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A Theoretical Framework for Enhanced Forecasting of Electrical Loads

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Abstract- Forecasting of electrical load is vital in electrical sector; it helps in the process of planning periodical operations and facility expansion. In the deregulated economy, it has many applications which include energy purchasing, and generation, load switching, contract evaluation and infrastructure development. Therefore finding the most appropriate forecasting method for a specific electricity network is not an easy task. Although many forecasting methods were developed none can be generalized for all load patterns. This paper presents a framework of various approaches to optimize the forecasting of electrical loads.

Index Terms- Forecasting, Electrical load, long term forecast, medium term forecast, short term forecast.

I. Introduction

Electrical load forecasting is the prediction and projection of peak load demand levels and over all energy consumption patterns that supports an electric utility future system and business operation [1]. It estimates what the load will be throughout the day, week, year, and next year or even in a decade. Electrical load forecasting provides a projection of electric energy peak, customer counts and energy demand within an area covering a period into the future to provide a good lead time for planning so that the utility company can arrange additions of equipment in a timely and efficient manner.

Optimization of forecasting of electrical loads is one which requires an alternative with the most cost effective or highest achievable performance under given constraints by maximizing desired factors and minimizing undersized ones. Electrical load forecasting can be divided into three categories: short-term forecasts which are usually from one hour to one week, medium forecasts, usually from a week to a year, and long term forecasts which are longer than a year [2]. Long-term local forecasts are very important during national development plan that can be as long as 25 years. Short-term forecasts are used to schedule the generation and transmission of electricity. Medium-term forecasts are used to schedule the fuel purchases. Long-term forecasts are used to develop the power supply and delivery system (generation units, transmission system, and distribution system) [3].

Most forecasting methods use statistical techniques or artificial intelligence algorithms such as regression, neural networks, fuzzy logic, and expert systems. Two of the methods, so-called end-use and econometric approach are broadly used for medium- and long-term forecasting. A variety of methods, which include the so-called 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. As we see, a large variety of mathematical methods and ideas have been used for load forecasting [2].

II. IMPORTANT FACTORS FOR FORECASTING OF ELECTRICAL LOAD

For short-term load forecasting several factors should be considered, such as time factors, weather data, and possible customers' classes. 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 age, the economic and demographic data and their forecasts, the appliance sales data, and other factors. The time factors include the time of the year, the day of the week, and the hour of the day. The load on different weekdays also can behave differently. For example, Mondays and Fridays being adjacent to weekends, may have structurally different loads than Tuesday through Thursday. This is particularly true during the summer time. Holidays are more difficult to forecast than non-holidays 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.

Most electric utilities serve customers of different types such as residential, commercial, and industrial. The electric usage pattern is different for customers that belong to different classes but is somewhat alike for customers within each class. Therefore, most utilities distinguish load behavior on a class-by-class basis [4].

III. VARIOUS METHODS OF ELECTRICAL LOAD FORECASTING.

The categories of load forecasting includes short-term, medium-term and long-term covering an hour to one weak, a weak to a year and from one year to 3 years or even 10 years or more; respectively.

3.1 Methods Developed for Short-Term Load Forecast :- This approach is based on searching the historical data for days with similar characteristics such as weather, day of the week and the date. In daily forecast in a week, the electricity consumption in normal working days is expected to be of high demand between 7.00pm to 11.00pm and lowest between mid-nights and 3.00am the next morning. The lowest electrical power demand is recorded between February to May because of dry season but demand appreciated from June and got to apex by August to September when the raining season and cold are at highest [2].

3.1.1 Regression Load Forecasting Method:- This is one of the most widely used statistical techniques employed in electric load forecasting to model the relationship of load consumption in relation to weather, type of day and customer class.

In [5], we see several regression models for the next day peak forecasting; incorporating deterministic influences such as holidays, stochastic influences like average loads and exogenous influences such as weather.

3.1.2 Time Series Load Forecasting Method:- This method is based on the assumption that the data have an internal structure, such as autocorrelation, trend, or seasonal variation; which it detects and explores. Load generally depends on the weather and time of day; therefore autoregressive integrated moving average of time series method is the most natural tool for load forecasting among the classical time series models [6].

