector machine (SVM) is developed to forecast the next 24-hour load (Jain et al., 2008). Four modules consisting of the Basic SVM, Peak & Valley SVM, Averager & Forecaster and Adaptive Combiner form the integrated method for load forecasting. Out of these four modules, one is the Basic SVM module to predict the next day '24' hour load and the second module is Peak & Valley SVM to predict the peak & valley loads of the next day. The third module comprises of two blocks Averager & Forecaster. The Averager computes the hourly averaged load of the day to be forecasted. The Forecaster calculates the next day '24' hour load by using the predicted peak & valley loads obtained from the Peak & Valley SVM and the hourly averaged load obtained from the Averager. Using Adaptive Combiner the final forecast for the next '24' hour load is done.

Medium Term and Long Term Electrical Load Forecasting Methods

The literature on medium term and long term electrical load forecasting reveals that the methods used for medium term and long term electrical load forecast are similar (Elias et al., 2009; Hong et al., 2014). There are fewer studies for medium term and long term electrical load forecasting. A comprehensive investigation of methods for long term electrical load forecasting is carried out in (Ghods et al., 2008; Ardakani et al., 2014).

The long term electrical load forecasting is broadly classified in two categories, viz. parametric methods and artificial intelligence methods as shown in Table 3.

Parametric Methods

Three types of parametric methods are used for load forecasting as follows: trend analysis, end - use modelling and econometric modelling.

Table 3. Methods for long term electrical load forecasting

(A) Parametric Methods	(B) Artificial Intelligence Methods
• Trend Analysis • End - use models • Econometric models	• Artificial Neural Networks • Wavelet Networks • Genetic Algorithms • Fuzzy logic model

Trend Analysis

Trend analysis extends past rates of electricity demand into the future, using techniques that range from hand drawn straight lines to complex computer produced curves. These extensions constitute the forecast. Trend analysis focuses on past changes or movements in electricity demand and uses them to predict future changes in electricity demand. The advantage of trend analysis is that, it is simple, quick and inexpensive to perform, while its disadvantage is that it produces only one result, future electricity demand (Da et al., 2000).

End - Use Models

The end - use approach directly estimates energy consumptions by using extensive information on end users, such as applications, the customer use, their age, size of houses, details of the appliance used and population. Statistical information about customers along with dynamics of change is the basis for the forecast (Murthy et al., 2001).

End-use models focus on the various uses of electricity in the residential, commercial and industrial sector. These models are based on the principle, that electricity demand is derived from customer's demand for lighting, cooling, heating, refrigeration and other appliances. Thus, end - use models explain energy demand as a function of the number of appliances in the market. Ideally, this approach is very accurate. However, it is sensitive to the amount and quality of end - use data. The disadvantage of end-use analysis is that most end-use models assume a constant relationship between electricity and end- use (electricity per appliance) (Ghods et al., 2008).

A pioneering research study on alternative power sector scenario of Karnataka on the basis of Development-Focused End-use-oriented (DEFENDUS) paradigm is conducted in (Reddy et al., 1991). The study includes an extensive application of the end-use method for generation of Long-Term Electrical Load Forecasts. The study adopts a year-by-year procedure for energy demand at the terminal-year starting from the end-use wise consumption in the base-year and introducing new energy consumption norms for retrofitting new connections and new growth rates.

A detailed study on Long-Term Electrical Load Forecasting for Bihar is carried out as a part of Power sector restructuring in Bihar (IRG, 1996). The study is based on a disaggregated approach with a view to group together, users whose behaviour in future would be as homogenous as possible, i.e., categorization of consumers at end-use level on the basis of social, economic, demographic and spatial levels. In this study electrical load forecasting is carried out by end-use method taking into account the conditions of change, structural changes influencing energy demand and energy policies.

Econometric Models

The econometric approach combines economic theory and statistical techniques for forecasting electricity demand. The approach estimates the relationship between energy consumption (dependent variables) and factors influencing consumption. The relationships are estimated by the least square method or time series methods. One of the options in this framework is to aggregate the econometric approach, when consumption in different sectors (residential, commercial, industrial, agricultural, public lighting and water supply) is calculated as a function of weather, economic and other demographic variables such as number of consumers, population and then estimates are assembled using recent historical data (Zachariadis, 2010).

