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ELECTRICITY DEMAND FORECASTING: A REVIEW

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ABSTRACT: Electricity forecasting is a very important tool in the energy industry. Electricity demand forecasting is an essential part of the electricity industry. It is widely used for planning towards building new power generating plants, energy resources demand planning, expansion of electricity supply network, policy making, electricity market analysis and many more reasons. Electricity demand forecasting provides enough data to make calculated and informed decision. Over the years, several methods have been developed to carry out electricity demand forecast. Each method has its advantages and disadvantages depending on the available data and the peculiarity of the country where the data is acquired. Nigeria has had deficit in the electricity industry due to improper planning for electricity supply. We are reviewing the different techniques which have been proposed for the purpose of electricity demand forecasting by various researchers and their different advantages depending on which one is applicable to a given situation. Techniques that are adaptive and accurate like artificial neural network are beneficial for forecasting in a situation where there is indirect relationship between the dataset. Making use of forecasting techniques will provide enough information for making informed decision that will help Nigeria meet the its growing electricity need and also manage its internal energy consumption efficiently.

I. INTRODUCTION

In a ley man definition, energy is the capacity to do work. Energy exists in many forms for example heat, light, chemical, rotary, electrical or mechanical energy. Although energy is used by man to do work, not all energy can be directly harnessed. They have to be converted from one form to the other to be able to meet the needs which they are required to meet. Modern civilization with all its technological advancements was achieved only because man mastered the art of converting energy from one form to the other for his use. In our solar system, the sun is the only star. It is surrounded by planets and radiates solar energy which is transferred to earth through space. The energy from the sun supports life on earth. This energy is absorbed by plants and animals enabling them to survive. Solar energy from the sun is used to convert water and carbon dioxide into oxygen and carbohydrates in a process known as oxygenic photosynthesis. This is a natural process which converts solar energy directly into chemical energy [1]. In the same way, the human body is designed to extract energy when food is consumed in a process called metabolism. With this energy, the body functions to produce heat and feed the muscles with the fuel to do work. Energy is a primary ingredient of life which is an important part of the world.

Work can be defined as energy transfer which occurs when an object is moved over a distance by an external force. Man initially relied on their physical strength to do work at the very early civilizations using crude tools to assist in hunting and gathering. In the Paleolithic period, hunting and gathering, fishing and chasing game all around the world as a means of survival. This survival method using crude stone tools required lots of energy. The discovery of fire was a milestone in the history of mankind and there are evidence that shows that the earliest control of fire by homo sapient man was done about 1.7 to 2 million years ago[2]. At this time fire was used mostly for heating during the winter, cooking and protection from wild animals. Gradually man evolved, learning to properly harness the heat energy to producing more useful work. The industrial revolution was a major turning point in human history. The industrial revolution describes the period whereby humanity had a speedy technological transformation and within this period the internal combustion engine was discovered. The invention of the internal combustion engine was a tipping point in the industrial revolution. Internal combustion engines were more efficient than the steam engines which brought about the industrial revolution. They had lesser weight and packed more power. This meant more powerful and efficient machines for textile and agricultural industries as well as for transportation and other uses. Nuclear energy was discovered towards the end of the industrial revolution. Nuclear energy which was initially being researched to be used a weapon was discovered to produce enough heat energy capable of being used in steam turbines for generating electricity. Electricity is an important need today. It is used for residential, transportation, industrial, military and many other applications. Useful electricity is not found naturally in nature hence it is called a secondary energy source.

This is because it is derived from the conversion of primary energy source e.g. fossil fuel, wind energy, solar energy etc. The importance of electricity in the modern era cannot be over emphasized. It is so important that a lack of electricity will be a disaster. Electricity was largely produced by combusting fossil fuel in energy conversion machines. The combustion of fuel in the energy conversion machines produced rotary motion used in rotating big generators. Some renewable energy resources are used for generating electricity but it makes up a small percentage when compared to fossil fuel. Fossil fuel dependent energy conversion technologies like gas turbines, steam turbines, and reciprocating internal combustion engines had the advantage of being cheaper in terms of compared to renewable conversion technologies. Fossil fuel is abundantly found in nature and over the years, the technologies for mining have improved greatly thereby driving the cost down. Until the invention of nuclear energy which produced a cleaner type of electricity, fossil fuel was the most preferred source for the generation of electricity. However, everything that has an advantage also has a disadvantage. Nuclear energy produces nuclear waste after it is used to generate electricity. Management of nuclear waste is a major issue because of the long half-life of the spent nuclear fuel. This means that the spent fuel must be properly stored and disposed in a safe way in other not to pose harm to humans [3]. Till date, the disposal of nuclear waste poses big problem. This disadvantage greatly affected the adoption of nuclear power as the main source of electrical energy worldwide.

In recent times, there has been so much concern on global warming and sustainability. Global warming is largely due to emission of green-house gases (GHG). Green-house gases like carbon dioxide which is a combustion product when fossil fuel is combusted is very harmful to nature due to their harmful effect on the atmosphere. The usage of fossil fuel degrades the environment over time. A sustainable energy resource is a resource that readily and sustainably available at a cost which is reasonable and can be utilized for all energy applications without causing any negative impact to the society [4]. Researching into renewable energy resources and technologies is a very important component of sustainable development. This is because they have less environmental impact compared to other energy resources, they cannot be depleted and they favor a more decentralized power system. This would mean gradual transition from fossil fuel dependence to renewable energy sources and greener alternatives for electricity generation in the future. Natural gas is favored as a transition energy resource because it has very low emission when compared with other non-renewable sources. However, just like all other non-renewable sources, it is limited in nature.

As with all commodities which are core to the human society, electricity is greatly affected by economic forces like demand and supply. Since electricity is not found naturally in nature, it is dependent on primary energy resources which are limited. Some of the main challenges with transformation of energy from fossil to renewable energy resources are energy storage, cost of the system, lifetime of the system and grid reliability. Apart from the technical performance of a renewable energy technology, the commercial feasibility is also very important. The cost of deploying a renewable energy technology is very important to the investor because the technology must show that it is viable and can compete with the cost of investing in other energy conversion technologies [5]. The cost of transitioning to more green electricity generating technologies is high. These factors and many more affect what shapes the future of electricity generation. With growing population and advancement in technology which require more energy, there is even more economic strain on electricity as a commodity. One property of electricity which makes it a unique commodity is that it is consumed as it is produced. There are few technologies currently available to store electricity but they are still a long short away from meeting electricity demand for huge demand and a long time. Electricity demand must always match the supply.

There is a need to properly plan and manage the generation of electrical energy. The costs associated with expanding power generation, increasing electricity demand due to increasing population growth, increasing energy needs due to technological advances, ensuring smooth transitioning to renewable energy technologies for electricity generation means that electricity generation must be carefully planned in order to meet both present and future demands. Every country differs in its electricity demand due to several factors like population, technological advancement, political environment etc. These factors must be considered by the governments in order to plan towards present and future energy needs of their country. Governments need to plan ahead to be able to properly utilize limited resources and also meet the energy needs of their people. Forecasting of energy demand is one way governments of various countries ensure they provide for their energy needs. Electricity demand helps the government plan for future electricity demand growth, energy resources utilization, electricity generation expansion. Forecasting plays a very important role in allocation of electricity, planning for future power generation facilities [6]. With a proper demand forecast, the government can as well use the information to plan towards transitioning to renewable energy resources.

Without proper forecasting, electricity demand will never be able to match with the supply. Forecasting is a technique that makes use of historical data to project future estimates that are predictive of a future trend. It is a very important tool for planning. Electricity is an important commodity in the world today. It is important for the development of nations. Basically all spheres of a society require electricity in order to function optimally. The importance of electricity makes it a resource which should not be played with. Careful planning is required to be able to provide for the growing demand of electricity. Forecasting is the right tool used for this. By making use of historical electricity demand, the future demand is estimated in a trend. The result of the forecast is used to plan for new power stations which will argument the demand for electricity in the future. Electrical forecasting is important because it helps a nation plan for generation, plan for its transmission expansion and also for financial planning. Further to all of this, electricity forecasting helps with planning for the spinning reserve required for the future demand, also the fuel required for the future electrical demand and other aspect of planning which will ensure an efficient delivery of electricity [7].

This article will help to give an insight on how to forecast electricity demand. Lots of work has been done over the years on electricity demand forecasting. Researchers have presented different ways to carry out electricity demand forecasting. Conventional methods have been used over the years and newer methods have been proposed along with hybrid methods which were developed to improve the accuracy of forecasting. Some work has been carried out to compare all these techniques developed with each other to ascertain the most accurate among them. This work will help give a good understanding of the works that have been done in the field of electricity demand forecasting and serve as a guide to select the appropriate technique in different situations.

II. ELECTRICITY DEMAND FORECASTING

Electricity demand forecast can be categorized into different groups. These are groups are based on the duration of the forecast which is conducted. The duration of the forecast is called forecast ranges. An accurate forecast is necessary for planning of electric power systems. This helps to plan for maintenance, scheduling, expansion and many other reasons. The purpose of the forecast determines the range the forecast will be done. Several factors affect electricity demand in different regions. Also the duration of the forecast determines the influence certain factors have on the dependent variable ‘electricity demand’ which in turn affects the electricity forecast. Factors like weather, demographic variables, socio-economic factors, relative humidity, population, gross domestic product etc. They are carefully selected depending on the range and type of the forecast.

Electricity Demand Forecasting Ranges: There are different forecasting ranges which are short term, medium term and long term [8].

