Comparison of Conventional and Modern Load Forecasting Techniques Based on Artificial Intelligence and Expert Systems

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Abstract

This paper picturesquely depicts the comparison of different methodologies adopted for predicting the load demand and highlights the changing trend and values under new circumstances using latest non analytical soft computing techniques employed in the field of electrical load forecasting. A very clear advocacy about the changing trends from conventional and obsolete to the modern techniques is explained in very simple way. Load forecast has been a central and an integral process in the planning and operation of electric utilities. Many techniques and approaches have been investigated to tackle this problem in the last two decades. These are often different in nature and apply different engineering considerations and economic analysis. Further a clear comparison is also presented between the past standard practices with the current methodology of electrical load demand forecasting. Besides all this, different important points are highlighted which need special attention while doing load forecasting when the environment is competitive and deregulated one.

1.0 INTRODUCTION

Electrical Load Forecasting is the estimation for future load by an industry or utility company. Load forecasting is vitally important for the electric industry in the deregulated economy. A large variety of mathematical methods have been developed for load forecasting. It has many applications including energy purchasing and generation, load switching, contract evaluation, and infrastructure development.

Now a days, development in every sector is a heading at a very rapid pace and in the same pattern, the demand for power is also growing. While speaking about electrical power, it is important to understand that it has three main sectors i.e. generation, transmission and distribution. Electrical power generated by any source is then transmitted through transmission lines at different voltage level and then distributed to different categories of consumers later on. It is not as simple as described in few words but every stage is a complete independent system in itself. Effective load forecasts can help to improve and properly plan these three fields of power systems [1].

Accurate models for electric power load forecasting are essential to the operation and planning of a utility company. Load forecasting helps an electric utility to make important decisions including decisions on purchasing and generating electric power, load switching, and infrastructure development. Load forecasts are extremely important for energy suppliers, ISOs, financial institutions, and other participants in electric energy generation, transmission, distribution, and markets.

Over the past decade, many western nations have begun major structural reforms of their electricity markets. These reforms are aimed at breaking up traditional regional monopolies and replacing them with several generation and distribution utilities that bid to sell or buy electricity through a wholesale market. While the rules of how various wholesale markets operate differ, in each case it is hoped that the end result is a decline in the price of electricity to end users and a price that better reflects the actual costs involved. To successfully operate in these new markets electricity utilities face two complex statistical problems: how to forecast both electricity load and the wholesale spot price of electricity. Failure to implement efficient solutions to these two forecasting problems can directly result in multimillion dollar losses through uninformed trades in the wholesale market.

Load forecasting is however a difficult task. First, because the load series 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 with the same denomination in the previous week. Secondly, there are many important exogenous variables that must be considered, especially weather-related variables. It is relatively easy to get forecast with about 10 % mean absolute error; however, the cost of error are so high that research could help to reduce it in a few percent points would be amply justified [2].

2.0 ELECTRICAL LOAD FORECASTING TYPES

The electricity supply industry requires to forecast electricity demand with lead times that range from the short term (a few minutes, hours, or days ahead) to the long term (up to 20 years ahead). Load forecasting has three techniques shown in Figure 2.1:

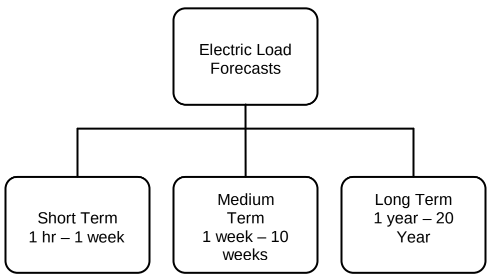

Figure 2.1 Basic Load Forecasting Techniques

Short term electric load forecast spans the period from one hour up to one week and it is mainly utilized for power system operation studies, losses reduction, voltage regulations, unit commitment and maximizing the utility revenues in the deregulated environment. Medium term electric load forecast spans the period from one week to several weeks, it is mainly utilized for predicting the necessary power to purchase or sell from other neighboring networks (inter-tie exchanged power) and also the fuel required by the utility in the near future. In short and medium electric load forecast, it is required to know how much power we will need and at what time of the day; the information regarding where this demand is required is not of a major concern [1].