3.1.3 Neural Network Short-Term Load Forecasting (NNSTLF) Method:-This method can also be called artificial neural networks and are essentially non-linear circuits that have the ability to do non-linear curve fitting. The outputs of an artificial neural network are some linear or non-linear mathematical function of its inputs. The most popular Artificial Neural Network architecture for electric load forecasting is back propagation. Back propagation neural networks use continuously valued functions and supervised learning [7]. Further, a multi-layered feed forward Artificial Neural Networks for Short-Time Load Forecasting system was developed and implemented by [8]. In the model, three types of variables are used as inputs to the neural network: season related inputs, weather related inputs, and historical loads.

3.1.4 Expert System Load Forecasting Method:-This load forecasting method incorporates rules and procedures used by human experts in the field of interest into software that is then able to automatically make forecasts without human assistance [7]. Rule based forecasting makes use of rules, which often heuristic in nature, to do accurate forecasting. This rule base is complemented by a parameter database that varies from site to site but with low forecasting errors.

3.1.5 Fuzzy Logic Short-Term Forecasting Method:- Fuzzy logic is a generalization of the usual Boolean logic used for digital circuit design. An input under Boolean logic takes on a truth value of "O" or "1". Fuzzy logic is basically a multi valued logic that allows intermediate values to be defined between conventional evaluations like "yes" and no", "true" and "false" to include a more human-like way of thinking in the programming of computer. [9].

3.1.6 Statistical Learning Algorithms for Short-term Forecasting:- Statistical approaches usually require a mathematical model that represents load as function of different factors such as time, weather, and customer class. The development, improvements, and investigation of the appropriate mathematical tools led to the development of more accurate load forecasting techniques that was lacking in the other entire short-term load forecasting methods [10] discussed above.

Two important categories of mathematical models are: additive models and multiplication models. The former is when the forecast load is the sum of a number of components and the latter represents the product of a number of factors [11]. In their work [11] presented an additive model that takes the form of predicting load as the function of four components:

$L= L_n+ L_w+ L_s+ L_r$, - - - - - - - - - -- - - - - (2.1)

Where, L is the total load, L_n represents the "normal" part of the load, which is a set of standardized load shapes for each "type" of day that has been identified as occurring throughout the year (Similar day Approach), $L_w$represents the weather sensitive part of the load, L_s is a special event component that creates a substandard deviation from the usual load pattern and L_r is a random noise component. They also suggested electricity pricing as additional term that can be included in the model. Therefore giving

$L= L_n+ L_w+ L_s+ L_r + L_p$ - - - - - - - - - (2.2)

Where, L_p represents electricity price

Naturally, price fluctuation affects electricity consumption. It was reported that accurate estimates were achieved more quickly with the inclusion of price data.

The second category is the multiplication model of the form [12]

$L = L_n.F_w . F_s .F_r$- - - - (2.3)

Where, L_n is the normal (base) load and the correction factors, F_w, F_s and F_r are positive numbers that can increase or decrease the overall load,

F_w represents current weather, F_s represents special events, and F_r represents random fluctuation, F_p for electricity pricing and F_g for load growth can also be included to have;

$\therefore L = L_n. F_w .F_s.F_r.F_n.F_g$ - - - - - - (2.4)

[

3.1.7 Support Vector Machines (SVMs):- Support vector Machines are a more recent powerful technique for solving classification and regression problems. It was originated from Vapnik's statistical learning theory [10]. The SVMs use simple linear functions to create linear decision boundaries in the new space. It has the advantages of performing a non linear mapping of the input data into a high dimensional space employing kernel function [13].

3.2 Medium – Term Load Forecasting (MTLF) Methods

3.2.1 End-Use Method of Load Forecasting:- This model involve direct estimates of energy consumption considering using extensive information on end-use appliances, their age, sizes of houses, end-use customers, customer behavior, population dynamics and technological changes.

The 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 high cooling, heating, refrigeration, etc. In effects, end-use models explain energy demand as a function of the number of appliances in the market [14].

Ideally, this end-use approach is very accurate but has the disadvantage of being sensitive to the amount and quality of end-use data.

3.2.2 Econometric method of load forecasting

This approach combines both economic theory and statistical techniques for forecasting electricity demand. It estimates the relationships between energy consumptions (dependent variables) and factors influencing consumption. The relationship of these two factors is estimated by the least squares method or time series methods. Historical energy and peak demand models were classified by methodology (statistical econometric end-use analysis) and demand class (residential, commercial, and industrial).. The other factors to be considered that influence consumption are weather, economic and other variables [15].