The advantage of econometric models is that they provide detailed information on future levels of electricity demand, while the disadvantage of econometric forecasting is that it does not take into account the technology determined coefficient like consumption norms.

A large number of studies are reviewed on application of econometric models for electrical load forecasting. Salient features of a few of them are presented in what follows.

A study is carried out in USA with 27 years data (1972-1998) (Kamersshen et al., 2004) to estimate residential, industrial and aggregate electricity demand by partial adjustment approach and by simultaneous equation approach. The study reveals that simultaneous equation models are more appropriate compared to the flow-adjustment models. An econometric analysis for long-term peak electricity load forecasting is carried out in Taiwan using co-integration (Chen, 1997). In the analysis double-log type load function is adopted to generate long-term forecasts.

A classical econometric model is investigated in (Bunn et al., 1985) for investigating the accuracy of forecasting based on historical annual energy and tariff data provided by Power Company of Australia. The evaluations are extended to include an advanced method which uses dynamical functional link net (FLN) and wavelet networks.

The consumption of previous year (one-year lag) and the ratio of GDP of current year to the previous year (one year lag), the ratio of power tariff of current year to the previous year (one year lag) and ratio of population of current year to the previous year (one year lag) are taken as inputs to forecast the energy consumption for the current year.

The time-of-use structure to estimate electricity demand for Switzerland is used in (Filippinni, 1995). The model termed as Almost Ideal Demand System (AIDS) operates in two stages. At the first stage, consumers allocate expenditures among various commodities including electricity and in the second stage, electricity demand is determined by price during peak and off-peak periods and total expenditure on electricity as obtained in the first stage.

Artificial Intelligence Methods

Artificial Neural Networks

Artificial neural networks (ANNs) have succeeded in solving several power system problems, such as planning, control, analysis, protection, design, load forecasting, security analysis and fault diagnosis (Hippert et al., 2001). The last three applications are the most popular. The ANNs ability in mapping complex non-linear relationships is responsible for the growing application to load forecasting. Most of the ANNs are applied to short term load forecasting. Only a few studies are carried out for medium term and long-term load forecasting. There are mainly two types of ANNs which can be useful for long term load forecasting viz. Recurrent Neural Network (RNN) for forecasting the peak load and Feed Forward Back Propagation (FFBP) for forecasting the annual peak load:

1. **Recurrent Neural Network:** Recurrent neural networks (RNN) contain feedback connections, which enable them to encode temporal context internally. This feedback can be external or internal. RNN has the ability to learn patterns from the past records and also to generalize and project the future load patterns for an unseen data (Kermanshahi et al., 2002). There are different types of RNNs, such as Jordan RNN, Elman RNN, Hopfield network and Boltzmann Machine network;
2. **Feed – Forward Back Propagation:** Feed – forward back propagation (FFBP) is one of the most widely used neural network paradigms, which is applied successfully in application studies. FFBP can be applied to any problem that requires pattern mapping (Kermanshahi et al., 2002). Given an input pattern, the network produces an associated output pattern. Its learning and update procedure is intuitively appealing, as it is based on a relatively simple concept.

In (Kermanshahi et al., 2002) long term electrical load forecasting (up to the year 2020) for Japan is carried out using Recurrent Neural Network (Jordan type – RNN) shown in Figure 2 and Back Propagation (BP) network shown in Figure 3. The RNN is applied for forecasting the peak loads of 1 – 3 years ahead i.e. 1996 – 99, while the BP is applied for forecasting the loads beyond 2000 up to the year 2020 in steps of 5 years. Ten factors are taken as input for the proposed ANN, the factors include GDP, GNP, population, number of households, number of air conditioners, amount of CO_2 pollution, index of industrial production, oil prices, electricity consumption and price. The results obtained show the ability of the model to forecast the future load with only a 3% error.

A study is carried out using different models of medium term electrical load forecasting for Thailand (Bunnoon et al., 2010) and it is observed that artificial intelligence technology has ability

Figure 2. Recurrent Neural Network (Jordan Type RNN). Source: Kermanshahi & Iwamiya, 2002; Kermanshahi et al., 2002.