Short Term Forecasting : The range of the forecast is dependent on the period of study. Short term electricity forecasting is usually referred to as hourly load forecast. It helps with day to day operation of utilities, electricity generation nomination, planned maintenance etc. This type of electricity demand forecast would consider factors that affect daily generation of electricity from previous data. Examples of such factors are weather, humidity, ambient temperature, human activities etc.

Medium Term Forecasting : Medium term forecasting is in the range of weeks to a few years. This forecasting is necessary in planning fuel consumption scheduling, unit maintenance and other economic decisions. Forecasting electricity for medium term will consider factors that can affect medium term electricity generation; factors like weather, ambient temperature, season etc. This type of forecasting will help with maintenance planning in power generating stations, planning of fuel supply, expansion of generating plants, etc.

Long Term Forecasting : Long term forecasting is known as the annual peak load and annual energy forecast. It is usually forecasted for a range of 5 to 25years. This type of forecast considers factors that affect long term electricity demand. Examples of some of these factors are GDP, seasons, population etc. Long term electricity forecast helps with planning towards the expansion of power generation plants, grid expansion, energy resources usage and demand and policy creation.

Classification of Forecasting Techniques : The use of forecasting techniques for electricity demand forecasting has been in use for a long time. Over the years different techniques have been developed for electricity demand forecasting and there are still new techniques being developed till date. Some of these techniques have been used for ages while some are more recent. According to Singh et al [8], forecasting is classified into 3 types namely;

1. Traditional forecasting techniques,
2. Modified forecasting techniques
3. Soft computing techniques.

Each of the three forecasting techniques is discussed in turn.

Traditional Forecasting Techniques: Traditional forecasting techniques have been used for years to carry out energy forecast. Regression is a statistical technique which is used to establish the relationship between two variables. Once the relationship is established, it can be forecasted using the relationship already defined. Different types of regression techniques have been developed over the year. Examples of some data driven techniques used for forecasting are multivariate adaptive regression spline (MARS), support vector regression (SVR), autoregressive integrated moving average (ARIMA), exponential smoothening (ES), kernel regression (also known as Nadaraya-Watson Estimator). Tradition forecasting techniques are methods used in forecasting using mathematical regression. Traditional forecasting techniques include regression, multiple regression, exponential smoothing and iterative reweighted least-squares technique. These methods are known as the traditional forecasting method because they are mathematical methods used in the early days to forecast. Regression technique is a very common forecasting technique. It can be employed in different fields of study. In the case of electricity demand forecasting, it is used to model the relationship between load demand factors like weather condition. The method uses previous historical data to predict future by modelling the pattern and finding the relationship between the factors that affect the parameter. Regression technique is used when the factors considered are few. Linear regression is technique used to find the relationship between different variables. The relationship found between two variables tested is called the simple linear regression while if it is found between more than two variables, it is called multi variable linear regression. Once the relationship is established between the variables, it can easily be projected to produce the forecast for that variable given the factors remain constant. Reddy et al [9] carried out a study to forecast the short term load demand for Rajiv Gandhi University of Knowledge Technologies-AP (RGUKT R. K) valley substation. Data was collected 30minutes every day for a month. The only known data was the load data collected and a linear regression technique was applied to forecast the load. To confirm the accuracy of the results, the performance was checked with least square error (LSE) method and mean squared error (MSE). The results obtained gave an LSE error of 132.4821 and an MSE error of 6.0219. Also root mean square error (RMSE) technique and mean absolute percentage error (MAPE) gave an error resulting in 2.453 and 0.029 respectively. Ade-ikuesan et al [10] explored the use of regression analysis to forecast the yearly consumption of electricity in Ogun state. Data was collected between 2016 and 2017 for the purpose of this research. The independent variable used was population and this data was also collected for the year in view. A Malthusian population growth equation was used to model the population growth for the work. The forecast range was for 10 years (2019-2028). The result obtained showed a linear increase between the variables, 3.5% increase was recorded over the range of forecast (10years). The forecasted value for the energy consumed in Ogun state at the end of the forecast period stood at 1,365,024MWh which is a 53% increase from the start of the forecast. The error derived for energy demand forecast stood at 5.98%.

Multiple regressions are used when the factors affecting main parameter being forecasted are many. The factors include weather, GDP, price of electricity and economic growth. Multiple regression uses the least square estimation. The least square method is a mathematical method which is used to determine the line of best fit in a data set thereby providing visually the relationship between data-points. This method is used to predict the way dependent variables behave and provides the rationale for the placement of the best fit lines among data-points. Ozveren and King [11] carried out a study to investigate short term demand forecast for South Sulawesi island in Indonesia. They applied the multiple linear regression method. Data was acquired during the rainy season and the dry season for the purpose of this study. The result obtained during the study contained several components of error. Modelling error introduced during regression, error caused by system disturbances and error of temperature forecast. The model was observed to be very sensitive to temperature change whereby a small change in temperature caused a significant change in load prediction. The results obtained from the mean average percentage error were 3.52% for dry season and 4.34% for the rainy season. Vasquez et al [12] worked on the forecasting the energy consumption of Puerto prices, a distribution system for the year 2019-2028 using multi linear regression.

The variables for this study were peak demand and number of customers. Load demand data was collected from the utility for a period of 10 years between 2014 – 2018.The results of the energy forecast in 2028 were projected at 566,078,019.1kWh. The regression results had an error performance of 0.995 and 0.991 with the mean average percentage error of 0.74% showing that the model developed is a good fit for the data set. Saravanan et al [13] studied the electricity demand forecast for India using regression analysis using artificial neural network and regression analysis with principle components. The forecast was done for a period of 19 years starting from 2012 to 2030. The input variables selected were amount of CO_2emission, population, per capita GDP, per capita gross national income, gross domestic savings, consumer price index, whole sale price index, imports, exports, per capita power consumption. The technique used combines statistical and artificial technique. Root mean square error (RMSE), mean absolute percentage error (MAPE) and mean bias error (MBE) were used to measure the accuracy of the results obtained from the forecast. The result obtained from the forecast showed that the artificial neural network with principal components (PC-ANN) had the most accurate forecast. MAPE for the PC-ANN resulted in 0.430% compared to 0.597% for Principal component regression (PCR) and 0.969% for regression analysis. The use of ANN gave more precise results compared to multi linear regression and PCR. The research concluded that PC-ANN approach was a suitable and accurate method for forecasting.

A time series data is a sequence of data collected in the order of time. It typically consists of data points measurements collected from the same source at an interval which is used to track changes of the particular data point over time. This data point can be analyzed using regression methods to find a pattern or relationship with other variables. Exponential smoothing is a method whereby dependent data is modelled based on previous data and then the model is used to predict the future. Exponential Smoothing is used for smoothing time series data using the exponential window function. This is done by using an exponential smoothing calculation which is called a smoothing factor. In this method exponentially decreasing weights are applied over time. It can be easily applied for determining forecast using previous assumptions. Exponential smoothing is a time series methods and it arises from monitoring industrial processes or tracking data. the data points taken over time in a time series method over time have an internal structure such as autocorrelation trend or seasonal variation. Exponential smoothing is based on times series and it takes into consideration the history of consumption so as to find a pattern in the past that is similar to present curves. This technique applies exponentially decreasing weights from recent observations to older observations. This will generate smoothed values which will be used to obtain the estimates. There are different exponential smoothing types which are the first order, second order, higher order exponential smoothing and the holts-winters mechanism [14]**.** Bindiu et al [15]carried out a study on a fittings manufacturer in Cluj-Napoca. The aim of the study was to carry out day ahead load forecast using the Holt-Winters method. The data was collected for about 4 months and then the forecast was done for a week. They argued that if the time series is stationary and the trend is similar to the past with little variance in time then exponential smoothing can be used instead of other more sophisticated methods that could easily introduce errors. The study modelled the load forecast of an industrial costumer who has a pretty fixed operation cycle therefore the load consumption is repeated and almost similar with historical data. The result was tested for accuracy using MSE and MAPE technique and it showed the MSE had better values within the acceptable limit but the MAPE had values which were too large or outside the acceptable range. From the result of the MAPE, the forecast carried out was not accurate enough to be depended on for a forecast. Contreras-Salinas and Rodrigeuz [16]applied the Holt’s method to forecast electricity demand in Colombia. Other parameters were also factored in in calculating the forecast. These are energy consumption, per capita GDP, purchasing power parity which they considered directly affects the behavior of the energy demand. Data was collected from the national interconnected system (SIN) and World bank to carry out the study for a period of 10 years spanning 2007 - 2017. Using the Holt’s method, a forecast for a period of 2018, 2019 and 2020 was done. The results obtained showed an increase in energy consumption grew slightly from 66,231GWk to 66,885GWK if the per capita remains in the range of 14880 to 15525.

Regression analysis is a set of methods means by which relationship between a dependent variable and an independent variable is estimated. Least square method is a type of regression analysis whereby a best fitting curve or line is found for a set of data points. By finding the relationship between the both variables, a trend of outcome can be estimated. Iterative reweighted least square (IRLS) method is also a type of regression analysis which makes use of an algorithm to carry out the forecast using weighted least square calculations. The algorithm is easy to implement because it makes use of standard regression procedures and a statistical package with command language can easily be used to implement it.