This approach is accurate since estimates are assembled using recent historical data. However, integration of the econometric approach into the end-use approach introduces behavioural components into the end-use equations and this is its disadvantage.

3.2.3 Statistical Model-based Learning

The end use and econometric methods above require a large amount of information relevant to appliances, customers, econometrics, etc making the application very complicated and requires human participation. In addition such information is often not available regarding particular customers, resulting in the use of an "average" customer or average customers for different type of customers. Therefore, the characteristics for particular area may be different from the utility which may not be available resulting in average value use [16] [17].

$L(t) = F(d(t), h(t)) \cdot f(w(t)) + R(t)$ - - - - - - (2.5)

Where, $L(t)$ is the actual load of time t, $d(t)$ is the day of the week, $h(t)$ is the hour of the day, $f(d, h)$ is the daily and hourly component, $w(t)$ is the weather data that include the temperature and humidity, $f(w)$ is the weather factor and $R(t)$ is the random error.

The $w(t)$ is a vector that consists of the current and lagged weather variables which reflects not only the current weather conditions but also on the weather during previous hours and days.

To estimate the weather factor $f(w)$, the regression model is used.

$f(w) = \beta_0 + \sum \beta_i X_i$ - - - - - - - - - - - - - - - - (2.6)

Where, β_0, β_i are the regression coefficients and X_i are explanatory variables which are non linear functions of current and past weather parameters.

3.3 Long – Term Load Forecasting (LTLF) Method

Long term electric load demand forecasting spans from one year through three years to fifteen years and presents the first step in planning and developing future generation, transmission and distribution facilities in a power system [18].

Accurate long-term demand forecasting plays an essential role for electric power system planning. It ensures load demand forecasting to have enough time to plan for long-term maintenance, construction scheduling for developing new generation facilities, purchasing of generating units, developing transmission and distribution systems.

Unfortunately, it is difficult to forecast load demand accurately over a long planning period of several years [19] [20].

3.3.1 Trend Analysis in Long Term Load Forecasting:- This method extends past rates of electricity demand to the future. It 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 but have the disadvantage of producing only one result, the future electricity demand [21].

3.3.2 End-Use Models in Long-Term Load Forecasting:- This method has been explained earlier in the medium term load forecasting methods. End-use forecasting method predicts the energy consumptions and the load factor could be calculated thus:

$$\text{Load factor} = \frac{\text{Average – Load Demand}}{\text{Peak – Load Demand}} = \frac{\text{Annual Kwh Energy}}{\text{Peak – Load Demand x 8760 hrs/years}} \text{ ----- } (2.7)$$

The long-term end use forecasting method has the disadvantage that most end-use models assume a constant relationship between electricity and end-use (electricity per appliance).

3.3.3 Econometric Model of Long-Term Forecasting:- This method has been explained earlier in the medium term load forecasting methods**.** The advantage is that it provides detailed information on future electricity demand increases, and also on how electricity demand is affected by all the various factors [2], [22] and [23].

3.3.4 Artificial Intelligence Based Methods:

Artificial Neural Networks (ANNs), have succeeded in several power system problems, such as planning, control, analysis, protection, design, load forecasting, security analysis, and fault diagnosis. The ANNs ability in mapping complex non-linear relationships is responsible for the growing number of its application to load forecasting [24] [25].

The design of neural network architecture involves decision making on type, size, and number of neural networks being used [26].

The result of output ANNs is

$Y_i = \sum_{i=1}^{n} W_i X_i$------------------------(2.7)

Where i= 1, 2 ----------- n, X_i is input, $W_i$is weight of network, and Y_i is one of the ANNs output

3.3.5 Wavelet Networks:- This 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 the extension of wavelet analysis and it has better frequency resolution [27], it utilizes the periodicities of past load demand data.

