Computational Modelling Technique for Short-Term Electric Load Forecasting

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Keywords:

Electric load consumption, Load forecasting, System management, Computational model, Seasons, Petri net, fuzzy logic

A B S T R A C T

One of the major crises facing developing countries of which Nigeria is not an exception is the problem of epileptic power supply. Fifty years after supposedly seeing the light of independence, Nigerians are still literarily living in the dark. This is due to such factors as poor and insufficient power infrastructure resulting from poor funding, mismanagement of the available power resources (both human and material), vandalism, etc contribute to the above problem. This problem has invariably led to stagnation in the kinds of investments in the country, as power is a crucial component of sustainable development. Hence, the need for developing a computational model that will help to produce a 24-hour forecast of electric load. The design was done using coloured petri net tool and implemented using fuzzy logic tool in Matlab 7. Result showed that percentage electric load consumption for raining season is lower than the one consumed in harmattan, therefore more focus should be given to generating more power during harmattan than during raining season for adequate management of the generated electric power.

1. Introduction

Fifty years after supposedly seeing the light of independence, Nigerians are still literarily living in the dark. The epileptic and poor quality of power supply remains a major problem in Nigeria. In Nigeria, such factors as poor and insufficient power infrastructure due to poor funding, mismanagement of the available power resources (both human and material), vandalism, etc contribute to the epileptic and poor quality of power supply. As at 2006, less than 50 percent of Nigerians have access to electricity (BPE, 2006). Available generating capacity (capacity utilization) is in the region of 50 percent of total installed capacity of about 6000 MW. As at 2013, 6056 MW was available out of the total installed capacity of 10,396 MW (KPMG, 2013). This capacity is grossly inadequate for a country of the size of Nigeria with a population of around 177 million people (CIA,2014). These factors, among others, have undermined the quality of electricity services in the country and this has invariably led to stagnation in the kinds of investments in the country, as power is a crucial component of sustainable development.

Load forecasting (LF) is a critical aspect of power system, because a good forecast serves as input to planning, analysis/ modeling as well as operational decision in the power sector. Load forecasting involves managing power generation capacity to meet customer demand, which varies on a daily, weekly and seasonal basis. This is a complex task, because available generation must match customer on an instantaneous basis. The forecasting must also respond to unforeseen events, such as demand exceeding expectations or the power outage from the generator. This process is now being done manually in most developing countries, including Nigeria; hence the demand for 24 hours presence of an operator.

Load Forecasting is very important in today's electric power management system because an accurate forecast results in substantial savings for power system in that this will help determine, how many plants can be efficiently run concurrently. For any electric utility, the estimate of the future demand is necessary in managing the production and purchasing in an economically reasonable way (Faleye, 2008).

Three types of load forecasting have been identified by Feinberg and Genethliou(2006); Short-term, Medium-term and Long-term. Short-term load forecasting attempt to predict electric demand from one hour to one week, Medium-term load forecasting are from one month to one year while Long-term load forecasting are more than one year. Tamimi and Egbert (2000) stated that load forecasting period may be in months or years for long- and medium-term forecasts and that the time range for short-term load forecasting might be an hour or day.

This work focuses on Short-term electric load forecasting (STELF) for period ranging from one hour to one day. STELF is a fundamental task that helps to prevent overloading of the system. It helps in making quick decision and its knowledge can be used for other types of load forecasting. It also provides information about system management on day-to-day operations. Above all, in most developing countries, for example Nigeria, it is easier to get the data