3.0 ELECTRICAL LOAD FORECASTING METHODS

A model or method is a mathematical description of how the complex elements of a real-life situation or problem might interplay at some future date. In projecting electricity demand, a method uses data on electricity prices, income, population, the economy, and the growth rates for each and then varies the mix according to varying sets of assumptions. Different assumptions produce different outcomes. The relationships between electricity demand and the multitude of factors that influence or affect electricity demand are expressed in mathematical equations called functions. A model is a collection of functions. A function, in turn, is made up of variables for which those factors which change or can be changed. Independent variables are those factors which influence the demand for electricity, and the dependent variable is electricity demand itself. In other words, the demand for electricity depends on population, income, prices, etc. Finally, elasticities describe how much the dependent variable (electricity demand) changes in sense to small changes in the independent variables. Elasticities are what the modeler uses to measure consumer behavior.

Energy planners often speak of scenarios. Hypothetical pictures of the future based on different assumptions about economic or political events. They make different projections for each scenario. For example, a low growth scenario might assume high energy prices and slow population growth, while a high-growth scenario would assume the opposite. These scenarios allow planners to see how electricity demand might change if the different assumed economic and political events actually occur. All of the forecasting methods are capable of looking at different scenarios and do so by changing their basic assumptions [5].

4.0 SHORT TERM LOAD FORECASTING METHODS

Short-Term Load Forecasting is basically is a load predicting system with a leading time of one hour to seven days, which is necessary for adequate scheduling and operation of power systems. It has been an essential component of Energy Management Systems (EMS). For proper and profitable management in electrical utilities, short-term load forecasting has lot of importance.

High forecasting accuracy and speed are the two most important requirements of short-term load forecasting and it is important to analyze the load characteristics and identify the main factors affecting the load. In electricity markets, the traditional load affecting factors such as season, day type and weather, electricity price that have voluntary and may have a complicated relationship with system load..

Various forecasting techniques have been applied to short-term load forecasting to improve accuracy and efficiency. In general, these techniques can be classified as either traditional or modern. Traditional statistical load forecasting techniques, such as regression, time series, pattern recognition, Kalman filters, etc., have been used in practice for a long time, showing the forecasting accuracy that is system dependent. These traditional methods can be combined using weighted multi-model forecasting techniques, showing adequate results in practical systems. However, these methods cannot properly represent the complex nonlinear relationships that exist between the load and a series of factors that influence it, which are typically dependent on system changes (e.g., season or time of day).

The short term load forecasting methods are

- Similar Day Lookup Approach
- Regression Based Approach
- Time Series Analysis
- Artificial Neural Network
- Expert System
- Fuzzy logic
- Support Vector Machines

4.1 Similar Day Look Up Approach

Similar day approach is based on searching historical data of days of one, two or three years having the similar characteristics to the day of forecast. The characteristics include similar weather conditions, similar day of the week or date. The load of the similar day is considered as the forecast. Now, instead of taking a single similar day, forecasting is done through linear combinations or regression procedures by taking several similar days. The trend coefficients of the previous years are extracted from the similar days and forecast of the concern day is done on their basis.

4.2 Regression Based Approach

The term "regression" was used in the nineteenth century to describe a biological phenomenon, namely that the progeny of exceptional individuals tend on average to be less exceptional than their parents and more like their more distant ancestors.

Linear regression is a technique which examines the dependent variable to specified independent. The independent variables are firstly considered because changes occur in them unfortunately. In energy forecasting, the dependent variable is usually demand or price of the electricity because it depends on production which on the other hand depends on the independent variables. Independent variables are usually weather related, such as temperature, humidity or wind speed. Slope coefficients measure the sensitivity of the dependent variable that how they changes with the independent variable. Also, by measuring how significant each independent variable has historically been in its relation to the dependent variable. The future value of the dependent variable can be estimated. Essentially, regression analysis attempts to measure the degree of correlation between the dependent and independent variables, thereby establishing the latter’s predicted values[3].