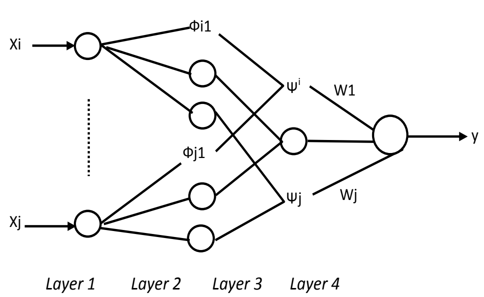

Fig. 1: Schematic diagram of Wavelet Network

For accurate forecast to be in place, the wavelet network must:

1. Select proper wavelet function for load forecasting.
2. Avoid border distortion during wavelet transform.

It has the advantage of not spanning inputs and has better accuracy of model than multilayer neural networks. It overcomes the shortcoming of single train set of fuzzy rules and therefore improves effectively the forecast accuracy and speed [28]. Also it overcomes the shortcoming of single train set of ANNs and hence improves effectively the forecast accuracy and speed [28].

3.3.6 Genetic Algorithms: Long-Term Load Forecasting

Genetic Algorithms (GAS) as robust stochastic search algorithm have been successfully applied in various areas such as, load flow problems, fault detection, stability analysis, economic dispatch, power system control and Successful load demand forecasting with a low error rate [29] [30].

Some of the attractive features of GAs are, learning, generic code structure, optimality of the solutions and advanced operators. The GAs approach presented is employed to find the optimum values of the state vector that minimizes the absolutes summation of the forecasting error r (t). in order to emphasize the "best" string and speed up convergence of the iteration procedure, fitness is normalized into range between Q and I. The fitness function (ff) adopted is [30]

$$ff = \frac{1}{1 + k\sum_{k=1}^{m}|r(t)|} \text{------}(2.9)$$

Where, k is a scaling constant (for example, k= 0.0001) others to be selected are site of population, probability of cross over and probability of mutation.

$r(t)$ is the error vector associated with, With $r(t)$, we can calculate the load demand forecasting by the following equation;

$P(t) = a_0 + \sum_{i=1}^{n} a_i t^i + r(t)$ - - - - - (2.10)

Where $P(t)$ is the Peak load demand of time t, a_0, a_i are regression coefficients relating the load demand $P(t)$ to the time t, $r(t)$ is the residual load at year (t)

3.3.7 Support Vector Machine (SVM) Long-Term Load Forecasting Method:- it is a useful technique for data classification in load forecasting. it has a challenging task because of the complex relationships between load and factors affecting load[31]. SVMs have been extended to solve non linear regression estimation problems [32].

The support vector machine (SVM) through the superior performance of Recurrent support vector Machine with genetic algorithms model has non-linear mapping capabilities and can more easily capture electricity load data patterns than can the ANN and regression models and improves the generalization performance compared to the ANN and regression models.

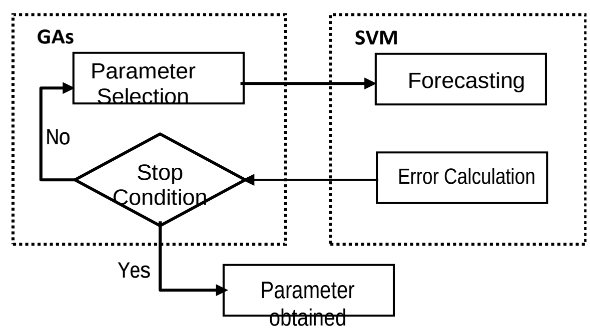

Fig. 2: Architecture of SVMG.

3.3.8 Fuzzy Logic Model of Long-Term Load Forecasting Method:- is a rule based systems in which a set of fuzzy rules represents a control decision mechanism to adjust the effects of certain stimulus such as load data. [33]. The fuzzy logic model provides an algorithm, which can convert the linguistic strategy based on expert knowledge into an automatic strategy. The fuzzy rule base is composed of some rules generated from the analysis of the historical load data [32].

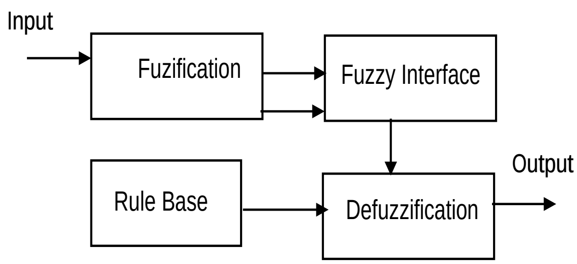

Fig. 3: Block diagram of the Fuzzy logic system

One of the applications of the fuzzy rules is an approach based on a hybrid fuzzy – neural technique which combines artificial neural network (ANN) and Fuzzy logic modeling for long-term industrial load forecasting in electrical power system. The strength of this hybrid technique lies in its ability to reduce appreciably computational time and its comparable accuracy with other modern methods[32].