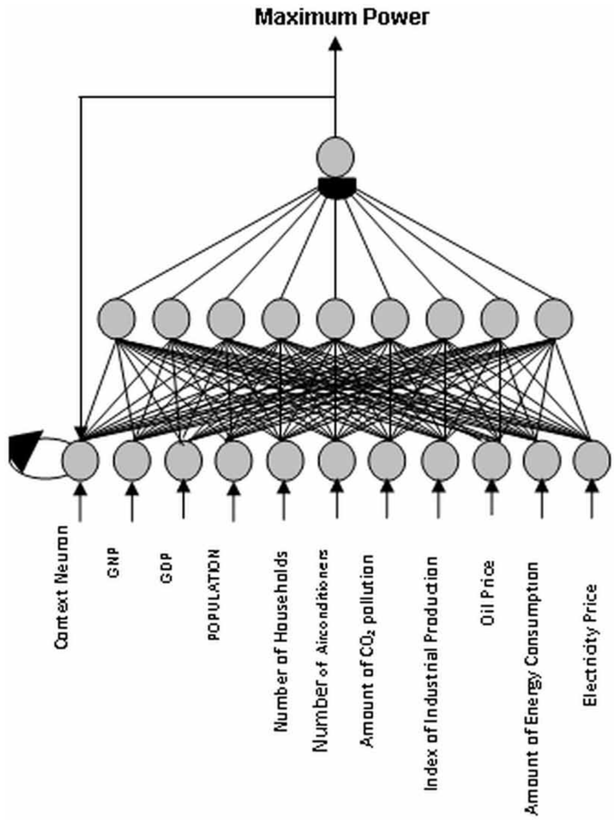
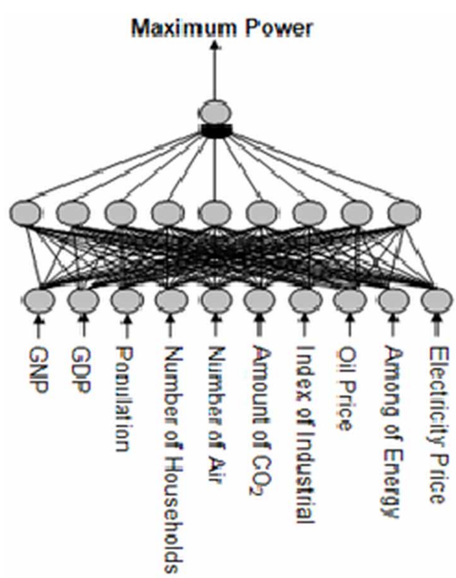


Figure 3. Back Propagation Neural Network (BPNN). Source: Kermanshahi & Iwamiya, 2002; Kermanshahi et al., 2002.



to work with non-linear data and can effectively be performed in complicated forecasting model for continuous data signal.

Wavelet Networks

Khoa et al. (Khoaet al., 2004) investigate the application of wavelet packet in electric load forecasting. Wavelet theory is introduced to electric load forecasting recently and received wide attention. Compared to traditional load forecasting methods, wavelet theory provides powerful and flexible tool to decompose load data into different frequency components, making it possible to analyze the characteristics of each component and improve forecasting accuracy. Wavelet packet analysis is an extension of wavelet analysis and gives better frequency resolution. The most advantageous factor of wavelet network is that the inputs are not spanned in large space unlike in a NN, the accuracy of wavelet network model is better than multi layer NN. It gives better results when applied to long term forecast.

Genetic Algorithms

Genetic Algorithms (GAs) have recently received much attention as robust stochastic search algorithms for various problems (Rajasekaran et al. 2003). This class of methods is based on the mechanism of natural selection and natural genetics, which combines the notion of survival of the fittest, random and yet structured, search and parallel evaluation of the points in the search space.

GAs are numerical optimization techniques. They combine a Darwinian survival of the fittest strategy with a random, yet structured information exchange among a population of artificial "chromosomes". This technique has gained popularity in recent years as a robust optimization tool for a variety of problems in engineering, science, economics and finance (Ghods et al., 2008).

In (Karabulut et al., 2008) a long-term energy consumption forecasting model is developed using genetic programming. A moderate city in Turkey is taken as a case study. The power consumption data is processed with both conventional regression analysis and genetic programming techniques. It is observed that the goodness of fit produced by genetic method by evaluating using sum of squares of error (SSE) method is better compared to other two methods of regression.