Regression is the one of 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. There are several regression models for the next day peak forecasting. Their models contain deterministic influences such as holidays, random variables influences such as average loads, and exogenous influences such as weather.

4.3 Time Series Analysis

Time series forecasting is based on the idea that

reliable predictions can be achieved by modeling patterns in a time series plot, and then extrapolating those patterns to the future. Using historical data as input, time series analysis fits a model according to seasonality and trend.

Time series models can be accurate in some situations, but are especially complex and require large amounts of historical data. Additionally, careful efforts must made to ensure an accurate time line through out data collection filtering modeling and recall processes. Time series analysis widely used in the martial management for forecasting of customer demand for goods services. Time series approaches are not widely used for energy industry forecasting. Because they typically do not take into account other key factor, such as weather forecasts [3].

Time series have been used for longtime in such fields as economics, digital signal processing, as well as electric load forecasting. In particular, ARMA (autoregressive moving average), ARIMA (autoregressive integrated moving average), ARMAX (autoregressive moving average with exogenous variables), and ARIMAX (autoregressive integrated moving average with exogenous variables) are the most used classical time series methods.

ARMA models are usually used for stationary processes while ARIMA is an extension of ARMA for 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.

4.4 Artificial Neural Networks

Artificial Neural Networks are still at very early stage electronic models based on the neural structure of the brain. We know that the brain basically learns from the experience. The biological inspired methods are thought to be the major advancement in the computational industry. In a neural network, the basic processing element is the neuron. These neurons get input from some source, combine them, perform all necessary operations and put the final results on the output. Artificial neural networks are developed since mid-1980 and extensively applied. They have very successful applications in pattern recognition and many other problems.

Forecasting is based on the pattern observed from the past event and estimates the values for the future. ANN is well suited to forecasting for two reasons. First, it has been demonstrated that ANN are able to approximate numerically any continuous function to be desired accuracy. In this case the ANN is seen as multivariate, nonlinear and nonparametric methods. Secondly, ANNs are date-driven methods, in the sense that it is not necessary for the researcher to use tentative modals and then estimate their parameters. ANNs are able to automatically map the relationship between input and output, they learn this relationship and store this learning into their parameters [3].

The first way is by repeatedly forecasting one hourly load at a time. The second way is by using a system with 24 NNs in parallel, one for each hour of the day. Estimating a model that fits the data so well that it ends by including some of In Multi Layer Perceptron(MLP) structure of neural network, the most commonly training algorithm use is the back propagation algorithm. These algorithms are iterative; some criteria must be defined to stop the iterations. For this either training is stopped after a fixed number of iterations or after the error decreased below some specified tolerance. This criterion is not adequate, this insure that the model fits closely to the training data but does not guarantee of good performance they may lead to over-fitting of the model. "Over-fitting" means the error randomness in its structure, and then produces poor forecasts. MLPs model is over-trained or because it is too complex. One way to avoid overtraining is by using cross-validation. The sample set is split into a training set and a validation set. The neural network parameters are estimated on the training set, and the performance of the model is tested, every few iterations, on the validation set. When this performance starts to deteriorate (which means the neural network is over-fitting the training data), the iterations are stopped, and the last set of parameters to be computed is used to produce the forecasts. Nowadays, other than MLPs to avoid the problems of over-fitting and over-parameterization, the ANNs architectures used for prediction of electrical load are Functional Link Network (FLN) model [1].