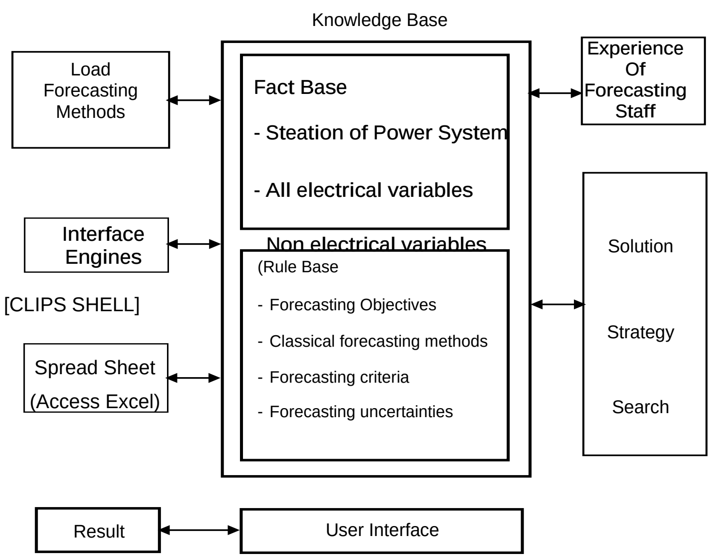

Fig. 4: Structure of ANN and Fuzzy based used

3.3.9 Expert System Method of Long-Term Load Forecasting:- It is a classical forecasting method, a long-term forecasting strategies using a knowledge – based expert system is applied to obtain the long-term load demand forecast, for typical fast growing utility as well as normal developing system [34]. The proposed expert system is applied successfully to forecasting for yearly peak load, for normal and fast developing power systems, it considers the influence of both history and future uncertain factors. Since the expert system is very flexible in updating the forecasting methods and heuristic rules, it is expected that the expert system can serve as a variable assistant to system planning in performing their annual load forecasting duties and also serve as a valuable assistant for training purpose [34].

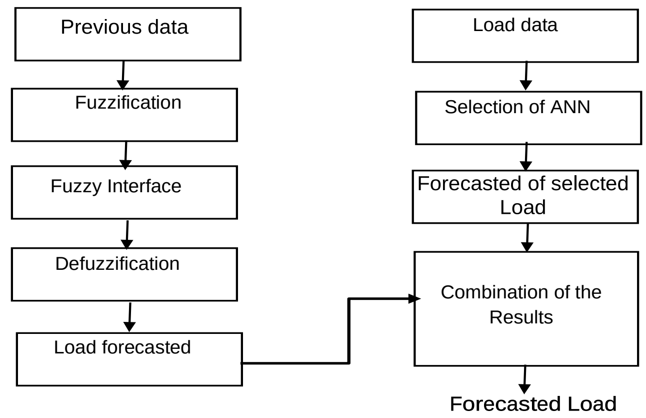

Fig. 5: Structure of Expert System Method

IV. NEW FORECASTING METHODS AND THEIR CONTRASTING FEATURES

Several statistical and artificial intelligence techniques have discussed earlier in this paper and also its development for short, medium and long term electrical load forecasting, the accuracy of the load forecasting could be improved if one would study these statistical models and develop mathematical theory that explains the convergence of the algorithms. There is no single model or algorithms that is superior for all utilities company, a better investigation on the boundaries, and the application of the developed models and algorithms must be earned out carefully. The utility Company service areas vary differently for the industrial commercial and residential customers, they also vary in geographic, climatologic, economic and social characteristics.

Selecting the most suitable algorithm by a utility can be done by testing the algorithms on real data. In fact, some utility companies use several load forecasting methods in parallel. As far as we know, nothing is known on a priority conditions that could detect which forecasting method is more suitable for a given load area. An important question is to investigate the sensitivity of the load forecasting algorithms and models to the number of customers, characteristics of the area, energy prices, and other factors.

In the short term forecasting weather seen to be the major factor that affect and influence load so the better method for forecasting in the short term of all the methods that would mentioned early to use the forecasted weather. Scenario as input in the recent development in the short term is the ensemble approach which consist of computing multiple forecast. Instead of using the single weather forecast which might not give the accurate result, the weather ensemble predictions can be used as multiple inputs for load forecasts.