Fuzzy Logic Model

Fuzzy control systems are rule based systems, in which a set of so called fuzzy rules represent a control decision mechanism to adjust the effects of certain stimuli. The aim of fuzzy control systems is normally to replace a skilled human operator with a fuzzy rule based system (Rajasekaran et al. 2003). The fuzzy logic model provides an algorithm, which can convert the linguistic strategy based on expert knowledge into an automatic strategy. The fuzzy logic method is applied for scoring. The application of fuzzy rules improves the model accuracy by avoiding arbitrariness for the purpose of the study. One of the applications of the fuzzy rules is to combine them with NN to train an ANN and have a better load forecasting. The benefit of the proposed hybrid structure is to utilize the advantages of both i.e. the generalization capability of ANN and the ability of fuzzy inference for handling and formalizing the experience and knowledge of the forecasters.

In (Farhat, 2004) NN technique and fuzzy inference method are used for long term industrial load forecasting and planning. The model is based on hybrid neural technique which combines ANN and fuzzy logic for long term industrial load forecasting in electrical power system. It is observed that large number of influencing factors are examined and tested for prediction of maximum electric demand and consumption for future '24' months. The fuzzy rules and training patterns for ANN models are collected from historical load data. Every ANN is trained using an error Back Propagation (BP) algorithm and Radial Basis Function Network (RBFN) with an adaptive learning rate and momentum.

Approach Followed for Long Term Demand Assessment by Govt. of India

Indian economy is a planned economy; the entire economic activity is broadly divided into 66 sectors with specific estimation of growth rate for each sector. As regards electricity, Central Electricity

Authority (CEA) is the apex body at national level, which coordinates with the electricity utilities of the state and union territories of India and provides them required inputs for long term planning of energy generation to meet the projected demand (CEA, 2000).

CEA conducts periodic electric power surveys (EPS) throughout the country to forecast demand on short, medium and long-term basis for electric utilities. The first survey report was published in the year 1963 and so far, 17 power surveys have been conducted by CEA. In EPS, demand forecast is made usually in two time frames, one for a period of 5 - 7 years and the other for 10 – 15 years (EPS, 2004). It makes use of "Partial End Use" method for forecasting.

LOAD FORECASTING SOFTWARE TOOLS AND SOLUTIONS

There are many tools available in the market that may be used for energy forecasting purposes. They all have different learning curves, levels of technical support, depth of forecasting procedures, and price tags. There is not yet one single tool that dominates all metrics. When considering which tools to use, utilities have to evaluate many factors, such as direct (i.e., license and service fees) and indirect costs (salaries and training costs for the users) of the software package, potential value-add, and implementation time. Two tools are widely used by utility analysts, MS Excel (from Microsoft Office) and EViews (from HIS Inc.). Spreadsheets are probably the most widely used forecasting tool, for its ease of use and low cost. EViews is a forecasting, econometric and statistical software package. EViews features a graphical object-oriented user-interface, making it an easy to use statistical package. This section introduces several more commercial load forecasting tools and solutions that have been widely used.

SAS

SAS® Energy Forecasting is built on the SAS family of software products which have been used by electric utilities since 1976. The solution is tailored for electric utility energy and load forecasting, automatically stepping through as many as nineteen models to select the best forecast model. For inexperienced forecasters, the process can be highly automated with few decisions required, while experienced users can expand the models with additional variables or import models into the solution. The SAS Energy Forecasting process is transparent, with model results at all stages of the process available for review and to archive for regulatory documentation. The solution is tailored for electric utility energy and load forecasting, automatically stepping through an intelligent model selecting methodology which is equivalent to enumerating thousands of model candidates to pick the best. Basic models are multiple regressions where additional variables and combinations are sequentially tested for model improvement. Models are tested each iteration to prevent over-fitting. Second stage models are developed using UCM, ARIMAX, Exponential Smoothing, and Neural Nets; testing for model improvement with automatic weather range scenarios and automatic economic growth scenarios.

GMDH Shell

This software puts the most recent mathematical algorithms into this task and provides quick and reliable electricity load forecasting basing on provided historical data. The program creates a set of models getting more and more complicated at each level. Such models are then applied to historical data and an error is calculated. Once the further complication of models stops producing decent increase in prediction quality, the process ends.