IRLS is a description of a computational algorithm whereby weighted least square regression steps are repeated with weights and possibly the dependent variable is recalculated each after each cycle. The data which is used for carrying out these studies are usually obtained from different sources. The inputs as we will see in artificial neural network is very key to the precision of the forecast. Therefore it will be an advantage to test the relations between data sets before using them in carrying out regression analysis or other type of modelling. Two methods of testing for correlation between time series data sets are granger causality test and cointegration analysis. These methods can be used to test the relationship between time series variables to ascertain how much they are related. Granger causality tests if one variable in the linear relation is dependent compared to another variable which is independent, if the relationship is unidirectional or bidirectional or if there is no relationship at all. While cointegration analysis examines the causal relationships among variables by checking if the trends in a group of variables are shared by the series [17]. Erdogdu [18] carried out a study on electricity demand in turkey. The study applied cointegration analysis and autoregressive integrated moving average modelling to carrying out a electricity demand estimation and forecast. Data on quarterly time series of electricity prices, GDP per capita and net electricity consumption per capita was acquired for this study from the international energy agency (IEA) and other energy organizations in Turkey. Cointegration analysis was used to analyse the properties of the data acquired for the study to ascertain the relationship between the time series data set. Combining cointegration analysis with autoregressive integrated moving average method is to ensure the result of the forecast obbtained is more accurate since the relationship between the data sets can be established before the model is developed. Autoregressive integrated moving average modelling was used in modeling future electricity demand and the results obtained were compared with the official projections in turkey. The results of the forecast revealed that there is an electricity demand growth in the years 2005 to 2014 with an annual rate of 3.3%. The results also revealed that customers response to price of electricity and changes in income is limited. Also the country's official electricity demand projections is grossly overestimated. This can affect the development of energy policies in the country which in turn can affect the electricity market.

Autoregressive integrated moving average method is a statistical analysis model which is used to analyse time series data to better understand the data set and predict the future by using the past values. A grey theory is a method which is used to construct a model where there are limited samples in order to provide a better forecasting advantage. Bilal [19] carried out a study to estimate the future electricity demand in Turkey. The purpose of the study was to forecast the forecast the electricity demand using Autoregressive integrated moving average (ARIMA)and grey models and compare the results with each other. The study also used models of analysis of energy demand (MAED) acquired from 1970 to 2013 to compare the results obtained. MAED models are used to evaluate future energy demand using medium and long term scenerios of socio-economic, technological and demographic factors that can affect demand. The results obtained from the MAED, Autoregressive integrated moving average (ARIMA) and Grey prediction (GP) models showed were compared by their estimated error to show the most accurate of them . Actual data was also used to compare with thte results obtained for a period of 2006 to 2013. Autoregressive integrated moving average (ARIMA) and Grey prediction (GP) forecasts showed an error of 4.9% and 5.6% compared to the MAED which was at 14.8%. The study concluded that the Autoregressive integrated moving average (ARIMA) and Grey prediction models gave more accurate results and are recommended for long term forecasts. SARIMA model (seasonal auto regressive integrated moving average) was used to forecast electricity demand in western region of Ghana by Andoh et al [20]. The study was focused on evluating the effectiveness of the SARIMA model in forecasting the electtricity demand within the region. Monthly electricity consumption was recorded by consumers in the region between january 2008 to December 2013. The results obtained from the forecast produced reliable results with a confidence level of 95%. While forcasting is a great tool for energy management, maintenance schedulling and investment planning, its result can be affected by other factors apart from the historical data which is inputed in the model. Mirasgedis, et al., [21]modelled electricity demand forecasting in greece using two multiple regression models incorporating autoregressive structures. Electricity demand was linked directly with climatic conditions, economy, and seasonal patterns. The models derived showed a high accuracy forecast for a period over 1-year as long as reasonable weather forcast is available. The error obtained from the yearly and monthly models were 4.6% and 2.8**%.**

Energy demand forecasting is a very useful tool in sizing electricity projects. Selecting the methods which will be applied in carrying out the forecast is also as important as the results. This is so because different approaches are suitable for different needs. Mirasgedis, et al.,[21] carried out forecasting from the time series of electricity demand in the past decade in Greece. Two statistical models were developed to provide a daily and monthly forecast for a period of 12 months. Their work considered meteorological factors like relative humidity and temperature changes in days. Data used was collected between 1993 and 2002 for the purpose of this research. The method used in this work was multiple regression models to develop the two models. Autoregressive structures were introduced to reduce serial correlation which affects the estimated effects the impact of meteorological parameters on electricity demand. Both models showed a high predictive value with an accuracy of above 96%. The two models were also used to predict the electricity demand in 2003 under different meteorological scenarios. The result showed that there would be an increase of 3.9% electricity demand from the previous year if the meteorological scenarios come to pass. Bianco et al[22] forecasted the electricity consumption in Italy up to 2030 using regression models. Different multi regression models were developed for this study and the variables- historical electricity consumption, gross domestic product (GDP), gross domestic product per capita (GDP per capita) and population were used for the forecast. Data was collected for electricity consumption within a period of 1970 – 2007 and this data was categorized in terms of usage. Population data and other information meant for this study were collected from the relevant institutions. Root mean square error analysis was used to calculate the accuracy of the models developed. The results from the regression models revealed that there would be an increase in electricity consumption in Italy at a rate of 2% every year.

Supapoet al [23]carried out a similar study to forecast the electricity demand for Aborlan-Narra-Quezon distribution grid in Palawan spanning a period of 10 years using multiple linear regression. They used actual historical data from the utility company, customer population for a period of 5 years, the development plans etc. The models developed were measured for accuracy using mean average percentage (MAPE). A MAPE result of less than 5% shows an acceptable result. The result obtained showed a MAPE of 2.26% which is a good one. Citroen et al [24] conducted a study on the long term electricity demand forecasting for Morocco. Autoregressive moving average was applied to carry out the forecast. The variables considered for the electricity demand model were electricity demand as the dependent variable, economic and social parameters like GDP, population, urbanization rate, electricity prices etc. were used as independent variables. Autoregressive moving average was selected to conduct this study because it is simple to use and accurate. This method also provides information of how various factors affect the dependent variable (electricity demand). Autocorrelation is a function of the autoregressive moving average which tells how much correlation or interdependence exist between neighboring data points in a time series. GDP, demography, net annual electricity consumption data were collected from a period of 1971 to 2012 for the time series model. Statistical tests carried out on the model developed showed that the model was accurate. The electricity demand forecast showed a continuous annual growth of 5.28% from 32TWH in 2012 to 62TWH in 2025.

Aslan and Yavasca [25] carried out forecast peak demand of electricity in the city of Kutahya using various approaches to propose the most suitable method. Five methods were used to model the system namely; simple linear regression, multiple regression, quadratic regression, exponential regression and artificial neural network. Peak load data was acquired for a period of 2000-2007 for this study and the data collected in 2008 was used to validate the models. The study showed that ANN approach produced a more accurate result when compared with the other methods. However, the study also concluded that with the use of more data, the error reduces. Using different methods to carry out electricity demand forecasting and comparing helps with getting the most accurate methods to be applied given the available data and the nature of the forecast to be conducted. Nalcaci et al [26]used forecasting models based on multivariate adaptive regression splines (MARS), artificial neural network and linear regression methods to develop the electrical load model of Turkish electricity distribution network. Load data and weather data were obtained from the relevant authorities to carry out the long term load forecast in this study. The weather data collected consist of wind, humidity and temperature information as well as the hourly load data and this data was collected for a period of 5 years. The data collected for a period of 2 years (2011 – 2013) was applied to train the model while the data from 2013 to 2015 was used to test the model to check its accuracy. Four methods were used to test the models for accuracy – mean absolute percentage error, multiple coefficients of determination, average absolute error and root mean squared error and correlation coefficient methods. According to the tests carried out on the models, the results from multiple coefficients of determination revealed multivariate adaptive regression lines had the most accurate result. Other test methods collaborated with the result given by multiple coefficients of determination. The R-value of MARS as revealed during the test for accuracy using correlation coefficient is also higher than the other methods applied. Using MAPE to check the accuracy, MARS method resulted in 0.040, while ANN was 0.045 and LR gave 0.047. The study therefore concluded that MARS had the most accurate result and it can be used for short term, medium term and long term electricity forecast. Regression analysis methods can also be used for medium term load forecast. Samuel et al[27] applied linear regression model, compound growth model and cubic regression model to forecast the medium term load demand forecast of Covenant University located in Nigeria. Data was collected on an hourly basis for a period of one year spanning from January 2012 – January 2013. The models were tested for accuracy using MAPE and RMSE, the linear model resulted in a MAPE of . The results from the test conducted produced results which were out of the range for accuracy meaning the models cannot be relied on for forecast.