To use the ANN in electric load forecast problems, distribution engineers should decide upon a number of basic variables, these variables include:

- Input variable to the ANN (load, temperature…etc)
- Number of classes (weekday, weekend, season…etc)
- What to forecast: hourly loads, next day peak load, next day total load …etc
- Neural network structure (Feedforward, number of hidden layer, number of neuron in the hidden layer…etc)
- Training method and stopping criterion
- Activation functions
- Size of the training data
- Size of the test data

4.5 Expert Systems

Expert systems are new techniques that have come out as a result of advances in the field of artificial intelligence (AI) in the last two decades. An expert system is a computer program, which has the ability to act as an expert. This means this computer program can reason, explain, and have its knowledge base expanded as new information becomes available to it.

The load forecast model is built using the knowledge about the load forecast domain from an expert in the field. The "Knowledge Engineer" extracts this knowledge from load forecast (domain) expert which is called the acquisition module component of the expert system. This knowledge is represented as facts and rules by using the first predicate logic to represent the facts and IF-THEN production rules. This representation is built in what is called the knowledge base component of the expert system. The search for solution or reasoning about the conclusion drawn by the expert system is performed by the "Inference Engine" component of the expert system. For any expert system it has to have the capability to trace its reasoning if asked by the user. This facility is built through an explanatory interface component.

An example demonstrating this approach is the rule-based algorithm which is based on the work of two scientists Rahman and Baba. This algorithm consists of functions that have been developed for the load forecast model based on the logical and syntactical relationship between the weather and prevailing daily load shapes in the form of rules in a rule-base. The rule-base developed consists of the set of relationships between the changes in the system load and changes in natural and forced condition factors that affect the use of electricity. The extraction of these rules was done off-line, and was dependent on the operator experience and observations by the authors in most cases. Statistical packages were used to support or reject some of the possible relationships that have been observed

The rule-base consisted of all rules taking the IF-THEN form and mathematical expressions. This rule-base is used daily to generate the forecasts. Some of the rules do not change over time, some change very slowly while others change continuously and hence are to be updated from time to time [4].

4.6 Fuzzy Logic

Fuzzy logic based on the usual Boolean logic which is used for digital circuit design. In Boolean logic, the input may be the truth value in the form of “0” and “1”. In case of fuzzy logic, the input is related to the comparison based on qualities. For example, we can say that a transformer load may be “low” and “high”. Fuzzy logic allows us to deduce outputs form inputs logically. In this sense, the fuzzy facilitate for mapping between inputs and outputs like curve fitting *[16]*.

The advantage of fuzzy logic is that there is no need of mathematical models for mapping between inputs and outputs and also there is no need of precise or even noise free inputs. Based on the general rules, properly designed fuzzy logic systems are very strong for the electrical load forecasting. There are many situations where we require the precise outputs. After the whole processing is done using the fuzzy logic, the "defuzzification" is done to get the precise outputs.

We know that power system load is influenced by many load factors such weather, economic and social activities and different load components. By the analysis of historical load data it is not easy to make the accurate forecast. The use of these intelligent methods like fuzzy logic and expert systems provide advantage on other conventional methods. The numerical aspects and uncertainties are suitable for the fuzzy methodologies[5].

4.7 Support Vector Machines

Support Vector Machines (SVM) are the most powerful and very recent techniques for the solution of classification and regression problems. This approach was come to known from the work of Vapnik's, his statistical learning theory. Other from the neural network and other intelligent systems, which try to define the complex functions of the inputs, support vector machines use the nonlinear mapping of the data in to high dimensional features by using the kernel functions mostly. In support vector machines, we use simple linear functions to create linear decision boundaries in the new space. In the case of neural network, the problem is in the choosing of architecture and in the case of support vector machine, problems occurs in choosing a suitable kernel.

Mohandes applied a method of support vector machines for short-term electrical load forecasting. He compares its method performance with the autoregressive method. The results indicate that SVMs compare favorably against the autoregressive method. Chen also proposed a SVM model to predict daily load demand of a month. Lots of methods are used in support vector machines [3].