Itron

MetrixND and MetrixLT are Windows applications designed specifically for utility forecasting processes. MetrixND is a statistical package that supports data transformation, statistical model estimation, model evaluation, and post processing. Statistical methods supported include, Exponential smoothing, Time series (ARIMA) modelling, Regression models with or without time series residuals, Neural Network models with or without time series residuals and Regression with ARCH (Autoregressive Conditional Heteroskedasticity) /GARCH (Generalized Autoregressive Conditional Heteroskedasticity) volatility models. MetrixLT is a specialized system that performs construction of billing cycle weighted weather variables, calculation of normal and rank and average weather values, calendar rotation of daily weather scenarios, aggregation of hourly loads and loss factor adjustments, calibration of hourly load forecasts to monthly energy and peaks and Calibration of bottom-up hourly forecasts to system forecasts.

LoadSEER

LoadSEER (Spatial Electric Expansion & Risk) is a spatial load forecasting software tool designed specifically for transmission and distribution (T&D) planners who face increasingly complex grid decisions caused by emerging microgrid technologies, extreme weather events, and new economic activity. The objective of LoadSEER is to statistically represent the geographic, economic, distributed resources, and weather diversity across a utility's service territory, and use that information to forecast circuit and bank level peak loads, sub-sections of the circuit, acre-level changes, and impacts from various scenarios over the planning horizon. Planners are able to decompose system impacts using map layers superimposed on the spatial representation of the T&D infrastructure.

CASE STUDY

Long Term Electrical Load Forecasting for A & N Islands

A & N Islands (Andaman & Nicobar Islands) is a Union Territory of India. It is a group of 572 Islands situated in Bay of Bengal with 92% of area covered under forest. It is one of the remotest parts of India where settlement started in 1858. Prior to 1858, only tribes used to stay in these islands. Out of 572 islands, only 37 islands are inhabited. A & N Island has tremendous strategic importance from the country's security point of view. The long term electrical energy forecasting for A & N Islands is carried out by CEA, Govt. of India through Electric Power Survey (EPS). EPS projections are carried out by using partial End Use technique. All the expansion projects under power sector are based on the EPS reports.

The 18th EPS projections for energy requirement carried out by partial End Use technique for A & NIslands[67] is compiled and compared with the actual requirement and shown in Table 4 . It

Table 4. Comparison of estimated energy requirement (EPS) with actual

Year		End Use (Projected 18th EPS)	
	Actual Value (MU)	Forecast value (MU)	% Error
2009	225	234	4.0
2010	238	311	30.7
2011	249	320	28.5
2012	256	328	28.1
2013	259	337	30.1
2014	272	347	27.6
2015	283	356	25.8

Source: Electric Power Survey, Ministry of Power, Govt. of India shows the percentage variation of energy requirement projected in EPS with actual. From the Table 4 it is observed that the End Use method is not acceptable because of the high error values. One of the reasons for that is the forecasting is carried out by taking all the 37 inhabited islands as a single entity with an assumption of same growth rate for all inhabited islands.

So here ANN technique is applied to the remote Island to check if it can give acceptable result. A three-layered architecture (i.e. input, hidden and output neuron) is selected. Feed forward back propagation network with adaptive learning rate and momentum is taken for building up the model. The log sigmoid function is used for all hidden neurons as an activation function. The linear activation function is employed for the output node. The sequence followed for building the forecasting model using ANN is given in Figure 4.

Following two models are developed for forecasting the energy requirement:

Model 1: Ten independent variables (number of consumers, consumption, population, tariff, per capita income, plan & non plan expenditure, wind speed, rain fall, humidity and temperature) with 27 years data are taken. 23 years data are used for training and 04 years for testing, the architecture is given in Figure 5.

Model 2: Past four year data (Consumption) is taken (for 27years) to train, test and forecast the T+1 year consumption, the architecture is given in Figure 6.

Figure 4. Flowchart showing the procedure for forecasting model building using ANN technique