MODIFIED FORECASTING TECHNIQUES : Modified forecasting techniques are traditional forecasting techniques which have been modified to automatically correct parameters in forecasting models in a dynamic environmental condition. Examples of these techniques include adaptive load forecasting method, support vector machine based techniques and stochastic time series method. Setiawan et al [28] carried out a study on forecasting the very short electricity demand using support vector regression (SVR). SVR was used to predict the electricity demand every 5 minutes based on the data collected from the Australian electricity operator, National Electricity Market Management Company Limited (NEMMCO) for a period of 2 years. Support vector regression is a type of Support Vector Machine algorithm which is used for forecasting. It uses optimization method to find the maximum margin hyper plane between different sets of data. The decision boundary is defined by a set of data which are called the support vector. Back propagation neural network which is a common forecasting method used by industry forecaster was compared with this method. Also simple linear regression and least mean square methods were also used. The result obtained revealed that the support vector method was more promising than the other forecasting methods which were compared with it. Support vector machine was applied by Kaynar et al [29] to forecasting the electricity demand for Turkey. Turkey is a country that depends on other nations for its energy supply which means any external political or economic forces can affect the energy supply chain positively or negatively and this can affect the stability of the country. This instability directly affects electricity demand. Turkey has an expected annual growth of 1.6% and this directly affects the economic growth. Also, since turkey imports energy resources to meet its energy needs, it was important to consider import and export while carrying out the forecast. The study was done using data from electricity consumption, population, import and export data ad GDP collected for the period of 1975-2014. 60% of the data collected was used to train the algorithm while 40% was used to test it. The study also applied chaotic particle swarm optimization algorithm to determine the parameters used by SVR to improve its accuracy. Chaotic particle swarm optimization (CPSO) technique is a computational method which solves a problem optimally by iteratively attempting to improve a candidate solution with respect to a given standard. It is basically an optimization technique which contributes to a solution by ensuring it provides the best possible solution. Combining both SVR and chaotic method was found to provide a simple and effective forecast while improving the accuracy and quality of the forecast in many studies. The result from their study proved that the combination of SVR method and CPSO was very effective giving an error performance of 1.46%. They concluded that this method can be used as an alternative to traditional regression and artificial neural networks.

Further study on support vector machine was carried out by Kichonge et al [30] on energy demand in Tanzania. They applied Pearson VII universal kernel (PUKF-SVR) which was proposed by Karl Pearson in 1895. This method is a special case distribution which was proposed noting that all distributions do not resemble the normal distribution. Kernel based algorithm was included to transform the data to a higher dimension. This will enable the problem to be solved as if the feature space was linear separable. Annual data was collected for a period spanning 1990 – 2011. The dataset collected included population, GDP, per capita energy consumption, total energy supply, gross national income per capita, electricity generation and emission data. Three variables; economic, energy and environment were selected as the indicators of the study. This selection was made to determine the influence of these indicators on the forecasting of energy demand in Tanzania. The study compared the result from the PUKF-SVR with normalized polynomial-SVR, polynomial –SVR and RBF-SVR to ascertain the most accurate method. Root mean squared error(RMSE), correlation coefficient (CC), mean absolute error (MAE), root relative squared error (RRSE) and relative absolute error (RAE) were the performance indices used to evaluate the estimating capabilities of all the methods tested. The results obtained showed that polynomial – SVR had the most accurate forecast.

A study was carried out to compare different regression techniques used in forecasting electricity demand in Queensland, Austrialia. Mohanad et al [31] used Multivariate adaptive regression spline (MARS), support vector regression (SVR) and autoregressive integrated moving average(ARIMA) to carry out the study. Half hour electricty data was acquired for a period between january 2012 to decemeber 2012 for the purpose of the study from the countries energy market operators. Partial correllation data was applied to the historical data to prepare the data for the MARS and SVR models while single input historical data was used to develop the ARIMA model. The data acquired were divided into two parts; the first part which is 80% was used for training the model while the remaining 20% was used for testing the model. The results obtained was tested for error using root mean square and mean absolute error and pearson product moment correlation coefficient. The results obtained showed that for the half hour and one hour short term forecast, the MARS model performed better than the other models while for the daily (24 hours) forecast, the SVR model performed better than the MARS and ARIMA models. The study concluded that the MARS and SVR model were more suitable for short term forecasting of electricity demand given the set of data used. Hong [32]proposed the use of support vector regression to forecast the Taiwan regional electricity load. The SVR model is combined with the novel immune algorith (IA) to determine three parameters in the SVR model. Support vector machines was initally proposed by Vapnik [33]. Support vector machines (SVM) solve classification problems by transforming them to convex optimization problems. SVM is transformed to SVR by introducing a region around the function called the an *e-tube* [34]. Immune algorithm was proposed by Mori et al [35]. Immune algorithm is deisgned to mimick the learning mechanism of the natural imune system. Immune Algorthim (IA) immitates the behaviour of our observed immune functions, principles and mechanisms to solve complex optimization problems.Combining both the support vector machines (SVM) and Immune algorithm (IA) produced the support vector regression immune algorithm(SVRIA) methodmethod being proposed. The performance of the SVRIA forecasting method was compared with three other methods; SVM model with genetic algorithm (SVGM), Artificial neural network (ANN) and regression models. MAPE was used to measure the performance of different forecasting results obtained from the methods used in this study. The result showed that the SVRIA model performed beter than the other models.

Adaptive demand forecasting is another forecasting method. Adaptive demand forecasting is a method whereby model parameters are automatically updated with the changing load conditions. Demand forecasting is adaptive in nature as conditions normally change in real life. In this method, the next state vector is estimated by using the current prediction error and the current weather data from acquisition projects. The statevector is determined by analyzing the historical data gotten. Load demand forecasting using time series stochastic method was used by Salah et al [36] to forecast the electricity demand in Libya. Time series method is a type of quantitative forecasting method. The other type of quantitative forecasting methods is the associative models. The time series method use past data patterns and attempts to predict the future while associative models assume that the variable being forecasted has a relationship with other variables and tries to forecast using the relationships. Time series is further divided into two types namely deterministic and stochastic time series. Data was collected for the work from 2000-2010. To carry out the study, ARIMA model was identified by creating a time series plot on a Cartesian coordinate and analyzing it if there is a stationary mean and variance or not. The model was tested for accuracy using MSE. The time series forecast revealed that there will be continuous growth of demand of oil and electricity which will lead to an increase in cost of energy due to rapid population growth. The results were used to provide information for an alternative policy option in their market.

Nogales, et al [37] used two-time series methods (dynamic regression and transfer function models) to forecast the electricity demand. The study proposed the use of these two time-series methods in forecasting the next day pricing for the electricity market in Spain and California. The data used for the forecast was collected between June 1st 2000 to august 20th 2000 and this data was used to forecast and validate the period selected (21st to 27th of august and November 13th to 19th, 2000). The same was done for the California electricity market; data was collected from January 1, 2000 to April 2, 2000 to forecast and validate the period selected for the study. The results of the forecast for the Spanish and California market was obtained as approximately 5% and 3% respectively for the weeks studied. The error shows that the forecast can be used since they fall within the acceptable range. There were some observations made from the forecast of the Spanish market; The Spanish market had a higher proportion of outliers and it also showed high dispersion which led to the conclusion that the Spanish market was less predictable and less accurate. Support vector method has shown greater promise when combined with other methods. Hong et al [38] used support vector regression with seasonal adjustment mechanism (SSVRCIA) combined with immune algorithm to carry out the monthly load forecast. Chaotic immune algorithm is modelled after the biological immune mechanism using mathematics and combines chaos operators with immune algorithm. The concept of immune algorithm is new. It learns from the concept of immunity in life science [39]. They considered the seasonal component of electric energy demand caused by seasonal fluctuations. A new method combining support vector regression (SVR) and hybrid chaotic immune algorithm (CIA) was proposed by Hong et al[40] to forecast the seasonal load demand. This method known as the support vector regression with hybrid chiaotic immune algorithm (SSVRCIA)was applied to investigate its application in forecasting electric load. The results from the SSVRCIA method were compared with some other methods e.g. ARIMA and e-insensitive loss function support vector regress - TF-ε-SVR-SA and SVRCIA method. An analysis of all the methods used showed that the SSVRCIA method performed better than all the other methods used in the study. SSVRCIA method resulted in a mean absolute percentage error (MAPE) of 1.766% and it was had the leasy error when compared to the other methods. Azad et al [41] carried out a study on predicting the future peak load demand based on historical data. Support vector regression was selected for predicting the peak load demand due to its structural risk minimization principle that minimizes the upper bound of the generalization errors [42]. The study was conducted by collecting the temperature and relative humidity for three consecutive years (between 2014 to 2016) in the city of Sharjah, UAE. UAE has moderate winter and very hot summer seasons. The hot summers leads to a surge in electricity demand due to high power consumption for air conditioning units. This weather condition affects the electricity demand as such it is very important during a forecast. The data collected in the first 2 years was used in training the SVM while the data of 2016 was used to test the model by comparing with the actual peak load demand in order to verify the accuracy of the model. SVR produced an excellent result for both the electricity demand weekend data and seasonal data applied. To further verify the accuracy of support vector machines(SVM), Mohandes [43] applied support vector machines to short term load forecasting and compared the result with autoregressive (AR) modelling. The results from the SVM and AR were tested using root mean square error (RMSE). SVM produced 0.0215 while the AR model was 0.0376. Abbas and Arif [44]utilized support vector machines optimized by genetic algorithm to forecast daily peak load long range demand. The load demand data was collected every half hour for this study was for a period from January 1997 to December 1998and also the daily temperature data was collected for the same period. Data collected from the period of January 1997 to December 1997, and February 1998 to December 1998 was used for training. The proposed algorithm emerged as the best model when compared to other methods.