5.0 MEDIUM AND LONG-TERM LOAD FORECASTING METHODS

These models are useful for medium and long term forecasting. The three types of electricity demand forecasting methods are:

1. Trend Analysis
2. End Use Analysis
3. Econometrics

Each of the three forecasting methods uses a different approach to determine electricity demand during a specific year in a particular place. Each forecasting method is distinctive in its handling of the four basic forecast ingredients:

1. The mathematical expressions of the relationship between electricity demand and the factors which influence or affect it - the function
2. The factors which actually influence electricity demand (population, income, prices, etc.) - the independent variables
3. Electricity demand itself - the dependent variable
4. How much electricity demand changes in response to population, income, price, etc., changes- the elasticities?

The only way to determine the accuracy of any load forecast is to wait until the forecast year has ended and then compare the actual load to the forecast load. Even though the whole idea of forecasts is accuracy, nothing was said in the comparison of the three forecasting methods about which method produces the most accurate forecasts. The only thing certain shut any long-range forecast is that it can never be absolutely precise. Forecasting accuracy depends on the quality and quantity of the historical data used, the validity of the forecasters basic assumptions, and the accuracy of the forecasts of the demand-influencing factors (population, income, price, etc.). None of these is ever perfect. Consequently, regional load forecasts are reviewed some are revised yearly. Even so, there is simply electricity demand will be exactly as forecast, no is used or who makes the forecast. Continually, and no assurance that matter what method is used or who makes the forecast [3].

5.1 Trend Analysis

Trend analysis (trending) extends past growth 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. Usually, there is not much explanation of why demand acts as it does, in the past or in the future. Trending is frequently modified by informed judgment, wherein utility forecasters modify their forecasts based on their knowledge of future developments which might make future electricity demand behave differently than it has in the past.

The advantage of trend analysis is that it is simple, quick and inexpensive to perform. It is useful when there is not enough data to use more sophisticated methods or when time and funding do not allow for a more elaborate approach.

The disadvantage of a trend forecast is that it produces only one result - future electricity demand. It does not help analyze why electricity demand behaves the way it does, and it provides no means to accurately measure how changes in energy prices or government policies (for instance) influence electricity demand. Because the assumptions used to make the forecast (informed judgments) are usually not spelled out, there is often no way to measure the impact of a change in one of the assumptions. Another shortcoming of trend analysis is that it relies on past patterns of electricity demand to project future patterns of electricity demand. This simplified view of electrical energy could lead to inaccurate forecasts in times of change, especially when new concepts such as conservation and load management must be included in the analysis [3].

5.2 End Use Analysis

The basic idea of end-use analysis is that the demand for electricity depends on what it is used for (the end-use). For instance, by studying historical data to find out how much electricity is used for individual electrical appliances in homes, then multiplying that number by the projected number of appliances in each home and multiplying again by the projected number of homes, an estimate of how much electricity will be needed to run all household appliances in a geographical area during any particular year in the future can be determined. Using similar techniques for electricity used in business and industry, and then adding up the totals for residential, commercial, and industrial sectors, a total forecast of electricity demand can be derived. The advantages of end-use analysis is that it identifies exactly where electricity goes, how much is used for each purpose, and the potential for additional conservation for each end-use. End-use analysis provides specific information on how energy requirements can be reduced over time from conservation measures such as improved insulation levels, increased use of storm windows, building code changes, or improved appliance efficiencies. An end-use model also breaks down electricity into residential, commercial and industrial demands. Such a model can be used to forecast load changes caused by changes within one sector (residential, for example) and load changes resulting indirectly from changes in the other two sectors. Commercial sector end-use models currently being developed have the capability of making energy demand forecasts by end-uses as specific as type of business and type of building. This is a major improvement over projecting only sector-wide energy consumption and using economic and demographic data for large geographical areas [1].