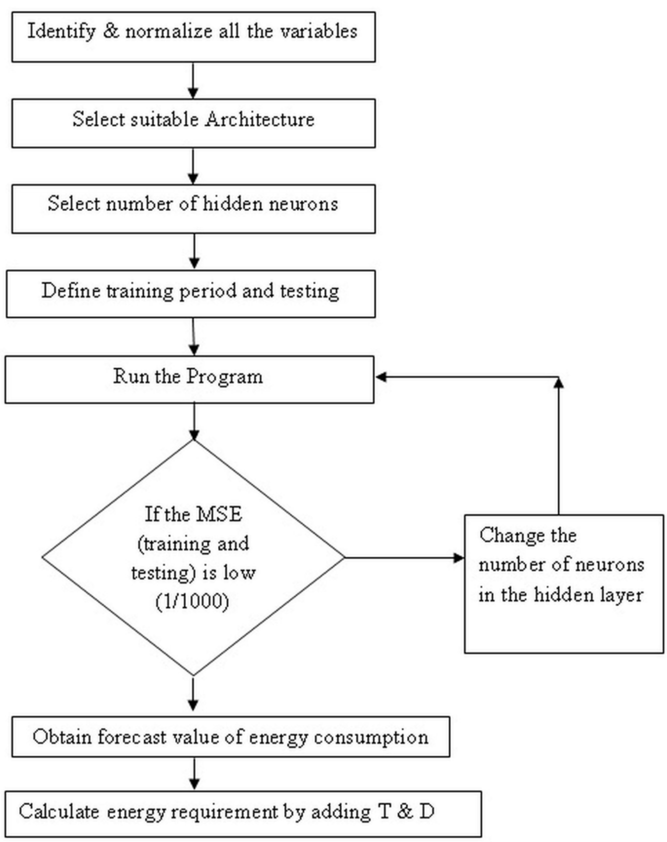


Figure 5. ANN architecture for Model 1

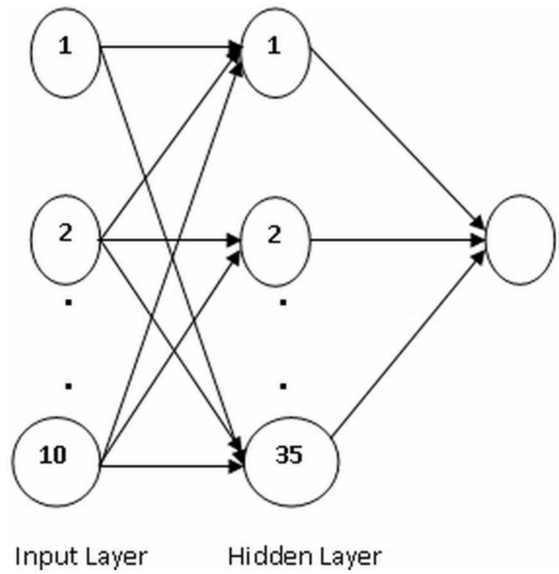
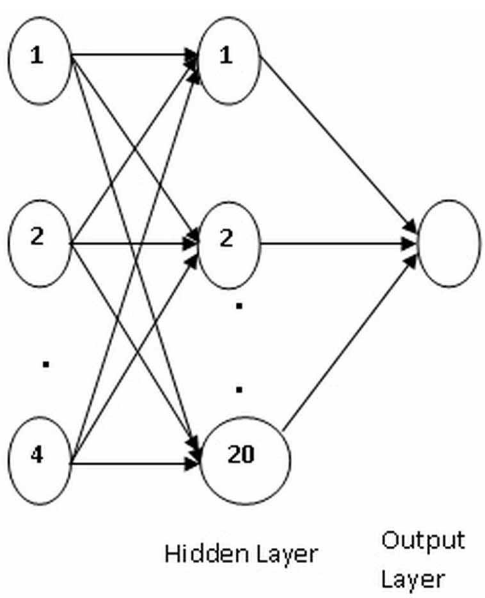


Figure 6. ANN architecture for Model 2



Forecasting of energy requirement using Model 1 and Model 2 of ANN is shown in Table 5.

It is seen from the Table 5 that model 2 is giving relatively better results. Both the models are obtained after running for few thousand iterations to arrive at the best mean square error, both for training and testing. The possible reason for better performance of Model 2 could be the nature of training. Model 1 learns to predict the consumption based on current values of independent variables,

Table 5. Forecasting of energy requirement for A & N Islands using Model 1 and Model 2 of ANN

Year	Actual energy requirement (in MU)	Forecasting of energy requirement (in MU)		%Error with respect to Actual	
		Model 1	Model 2	Model 1	Model 2
2009	225	213	227	-5.3	0.9
2010	238	225.4	228	-5.3	-4.2
2011	249	205	239	-17.7	-4.0
2012	256	217	238	-15.2	-7.0
2013	259	232	242	-10.4	-6.6
2014	272	244	268	-10.3	-1.5
2015	283	262	291	-7.4	2.8

whereas Model 2 learns from a time-dependent model as a function of past values of the consumption data. Results indicate that for the A & N Island data, a model that takes into account temporal variations such as Model 2 seems more appropriate. Since model 2 is giving relatively better results, the output of Model 2 is taken for comparison in subsequent sections. It is implemented in MATLAB version 7.9 (Linux). The graph showing the actual and forecast values using ANN Model 2 is shown in Figure 7.