Deng and Jirutitijaroen [45]used two-time series methods; multiplicative decomposition and the seasonal ARIMA model to forecast the short term electricity demand for Singapore. The multiplicative decomposition data has a mathematical expression with a cyclic component which is applied for long term forecast. Since range of the forecast is a short term , the expression is modified for this study to exclude the cyclic component. The results obtained from the forecast showed that the decomposition model is more accurate than the seasonal ARIMA model. The lowest value from the forecast using MAPE was 0.761% for the multiplicative decomposition method while 4.8045% for the seasonal ARIMA method. Sigauke and Chikobvu [46] applied time series regression to carry out a short term forecast of South African electricity demand. Data was acquired for a period of 10 years between 2000 to 2010 for this study. The study evaluated the effect of temperature on the peak electricity demand. Three different time series regression models were applied to the data in this study. The results revealed that the time series model with the temperatures included through regression splines performed better than the model which used heating and cooling degree days. Taylor et al[47]carried out a research to find the univariate forecast using half hourly data in England and Wales. Electricity load data collected at half-hourly basis would reveal more than one pattern. Within a 24hour cycle, there would be peak demands due to the time of the day, ambient fluctuations due to weather etc. The work conducted proposed the use of multiplicative seasonal ARIMA model and double seasonal holt-winters exponential smoothing method which are able to capture within day and within week seasonal influences on load demand. The multiplicative seasonal ARIMA model can be modified to accommodate three or more patterns by introducing additional polynomial functions. The Holt-Winters method is applied where there are two or more seasonal patterns in the time series. The proposed multiplicative seasonal ARIMA method outperformed the standard Holt-Winters method for forecasting. Double seasonal Holts-Winters method also outperformed the standard holt-winters methods as observed by the results obtained.

Soft Computing Technique : Soft computing technique is a new technique which is used to mimic the ability of a human mind to reason out and learn when placed in an environment of uncertainty. They are usually applied when the system which is to be forecasted is uncertain and very hard to model precisely. Soft computing forecasting techniques include fuzzy logic, neural networks, and evolutionary algorithms like genetic algorithm. Ashigwuikeet al, [48]compared artificial neural network with multiple regression technique. They carried out the study using data of monthly load from Abuja municipal area council, Nigeria. Data was obtained from 2012 to 2018 from the Abuja electricity distribution company for this study. Average growth rate was extrapolated from the world population site to calculate the average population for the year 2018 to 2020 in Abuja. In addition to the population, ambient temperature was collected from 2012 to 2018 for this study. The results of the forecast obtained were tested with MAPE and R-value deviation for accuracy. The results obtained for the artificial neural network showed an average of 0.00197 error when applying mean absolute percentage error calculation (MAPE) and the multiple linear regression had a value of 0.004545. For R-value deviation, ANN was 8.06% while multi linear regression (MLR) was 34.42%.

Artificial neural network (ANN) is a fascinating new field. It is a replication of the human brain and has the ability to learn new things, adapt to new environment and situations. Using ANN for forecasting is one of the many applications of the method which has gained much acceptance in recent years. An artificial neural network consists of nodes or processing units called neutrons. Each neutron has a function attached to it. Some advantages of ANN are that it is adaptive, it is self-tolerant and it can accommodate fault. ANN was applied by Akarslan and Hocaoglu [49] to carry out a short term electricity demand forecast of a campus area. Data was colledcted from the ANS-campus for a period of one year (2015) to train the ANN while the data collected for the first six months of 2016 was used to test the model. The neural network design has three inputs which include the time information hour, the actual consumption and the season. These factors are very inportant in the forecasting in short term. The ANN obtained satisfactory result in the forecast. They also concluded that increasing the input parameters increased the accuracy of the results of the ANN. The more the inputs into the ANN, the more accurate the forecast obtained. Çunkaş and Altun [50] developed an ANN model using multiple inputs. They modelled their networks using two types of structures namely the recurrent neural network(RNN) and the back propagation (BP) neural network structure. The RNN structure contains loop which help it to retain the influence of information inputed while the BP is a simple and effective structure containing 3 layers – input, hidden and output layers. The results from the two ANN structures used to forecast the system were compared to obtain the best results. The RNN model produced the best result. It was also observed that the past and present economic situations were key inputs in the forecast showing that the changes in the electricity demand was tied to the economic situation of the country. The recurrent neural network (RNN) model produced an error of 0.77% while back propagation (BP) produced an error of 1.53%. Both models developed showed a error less than 2.5%. Increasing the inputs into the artificial neural network has been shown to increase the accuracy of the forecast. Other ways to increase the accuracy have been explored by other researcher in the field of forecast.

Fuzzy logic is also widely used in carrying out forecasting. It is a method whereby multiple possible truth values are processed through the same vairable. It relates the highly nonlinear relationsheip between factors like weather and how thy affect the load variations within a period in the year. Ali et al [51] considered temperature and humidity as inputs to a fuzzy logic model whereby the output was load while carrying out long term forecast for an area in adamawa state in Nigeria. Data was acquired for weather and power consumption for the area within the period in view. The result of the forecast showed an error of 6.9%. To have a better understanding of the Nigerian electricity demand trends, Idoniboyeobu et al [52] carried out a forecast using exponential regression model. The forecast was projected for a period of 20 years (2013 to 2032). To carry out this study, data was collected from 2000 to 2012 from Nigerian Bureau of statistics and the Central Bank of Nigeria. Modified exponential tehcnique was used to develop the model describing the relationship between different parameters; capacity allocation and capacity utilization. Other methods used in this study to compare with exponential regression model are least square method, modified exponential regression model. The results obtained showed the projected energy demand 20 years into the future in Nigeria to be 395,870MW.

Fuzzy logic and artificial neural network were used in forecasting the long term electric load forecast for the Nigerian Transmission Grid by Melodi et al [53]. Monthly data of the electricity grid was recorded within a period of 2000 to 2014. The data obtained was applied to create an artificial neural network and fuzzy logic forecasting algotrithm. The result for a period of 15 years was obtained and it showed 7853MW and 8189MW for the fuzzy logic and artificial neural network respectively for the year 2029. The forecasting accuracy was calculated using absolute and mean absolute percentage errors. The results for mean absolute percentahe errors showed a 0.45% and 2.4 percent accuracy for the artificial neural network and fuzzy logic algotrithm respectively. Both techniques returned values which are within the tolerance range which **should not**exceed 2% to 3%. The artificial neural network gave a more accurate value than the fuzzy logic. Kandananond [54] carried out electricity forecast in Thailand using different methods. This work compared the results obtained from different forecasting methods to show the method which had the most accurate forecast. The methods used to model the electricity demand were; autoregressive integrated moving average, artificial neural network and multiple linear regression. Historical data was used in carrying out the modelling considering some factors like GDP, stock index, revenue from export etc. The historical data obtained were from 1986 to 2010. The results obtained showed that the ANN method had the highest accuracy when measured giving mean absolute percentage error (0.996%) compared to the ARIMA and MLR methods. However, further comparisons carried out showed other methods have the advantage of having simpler structure and competitive performance when compared to ANN.

In a derregulated power environment, forecasting is a very important tool in ensuring electricity demand is met. It would help with providing a bigger picture of the power needs in the future which will in turn inform the decisions for executing power projects. An approach to forecast the energy demand in a Spanish Peninsula was carried out by González-Romera et al [55]. The approach focused on spliting the monthly electricity demand time series into two series (the trend and the flunctuations around it) and the two series were forecasted seperately using neural networks. Both forecasting were then combined to make up the overall forecast. Moving averages and smoothing splines were used in seperating the demand time series. Artificial Neural Netwerks were used in forecasting the consumption trend and the flunctuations trend obtained from the demand time series. After forecasting both trends, they were combined to obtain the consumption trend. The result obtained showed that extracting the trend improved the accuracy of the forecast when compared with forecasting the demand using a single network. For a more accurate prediction, it is recommended to follow this approach. Energy demand forecasting can also be carried out by combining methods.González-Romera et al [56] carried out energy demand forecasting using neural networks and fourier series. In this approach, the periodic behaviour is forecasted with the fourier series, while the trend is forecasted by neural networks. Combining both methods in the forecast provided a more accurate result and lower than 2% MAPE . This approach using nueral network and fourier series provided a simpler structure compared to the approach used by González-Romera et al [55].

Research has been ongoing for years to find other forecasting methods which are accurate and easier to compute. One of such method is the grey theory method. Grey theory is a method which can be used to construct a model having limited samples. It is best applied where there are incertainty and it is applied to reduce this uncertainty by using the initial data to carry out a mathematical model. The model forms a differential equation and it is based on the grey number [57]. It is used for power system load forecasting especially with fewer amount of data available. Electricity demand forecasting using the grey method in Turkey was carried out by Akay et al[58]. Turkey's electricity consumption has been chaotic and non linear due to uncertain economic structure of the country. The grey method was used due to its ability to use less data and high accuracy. Data acquired were the annual industrial consumption in Turkey and the total electricity consumption from 1974 to 2004. The results obtained were accurate and showed a 50% increase in electricity consumption between 2006 to 2015. Pi et al [59] used the grey model to forecast the electricity demand in China. They combined the grey model approach with 3 points average technique to improve the results which was obtained. Data was sourced from the national bureau of statistics of China for the period of 1985 – 1989 to carry out their work. Also they collected data for the period of 1990 – 2006 for testing of the model to compare the results obtained in their work to ascertain the error in forecasting. The forecast was further projected from 2007 to 2015. The results obtained showed that the grey method combined with 3 points averaging technique produced more accurate data with lower error rate. Also the forecast revealed that the electricty demand will increase by about 190% within the period. They also carried out energy demand forecast for the period to show the increase in demand for energy resources within the period.