The disadvantage of end-use analysis is that most end-use models assume a constant relationship between electricity and end-use (electricity per appliance, or electricity used per dollar of industrial output). This might hold true over a few years, but over a 10-or 20-year period, energy savings technology or energy prices will undoubtedly change, and the relationships will not remain constant. End-use analysis also requires extensive data, since all relationships between electric load and all the many end-uses must be calculated as precisely as possible. Data on the existing stock of energy-consuming capital (buildings, machinery, etc.) in many cases is very limited. Also, if the data needed for end-use analysis is not current, it may not accurately reflect either present or future conditions, and this can affect the accuracy of the forecast. Finally, end-use analysis, without an econometric component that is explained above, does not take price changes (elasticity of demand) in electricity or other competing fuels into consideration.

Ideally this approach is very accurate. However, it is sensitive to the amount and quality of end-use data. For example, in this method the distribution of equipment age is important for particular types of appliances. End-use forecast requires less historical data but more information about customers and their equipment [1].

5.3 Econometric

Econometrics uses economics, mathematics, and statistics to forecast electricity demand. Econometrics is a combination of trend analysis and end-use analysis, but it does not make the trend-analyst's assumption that future electricity demand can be projected based on past demand. Moreover, unlike many end-use models, econometrics can allow for variations in the relationship between electricity input and end-use.

Econometrics uses complex mathematical equations to show past relationships between electricity demand and the factors which influence that demand. For instance, an equation can show how electricity demand in the past reacted to population growth, price changes, etc. For each influencing factor, the equation can show whether the factor caused an increase or decrease in electricity demand, as well as the size (in percent) of the increase or decrease. For price changes, the equation can also show how long it took consumers to respond to the changes. The equation is then tested and fine tuned to make sure that it is as reliable a representation as possible of the past relationships. Once this is done, projected values of demand-influencing factors (population, income, prices) are put into the equation to make the forecast. A similar procedure is followed for all of the equations in the model.

The advantages of econometrics are that it provides detailed information on future levels of electricity demand, why future electricity demand increases or decreases, and how electricity demand is affected by various factors. In addition, it provides separate load forecasts for residential, commercial, and industrial sectors. Because the econometric model is defined in terms of a multitude of factors (policy factors, price factors, end-use factors), it is flexible and useful for analyzing load growth under different scenarios.

A disadvantage of econometric forecasting is that in order for an econometric forecast to be accurate, the changes in electricity demand caused by changes in the factors influencing that demand must remain the same in the forecast period as in the past. This assumption (which is called constant elasticities) may be hard to justify, especially where very large electricity price changes (as opposed to small, gradual changes) make consumers more sensitive to electricity prices *[3]*.

Also, the econometric load forecast can only be as accurate as the forecasts of factors which influence demand. Because the future is not known, projections of very important demand-influencing factors such as electricity, natural gas, or oil prices over a 10- or 20-year period are, at best, educated guesses. Finally) many of the demand-influencing factors which may be treated and projected individually in the mathematical equations could actually depend on each other, and it is difficult to determine the nature of these interrelationships. For example, higher industrial electricity rates may decrease industrial employment, and projecting both of them to increase at the same time may be incorrect. A model which treats projected industrial electricity rates and industrial employment separately would not show this fact.

Econometric models work best when forecasting at national, regional, or state levels. For smaller geographical areas, meeting the model can be a problem. This is oddly shaped service areas for which there demographic data.

6.0 COMPARISON OF ELECTRICAL LOAD FORECASTING TECHNIQUES

In the previous discussion we focus on electrical load forecasting techniques, most forecasting methods use statistical techniques or artificial intelligence algorithms such as regression, neural networks, fuzzy logic, and expert systems. Two of the methods named trend analysis, end-use and econometric approach are broadly used for medium- and long-term forecasting. A variety of methods, which include the similar day approach, various regression models, time series, neural networks, statistical learning algorithms, fuzzy logic, and expert systems, have been developed for short-term forecasting.