From Figure 7, following observation is made on the applicability of ANN model to A & N Islands, the error is within acceptable limits during testing & training period. The slope of the graph is reducing during the forecast period; hence, the forecast value is lower than the actual (-ve error). The negative error in this case tends to continue as the forecasting period is increased.

The comparison in Table 6 clearly shows that, ANN is the better approach for long term forecasting of remote Islands. The error can be reduced if the neurons are trained based on the past data, efficiency improvement, the change in economic scenarios, and demand side management. Long term estimation of the independent variables like number of population, consumers, per capita income, tariff, plan and non-plan expenditure, rain fall, temperature and humidity is very difficult for isolated and remote regions which in turn will affect the load forecasting.

Figure 7. The graph of actual vs forecast consumption (results of ANN Model 2)

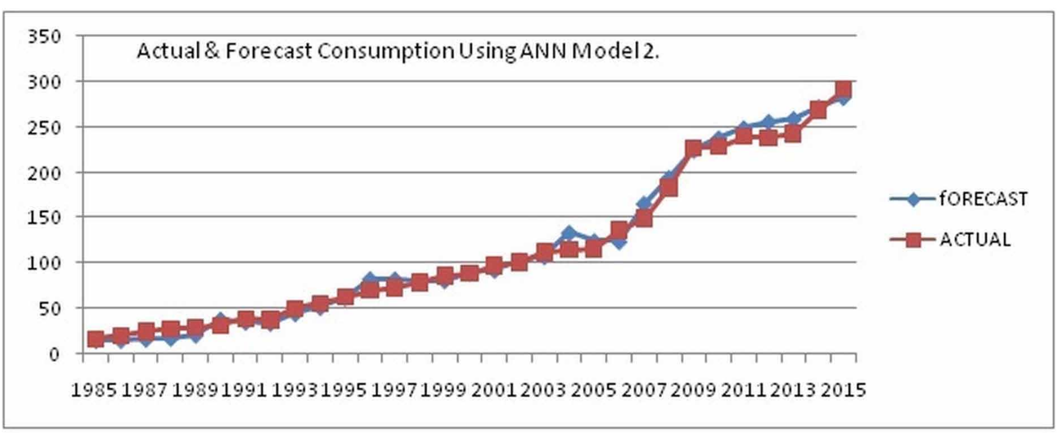


Table 6. Comparison of forecasting results between end use method and ANN method for A & N islands

Year		End Use (Projected 18th EPS)		ANN (Model 2)	
	Actual Value	Forecast value	% Error	Forecast value (MU)	% Error
2009	225	234	4.0	227	0.9
2010	238	311	30.7	228	-4.2
2011	249	320	28.5	239	-4.0
2012	256	328	28.1	238	-7.0
2013	259	337	30.1	242	-6.6
2014	272	347	27.6	268	-1.5
2015	283	356	25.8	291	2.8

CONCLUSION

This study is made to introduce the concept of electric load forecasting. Emphasis is laid on the methods used for carrying out short term, medium term and long term electrical load forecasting. From the literature it is found that a lot of studies have been done on short term forecasting than other two types. There is a scope for more studies on long term forecasting. It is also concluded that there is huge impact of socio economic factors on load forecasting. So, the same techniques cannot be used for developed and developing regions or countries. In countries like India, where the economic status of states varies a lot, same methods cannot be applied to all states. Some widely used software tools are also discussed to help the researchers to choose the best one for their applications.

Although, many studies have been carried out on electrical load forecasting for the entire county or state, apparently there are no studies on long term electrical load forecasting for an isolated remote region. More studies can be done to understand the commonly used long term electrical load forecasting techniques namely End Use, Econometric and ANN. Here the remote Andaman Nicobar Island is taken as the case study. ANN and End Use method is applied for long term forecasting. It is concluded that ANN is the better technique between these. But there is enough scope to improve the errors. For future study, combination of more than one technique must be applied for long term electrical load forecasting. This study will help the researchers to find the appropriate technology for long term forecasting based on cost of generation by considering the environmental aspects.

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