Hamzacebi and Huseyin [60] investigated the use of optimized grey modeling in forecasting the total electricity demand of Turkey. Grey model was used to predict the electricity consumption of Turkey. Some parameters of the grey model were further optimized to produce an improved forecast. The study posits that an optimized grey model will produce a more accurate forecast. The optimized grey model was applied in both direct and iterative methods. The data used for this study was obtained from the Turkish statistical institute (TUIK) for a period spanning from 1945 to 2010. Data collected frrom 1945 to 2005 was used as the modelling data while 2006 to 2010 was used as the test data for the study. The model was then used to forecast the electric energy demand in Turkey for a period of 2013 to 2015. From the result obtained, it was deduced thatoptimized grey modelling direct forecasting produces a better result than the iterative forecasting approach. The performance of the forecast was measured using three methods; mean absolute error, mean absolute percentage error and post error ratio (C). Hsu and Lin [61] stated that if the value of MAPE is less tha 10%, then the forecast was successful. The direct grey model performs better than the iterative forecasting approach because the direct approach makes use of real past data for forecasting long terrm while the iterative approach uses the predicted values as input. The direct approach had a MAPE of 3.2% which is lower than the iterative approach having 5.36%.

Kartikasari and Prayogi [62] presented a study which compared three time series models to ascertain the most accurate amongst the series. The study predicted the electricity demand in indonesia using three different time series models, namely: double moving average, grey model and holts exponential smoothing models. Time series model is mostly prefered when there is sufficient data for modeling. In situations whereby data is limited, double moving average, grey model and Holts exponential model are best suited to develop the model and forecast. Moving average is used to smoothing the past historical data while exponential smoothing uses exponential weighted smoother for smoothening the data used for the model. The results from the three methods were compared using MAE, MSE and MAPE. Based on the results obtained, grey model resulted in the least error in MAE, MSE and MAPE. They concluded that grey model is the best model for predicting electricity demand in Indonesia. The markov model is a method which is used to model probabilities of different states and how they transit between them. It is a stochastic model that is used to model randomly changing systems [63]. The model is developed using just the current state and not events that occurred before it. Wang and Meng [64] combined the grey method and the markov method to forecast the total electricity consumption in Shanghai, China. Both the grey model and the grey combined with the markov model were applied using historical data from Shanghai from 1999 to 2004. The results obtained from the forecast carried out by Wang and Meng showed that the grey method combined with markov method resulted in a 99.46% accuracy year 2005 when compared to 92.06% accuracy obtained from using the grey model. From the results obtained, combining the grey model with the markov method increased the accuracy of the prediction.

Abdulsalama and Babatundea[65]carried out electricity forecast in Lagos state using artificial neural network while comparing the forecast with the actual data to ascertain the accuracy of the prediction. Data was obtained from National Population Commission, World Bank data base, and global temperature database for the period of 1971 to 2009 to develop the model. The data acquired consisted of the electricity consumption within the period, socio-economic factors like GDP, demographic factors and temperature readings. The data collected was processed for usage. The result from the forecast was similar to the actual data for the period forecasted.

Several factors affect the outcome of electricity demand forecasting. These factors are very important when carrying out a forecast because when they are considered, the results of the forecast are more accurate. Taylor et al.[66] considered the factor of weather in carrying out electricity forecast; they applied weather ensemble method to forecast. An ensemble prediction makes use of multiple members. In their case they considered 51 members each having a different scenario of the future value of the weather variable. The ensemble considers the degree of uncertainty of the weather variable in the model. The result obtained from the work showed that taking the average of the scenarios produced a more accurate result. Combining different methods with traditional forecasting methods have been shown to improve the accuracy of the forecast. Chang et al[67] developed a weighted evolving fuzzy neural network to carry out the demand forecast in Taiwan. Data was collected for a period of 1997 to 2006 which was used to develop the time series. Evolving fuzzy neural network framework (EFuNN) was modified to include a weighted factor. Also they included an exponential transfer function which was used to transfer the distance of any two factors to similar values in different rules. The weighted evolving fuzzy neural network (WEFuNN) which is being used applies a weighted factor to evaluate the importance of each factor. This method uses a five-layer network whereby nodes and connections are created each by the data samples. They compared the WEFuNN method to evolving neural network (ENN) method to ascertain the accuracy of the method applied. Their result showed that the WEFuNN method was more accurate than the ENN method. Compared to the EFuNN where the same weight was attributed to each factor applied, the WEFuNN method also proved to be better since it allocated weights according to the degree of importance of the factor.

Al-Saba and El-Amin[68] applied artificial neural network in the long term forecasting of annual peak electricity for a Saudi electric utility. The electricity demand is influenced by crude oil production, humidity, high ambient temperature and other factors. The aim of their study was to compare the results obtained from the artificial neural network to time series models. The time series model developed for this study were auto regressive, autoregression integrated moving average and auto regressive moving average. An artificial neural network model was developed using peak load data from 1981 to 1996. This data was used to train the ANN afterwhich it was used to forecast the peak electricity demand for 1997 through 2006. A comparison of the error between the ANN forecast and the time series model showed that the ANN model has the lowest error among all the methods used. Hsu and Chen [69] proposed an improved grey theory which is a modification of the original gey theory developed by Deng [70]. Grey theory can model systems having poor data or whereby there is a lack of data. When using the grey theory, assumptions regarding the statistical distribution of data are not important. Deng [70] also developed a residual modification model whereby the difference between the real values and the forecasted values is defined as the residual series. The proposed improved grey theory by Hsu and Chen which solves the problem presented while using the residual modification model. When using the residual modification model, the residual series depends on multiple data points with same signs. The datapoints with same signs tends to be few when there are few observations causing the residual model not to be established. This study proposed the use of an artificial neural network for residual sign estimation while combining with the residual grey model forecaster which uses absolute values of the residual series. The forecast obtained from the grey model (GM), improved grey model and ARIMA model were compared to check the error each method had. The improved grey model had the least error. In conclusion, the modification of the grey model using ANN was beneficial and greatly reduced the model prediction errors.

Sulandar et al.[71]proposed a new method to forecast the short term electricity demand in Indonesia. Due to disimiliarities in the load data series, that is, load data series having linearities and non-linearities, this may pose a problem for the exponential smoothening method because exponential smoothening method cannot handle non-linearities.This hybrid method was proposed to solve this problem. The hybrid approach combines exponential smoothening and artificial neural network to improve the accuracy of the forecast. The expoential smoothening is used to identify the trends, seasonal and irregular components and other parameters before it is inputed to the artificial neural network where the non-linearities are captured in the data. The ANN model is then developed by using the trends; seasonal and irregular components as inputs into the model. Trigonometric seasonality, Box-Cox transformation ARMA errors, trend annd seasonal components (TBATS)was used to break down the load time series data into level, trend, seasonal and irregular components which were then used as inputs to the ANN model. TBATS is a forecasting methd which is used to model time series data. It is aimed at forecasting time series which have complex seasonal patterns using exponential smoothening method. The error in the methods were measured using root mean square errorand mean absolute percentage error. Comparing the error obtained from the hybrid TBATS-ANN method against TBATS, double seasonal holt-winter method (DSHW) and ANN method established that the hybrid method produced less error than the other methods. Using MAPE, TBATS-ANN resulted in an error of 0.8934% while ANN resulted in 0.9325%.The hybrid approach produced the best foresting performance.

Srinivasan [72] presented a study on a new method of modeling called the group method of handling data (GMDH) that is capable of forecasting energy demand for each of the end user consumption of the energy system in Asia. The end user consumption sector is made up of residential, indusjtial, non industrial, commercial, entertainement and lightening load. To carry out the forecast of monhtly energy demand, data was acquired from and electricity utility companyin Asia. The data contained energy consumption for the six categories of end users for a period of eight months. Six methods were used to carry out the forecast; multi-layer perceptron (MLP) neural network, group method of handling data, double moving average, single exponential smoothening, doubble exponential smoothening and ARMA. Mean absolute percentage error was used to evaluate the results of the forecast carried out on all the models which were developed using the six methods. The results of the MAPE showed that the GMDH results were significantly more accurate than the other methods used. The major advantage of the GMDH method is that it is more accurate and less labour intensive than other methods. Also, it enables the user to forecast individual groups of customers.

While it is very important to review other studies conducted, it is very necessary to have an idea of methods and techniques used to carry out these studies in different horizons. Different locations experience different challenges. Example of such challenges is lack of adequate data. These challenges directly affect the methods which will be most effective in carrying out electricity demand forecast in those areas. Mir, et al. [73] carried out a study to review the different electricity forecasting methodology which is used in different countries. The study analyzed 69 research articles from 16 countries. the frequently used methods in the articles analyzed were bottom-up models, top – down models, time series technique, regession analyses, Artificial intelligence based techniques and additive models. For long term load forecasting, demand determinants mostly used are gross domestic product (GDP), poulation, industrial development, previous growth data, consumer growth rate, energy intensity, income growth rate, electricity prices. For medium term load forecasting and short term load forecasting, weather vaiables and previous data were used. Mir, et al. [73] discovered that for long term and medium term load forecasting, time series was extensively used. Artificial inteligence techniques were mostly used for short term forecast. For the different ranges of forecast, long term load forecast (LTLF) used GDP, population and previous load data as demand determinant, medium term load forecast (MTLF) used GDP, Previous load and weather datawhile for short term load forecast (STLF), weather data and previous load were signifant.