The method for short-term forecasting are similar day approach, various regression models, time series, neural networks, statistical learning algorithms, fuzzy logic, and expert systems. ***Similar day approach*** is based on searching historical data of days of one, two or three years having the similar characteristics to the day of forecast. ***Regression*** is the one of 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. There are several regression models for the next day peak forecasting. Their models contain deterministic influences such as holidays, random variables influences such as average loads, and exogenous influences such as weather. ***Time series*** is a very popular approach for the electrical load forecasting. Two important models of time series are ARMA and ARIMA. 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 *[2]*.

The other methods are based on Artificial intelligence, they are called Intelligent Systems. In ***Artificial Neural Network***, forecasting is based on the pattern observed from the past event and estimates the values for the future. ANN is well suited to forecasting for two reasons. First, it has been demonstrated that ANN are able to approximate numerically any continuous function to be desired accuracy. In this case the ANN is seen as multivariate, nonlinear and nonparametric methods. Secondly, ANNs are date-driven methods, in the sense that it is not necessary for the researcher to use tentative modals and then estimate their parameters. ANNs are able to automatically map the relationship between input and output, they learn this relationship and store this learning into their parameters. An ***Expert System*** is a computer program, which has the ability to act as an expert. This means this computer program can reason, explain, and have its knowledge base expanded as new information becomes available to it. The load forecast model is built using the knowledge about the load forecast domain from an expert in the field. This knowledge is represented as facts and rules by using the first predicate logic to represent the facts and IF-THEN production rules. This representation is built in what is called the knowledge base component of the expert system. The search for solution or reasoning about the conclusion drawn by the expert system is performed by the "Inference Engine" component of the expert system. For any expert system it has to have the capability to trace its reasoning if asked by the user. This facility is built through an explanatory interface component. ***Fuzzy logic*** based on the usual Boolean logic which is used for digital circuit design. In case of fuzzy logic, the input is related to the comparison based on qualities. The advantage of fuzzy logic is that there is no need of mathematical models for mapping between inputs and outputs and also there is no need of precise or even noise free inputs. Based on the general rules, properly designed fuzzy logic systems are very strong for the electrical load forecasting.

The methods for long- and medium-term forecasting are trend analysis, end-use and econometric approach. The advantage of ***trend analysis*** is that it is quick, simple and inexpensive to perform and does not require much previous data. The basic idea of the ***end-use analysis*** is that the demand for electricity depends what it use for (the end-use). The advantages of end-use analysis is that it identifies exactly where electricity goes, how much is used for each purpose, and the potential for additional conservation for each end-use. The disadvantage of end-use analysis is that most end-use models assume a constant relationship between electricity and end-use (electricity per appliance, or electricity used per dollar of industrial output). This might hold true over a few years, but over a 10-or 20-year period, energy savings technology or energy prices will undoubtedly change, and the relationships will not remain constant. The advantages of ***econometrics*** are that it provides detailed information on future levels of electricity demand, why future electricity demand increases or decreases, and how electricity demand is affected by various factors. A disadvantage of econometric forecasting is that in order for an econometric forecast to be accurate, the changes in electricity demand caused by changes in the factors influencing that demand must remain the same in the forecast period as in the past *[5]*.

7.0 CONCLUSION

Modern load forecasting techniques, such as expert systems, Artificial Neural Networks (ANN), fuzzy logic, wavelets, have been developed recently, showing encouraging results. Among them, ANN methods are particularly attractive, as they have the ability to handle the nonlinear relationships between load and the factors affecting it directly from historical data.

The trend analysis, end-use modeling and econometric modeling are the most often used methods for medium- and long-term load forecasting. Trend analysis (trending) extends past growth rates of electricity demand into the future, using techniques that range from hand-drawn straight lines to complex computer-produced curves. Descriptions of appliances used by customers, the sizes of the houses, the age of equipment, technology changes, customer behavior, and population dynamics are usually included in the statistical and simulation models based on the so-called end-use approach. In addition, economic factors such as per capita incomes, employment levels, and electricity prices are included in econometric models. These models are often used in combination with the end-use approach. Long-term forecasts include the forecasts on the population changes, economic development, industrial construction, and technology development.

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