While in the long term forecasting the various method mentioned early has their better advantage like the wavelet network.

The Genetic Algorithm (GA) for forecasting results to be the best by researchers because of its numerical optimization technique which indicates that the GA approach is quite promising and deserves serious attention of it's robustness and suitability for parallel implementation.

Fuzzy system as another method is normally to replace a skilled human operator with a fuzzy rule-based system. One of the applications of the fuzzy rules is to combine them with neural network to train ANN and have a better load demand forecasting.

While expert system, we can use traditional methods to forecast the peak load forecasting. The expert system is very flexible in updating the forecasting methods and heuristic rules, it is expected that the expert system can serve as a valuable assistant to system planners in performing their annual load forecasting duties.

Now there is a new method for forecasting future load without restriction to term length either 6long, medium or short and it's the based on the principles of time series and it's the time series segmentation and decomposition. It has some additional statistical analysis which follow with the aid to the decision making based on the adopted forecasts such as probability plots [3]. This method can be shown in the diagram below:

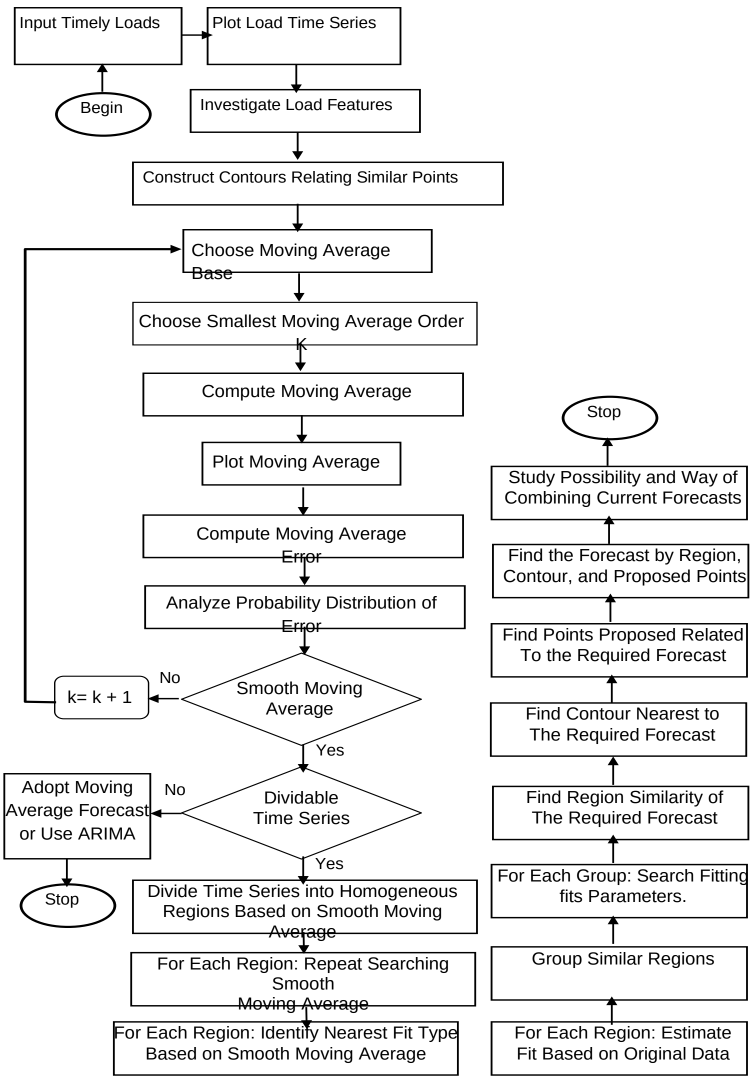

Fig. 6: Flowchart for the time series segmentation and decomposition method

V. CONCLUSION

Various method of load forecasting in the various terms (short, medium, long) were presented and it was discovered that there is no suitable method that supersedes the other in getting the best result of the forecasting. In order to get a more accurate result in load forecasting we need to study the load carefully to get the optimal result and know which statistical or/and artificial intelligence technique that should be used for electrical load forecasting. It is very important for electrical utility companies to get the accurate load forecasting that would be used in their competitive environment created by the electrical industry deregulation.

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