In addition to the traditional methods of forecasting, other methods have been proposed to solve the gaps identified in studies carried out in the past. Electricity demand forecasting is dependent on several parameters. Due to the complex nature of the data sets, not all methods accurately model these non-linear data sets. Medium term system load forecasting was carried using dynamic neural network model (DAN2) [74]. This study proposes the use of dynamic artificial neural network architecture to carry out medium term load forecasting. The working philosophy of the dynamic neural network model is the principle of learning and accumulating knowledge. The model proposed uses the knowledge gained and propagates the knowledge forward in the next layer. This step is repeated until the desired performance criteria for the network is achieved. This makes the dynamic neural network model a purely feed-forward model. The sample data collected for this study were from the period of 1982 to 1996 which were used to develop and train the model while the data from 1997 was used to test the effectiveness of the model. The model developed using the DAN2 method was compared with MLR, ARIMA and Feed forward back propagation (FFBP)-based neural network system and the result showed that both the yearly and seasonal DAN2 models provided the most accurate results when checked using MAPE. The study also concluded that when yearly forecast is done, weather information improves forecasting accuracy greatly. Wen et al [75]used a deep learning model in forecasting the load demand for a residential building over a short and medium term period. The study proposed the use of deep recurrent neural network (DRNN) which incorporated gated recurrent unit to carry out the forecast. Gated recurrent unit (GRU) which is a variant of long short-term memory method is a novel, efficient based method which is proposed to solve the problem of vanishing or exploding gradient. The performance of the proposed model was measured using root mean square error, mean absolute error, Pearson correlation coefficient (PCC) and mean absolute percentage error. To carry out this study, data was obtained in one-hour intervals for a period spanning from January 1, 2017 to march 1st, 2018. The data collected were divided into two; data from January 1, 2017 to January 1, 2018 were used to train the model while the data from January 1, 2018 to march 1, 2018 were used to test the model. The proposed DRNN-GRU method was tested with other methods to compare its accuracy with the others. The proposed method resulted in the most accurate performance result which gave a MAPE of 3.504%. However, the study noted that the DRNN-GRU model assumes future weather data which could affect its accuracy.

Machine learning is the use of computer algorithms to solve problems which are capable of improving automatically through experience and by using data inputted into it. Deep learning is a sub field of machine learning which is inspired by the functioning and structure of the neural network of the human brain. Shirzadi et al [76]carried out a study to compare the electricity demand forecast using both machine learning methods and deep learning methods. Random forest, support vector machine, nonlinear autoregressive exogenous neural network (NARX) and artificial neural network were used in this study. Random forest is a learning technique that uses decision tree. This technique has simplicity of training and ease of interpreting results. Data was collected from the region of Bruce County in Ontario Canada for this study for the period of 2010 to 2019. Hourly weather data and hourly electricity consumption were collected for the period in view. The data collected revealed that the temperature followed a seasonal behavior. The electricity consumption behavior was observed to strongly correlate with the ambient temperature. From different models which were produced for this study, the results obtained from the accuracy test showed that NARX produced more accurate results than the other methods tested.

Some newer methods have been proposed which are hybrids and have proven to have better accuracy. A new approach for forecasting short term load demand was proposed [77]. Advanced wavelength Neural Network (AWNN) is a novel approach which breaks down the complex electricity load data into components having different frequencies which are then predicted separately. This method applies a wavelet decomposition method to find a set of optimal frequency components separately. The study used data from two countries (Australia and Spain) having different time resolutions. To measure predictive accuracy, MAE and MAPE were applied to the models which were used for comparison. The proposed method achieved a prediction error of 0.268% for MAPE (Australian Data) and 1.716% for Spanish data. The proposed method outperformed other methods compared with it. Dai et al [78]proposed a method which was used to forecast daily peak load. The method complete ensemble empirical mode decomposition with adaptive noise and support vector optimized by modified grey wolf optimization algorithm (CEEMDAN-MGWO-SVM) is a hybrid method. It applies the complete ensemble empirical mode decomposition with adaptive noise method to decompose the daily peak load sequence into sub sequences after-which the result is modeled with modified grey wolf optimization and support vector machine (MGWO-SVM) to forecast the sequences obtained from the first process. The results are then combined to get the forecast. The results from the proposed model were compared with ensemble empirical mode decomposition and support vector machine optimized by modified grey wolf optimization algorithm (EEMD-MGWO-SVM), support vector machine optimized by grey wolf optimization algorithm (MGWO-SVM), support vector machine optimized by grey wolf optimization algorithm (GWO-SVM), support vector machine (SVM) and BP neural network. For the work, data was collected for 92 days spanning between March and May 2017 from China state grid. Daily peak load, daily maximum temperature, daily minimum temperature, daily average temperature, daily average relative humidity, maximum daily wind speed and other data were collected for this study. Mean impact value was applied to the data collected to select the data which had the most influence on peak load. The performance of each of the methods were tested using mean average percentage error, non-linear function goodness of fit (R^2), Akanke information criterion (AIC) and Bayesian Information criterion (BIC). The results from the test revealed a MAPE of 0.2527% which was more accurate than all other methods tested. This shows the proposed method CEEMDAN- MGWO-SVM is fit for forecasting. Dudek [79]proposed the use of random forest model for short term electricity load forecasting. Random forest (RF) method applies ensemble learning methods to generate many regression trees (Classification and regression trees- CART algorithm) and then collect their results. The performance of this proposed method is compared with ARIMA, exponential smoothing and neural networks. Data for this work was collected for the period of 2002 to 2004 of a Polish power system while the test sets were collected in January and July 2004. To test the performance of the item, MAPE and interquartile range were used. The results showed the RF model and the ANN method outperformed other methods which were used. The mean MAPE for the best methods were 1.16% for RF while ANN was 1.14%. However, the RF model is easier to train and use than any of the other methods applied in the study.

Aprillia et al [80] studied the use of a novel method Whale Optimization Method, discrete wavelet transforms and multiple linear regression (WOA-DWT-MLR) model to forecast a high accuracy short term load forecast. The method combines whale optimization algorithm (WOA) to optimize the best combination of detail and approximation of the signals form discrete wavelet transformation to create a multiple linear regression model. The proposed method is validated by comparing its performance with the traditional multiple linear regression method, artificial neural network, autoregressive moving average with exogenous input (ARMAX), support vector regression (SVR) and particle swarm optimization, discrete wavelet transformation in multiple linear regression (PSO-DWT-MLR).Data was collected for a period of two years for this study (January 2016 to December 2017) which represented the load demand of a building in National Cheng Kung University, Taiwan. Weather data was also collected for that period. The method used to test the performance was MAPE and the results revealed the new proposed method had a better accuracy when compared to the other methods.

Dharma et al [81] proposed a type of fuzzy logic called the interval type-2 fuzzy logic to carry out short term load forecasting. The method proposed used a special concept called footprint of uncertainty (FOU) which provides an extra mathematical dimension which improves the performance of the method. The accuracy of the method was tested using MAPE. The results obtained from the MAPE were 1.0355% and 1.5083% for the years 2005 and 2000 which shows how accurate the method can be used for forecasting short term load forecasting. Hernandez et al [82] applied self-organizing maps (SOM) which is a new model-based off the Artificial Neural Network method to carry out short term forecasting of load demand. The model, when tested produced more accurate results compared with other methods. Numerous methods have been proposed and applied for the purpose of energy forecasting. Some methods are best suited for particular scenarios while others are easy to apply and produce more accurate results. The choice of method is determined by the researcher and the type of work he or she is working on. Different methods have been used in different studies in this work. The applications of the different methods in forecasting the load demand in different locations which are presented with different factors which affect them. Tables 1 to 4 summarized the most accurate methods used for different forecasting ranges. Mean average percentage methods and other methods were used in the various studies to measure the accuracy while comparing different methods. The tables contain the most accurate methods which were used in the different studies.

Table 1: Most accurate short term load forecasting methods

S/N	Method	Accuracy	References
1.	Fuzzy Logic	1.0355% (MAPE)	[81]
2.	Linear Regression Technique	2.9% (MAPE)	[9]
3.	Multi Linear Regression Technique	3.52% Dry season 4.34% Rainy Season	[11]
4.	Support vector machines	0.0215 (RMSE)	[43]
5.	Time series methods; multiplicative decomposition	0.761% (MAPE)	[46]
6.	Artificial Neural Network	0.00197 (MAPE)	[49]
7.	Advanced Wavelength Neural Network	0.268% for MAPE (Australian Data) and 1.716% for Spanish data	[78]
8.	Random Forest Method	1.16% MAPE	[80]
9.	Multiplicative decomposition method	0.761% (MAPE)	[46]
10.	Recurrent Neural Network	0.77% (MAPE)	[51]

Table 2: Accuracy levels medium term load forecasting methods

S/N	Method	Accuracy(Error)	Reference
1.	Linear Regression Splines	5.67% (MAPE)	[27]
2.	Deep Recurrent Neural Network `	3.504%. (MAPE)	[76]

Table 3: Accuracy levels of long term load forecasting methods

S/N	Method	Accuracy(Error)	Reference
1.	Multivariate Adaptive Regression Splines	4.0% (MAPE)	[26]
2.	Multiple linear regression	0.74% (MAPE)	[12]
3.	Principle component artificial neural network	0.43% (MAPE)	[17]
4.	Autoregressive integrated moving average (ARIMA)	4.9%(MAPE)	[19]
5.	Grey Prediction (GP)	5.6% (MAPE)	[19]

From the tables presented above, you can deduce that Artificial Neural Network method resulted with the least errors for short term load forecasting, Deep recurrent neural Network method had the least error for medium term while principle component artificial neural network resulted in the least error for long term load forecast.
Hybrid methods for load forecasting were cited in this work. Below is a table showing the different hybrid methods and the errors in their forecasts.

Table 3: Accuracy levels of hybrid load forecasting methods

S/N	Method	Accuracy(MAPE-Error)	Range	Reference
1	Trigonometric seasonality, Box-Cox transformation ARMA errors, trend annd seasonal components (TBATS)	0.8934%	STLF	[73]
2	complete ensemble empirical mode decomposition with adaptive noise and support vector optimized by modified grey wolf optimization algorithm (CEEMDAN-MGWO-SVM)	0.2527%	STLF	[79]
3	Artificial neural network with principal components (PC-ANN)	0.430%	LTLF	[13]
4	Chaotic particle swarm optimization (CPSO) and Support Vector Regression	1.46%	LTLF	[29]

Other hybrid methods which were used for forecasting energy demand are polynomial support vector regression (P-SVR), Co-integration and ARIMA model. According to Feng et al [83],
Grey model is best suited for load demand forecasting because it requires lesser input data and is more suitable for load demand forecasting. Load data usually fluctuates and can be characterized by poor data.

III. ELECTRICITY DEMANDAND ELECTRICITY DEMAND FORECASTINGIN NIGERIA

Nigeria is one of the largest countries in Africa with a population of over 206 million people [84]. It has an installed power capacity of 13.5GW while peak demand is at 8.25GW and available capacity in 2019 at 3.7GW. Statistics show that about 60% of the load demand is for residential use while commercial and public services amount for the remaining 40%. [85]. The transmission network in Nigeria consists of high voltage substations with a total wheeling capacity of 7500MW(theoretical) while the actual wheeling capacity is about 5300MW [86]. The Nigerian electricity sector suffers from a myriad of problems and one of which is most of the facilities in power plants and transmission facilities are old technologies. This poses a major challenge in acquiring data from these facilities [87]. Most modern equipment has modern real time monitoring technologies incorporated in them which enables electricity data to be captured.

Numerous studies have been carried out to forecast electricity demand in Nigeria over the years using various methods. Adewusi et al [88] conducted a study to use deep learning techniques in carrying out short term electricity demand forecasting in Nigeria. The deep learning techniques proposed for the research are convolutional neural network (CNN), long short-term memory (LSTM) and multilayer perceptron (MLP). Convolutional neural network is a type of deep learning algorithm which takes its input, assign learnable weights and biases to different aspects of the input and this can be used to forecast. Long short-term memory a method based on artificial recurrent neural network (RNN) model. It is characterized by having feedback connections unlike the standard feed-forward neural networks. Multilayer perceptron is a type of feed-forward artificial neural network (ANN). The datasets used for this study consisted of 25751 data samples. The data was collected at an interval of one hour within 3 years from the transmission company of Nigeria 132/33kv substation at Ile-Ife. The dataset was split 80% for training and 20% for testing the model. Three different methods were used to check the accuracy of the forecast done using the different models; mean square error (MSE), Root mean square error (RMSE) and Mean absolute error (MAE). The results obtained from the forecast showed that LSTM performed best compared to the other models developed. Okakwu et al [89] carried out the comparative forecasting of electricity load demand using different forecasting methods. Moving average (MA), Autoregressive Model (AM), exponential smoothing model and Harvey model (HM) were used for this study with the aim of recommending the best model for use in Nigeria. Data was collected for this study from 2008 to 2017 from the National control center. The models developed were tested using RMSE, MAE, MAPE and Theil inequality coefficient (TIC) and the results obtained showed that the Harvey model outperformed the other models developed which used the other methods. Harvey model resulted in a mean absolute percentage error of 2.3579% compared to 3.8113%, 7.2494% and 6.2481% for AR, MA and exponential smoothening models respectively.

Maliki et al [90] carried out a study to forecast the electricity demand in Nigeria using Artificial Neural Network (Multilayer Perceptron) and Multiple regression analysis. The study modeled a long term long term electricity forecast of Nigeria up until 2036 using these methods mentioned above. The error in the models developed were tested using mean absolute error (MAE), mean square error (MSE) and Root mean squared error (RMSE). The results from the error analysis showed that Artificial Neural Network model outperformed multiple regression analysis. Adams et al [91] used univariate time series models in carrying out an electricity demand forecast in Nigeria. Box-Jenkins autoregressive integrated moving average (ARIMA) method was applied to carry out the forecasting of electricity demand in Nigeria using data generated between 1970 and 2009. The model developed forecasted that the electricity generation will have a peak increment of about 3088.22 megawatt in the year 2011.

Olagoke et al [92] applied artificial neural network (ANN) and optimized using genetic algorithm (GA) to carry out an electric demand forecast of a 330/132/33kv substation in Ganmo, Kwara state for the month of May in 2014. Electricity demand data was collected from the substation for a month. The first 21 days in the month was used for training the network and the remaining days were used to validate the model created. The electricity demand data was collected on an hourly basis as well as the average temperature and the day of the week to make up the input variables for the neural network algorithm while the output of the ANN is the forecasted electricity demand and the forecasted day. Genetic algorithm was used to optimize the ANN to design the ANN. The advantage of using genetic algorithm in the design of ANN is that it automates the network design and the design process is similar to a biological process. The results of the forecast were measured for error using mean absolute percentage error (MAPE) and the results showed an error of 4.705%. This shows that the method can be applied in future forecasting. Regression technique was applied by the authors in [93] to carry out medium term load forecast for Abeokuta region of Ibadan Electricity Distribution Zone in Nigeria. Three different methods were used for the study; Linear regression, compound growth and quadratic regression techniques. Compound growth regression technique uses the relation between the actual value of the load and the value assigned to each month. Monthly electricity consumption from January 2017 to December 2017 was collected from the Abeokuta regional headquarters of Ibadan Electricity Distribution Company on a monthly basis. The accuracy of the methods applied was measured using mean absolute percentage error (MAPE) and Root mean squared error. The results from the performance test showed that the linear regression technique performed the best with the least MAPE value of 3.3431% compared to 3.6584% for compound growth technique and 34.1385 for quadratic regression. The forecast revealed a load demand growth from July – December 2018.

Eneye et al [94] applied same methods as used by [93] to carry out the load demand forecast for Ikorodu in Lagos State, Nigeria. Two different scenarios were modeled in this study; residential and non-residential load in the area. The results of the forecast for residential load demand were evaluated using mean absolute percentage error (MAPE) for performance evaluation. Unlike the previous study, quadratic regression technique performed the best with an error of 0.012992% compared to 0.025856% for linear regression and 0.0326212% for compound growth. The last two studies clearly show that many factors affect the accuracy of the methods applied. Both studies applied same results but it resulted in different MAPE accuracies for the different methods. Environmental factors affect the electricity load demand in an area as well as GDP and other factors which have earlier been mentioned. The amount of data points used to carry out the forecast is also very crucial to the success of the electricity demand forecast. A study conducted by [95] showed that some methods like autoregressive moving average (ARMAX) performed better than other linear regression models if given enough data. They also showed that linear models are not as effective in forecasting peaks and troughs no matter the amount of historical data provided. Their study showed artificial neural network provided the best results for forecasting the electricity demand of Taiwan due to the nonlinear nature of the factors which affect electricity load demand. Taiwan is a developing nation like Nigeria as such it will share similar characteristics especially regarding non linearity of data sets. Example of such non-linearity is the relationship between economic variables, weather variables and other variables which affect electricity load demand. Also a lack of adequate data capturing technologies can be a problem as well as the earlier mentioned old and outdated technologies which require upgrade.

Electricity demand is tied to factors around a economic factors, weather factors, and various other variables. Forecasting requires a lot of historical data and this has to be sourced from government insitutions responsible for keeping the electricity demand data. However, many factors affect the efficient collection og data in Nigeria and this greatly affects the ability to carry out accurate electricity demand forecast. Different methods previously used by researchers reveal that some methods like the Artificial intelligence methods produce a more accurate result than conventional methods like regression when provided with less data. Artificial Neural Network and Grey models are examples of such methods. Also some methods perform better for long term electricity demand forecast (LTLF) while others perform better for medium term load forecast (MTLF) and short term load forecast (STLF). For best results, the researcher must select the best method which has resulted in low errors given the variables presented in his/her studies. This being said, electricity demand forecasting is very important ensure the electricity generation in a nation is always following the electricity demand to guarantee the growth of the nation. Forecasting is a very important tool used in planning and with proper planning, Nigeria would be able to meet its energy needs in the future.

IV. CONCLUSIONS

Electricity demand forecasting is an essential part of the electricity industry. From the planning of electricity generating plants, expansion of electricity supply network, policy making, electricity market analysis and many more reasons electricity demand forecasting provides enough data to make calculated and informed decision. Several methods have been researched on for electricity demand forecast. Each method has its advantages and disadvantages depending on the available data and the peculiarity of the country where the data is acquired. Over the years, Nigeria has failed to plan for electricity supply. Some of the reasons for this are political, others are infrastructural, economical and on a lighter note, one would add spiritual. Forecasting is a tool which helps with planning into the future. Different techniques have been proposed for this purpose by different researchers and they have different advantages depending on which one is applicable given the situation. Techniques that are adaptive and accurate like artificial neural network are beneficial for forecasting in a situation where there is indirect relationship between the dataset. Making use of forecasting techniques will provide enough information for making informed decision that will help Nigeria meet the its growing electricity need. In addition to the planning of electricity demand into the future, forecasting of electricity demand in Nigeria will help to plan for natural gas sustainability. Natural gas is limited and found in large deposits abundantly in Nigeria. Nigeria depends majorly on exportation of energy resources to sustain the economy and also relies on this same energy resources for its electricity needs. Accurate determination of electricity demand will aid in determing the gas consumption in the future.

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