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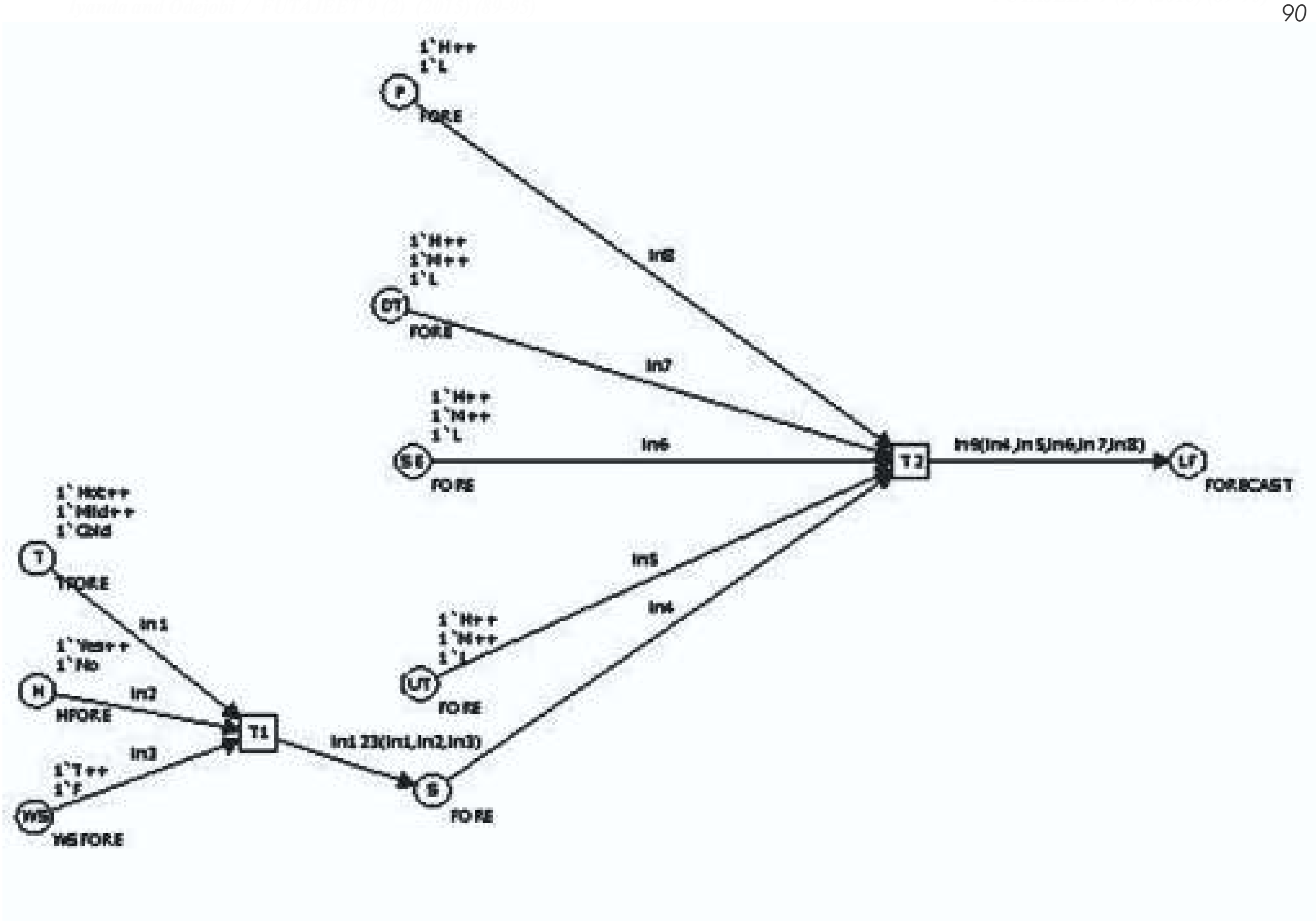

Figure 1: System Design

The fuzzy rule based consists of 15 If-Then statements that characterized the behaviour of the Fuzzy Logic module. These rules are formed using the following guidelines:

(i.) if all the input parameters are high then electric load consumption is characterized by L15.

(ii.) if four of the input parameters are high and one is mid then electric load consumption is characterized by L14.

(iii.) if three of the input parameters are high and two are mid then electric load consumption is characterized by L13.

(iv.) if four of the input parameters are high and one is low then electric load consumption is characterized by L12.

(v.) if two of the input parameters are high and three are mid then electric load consumption is characterized by L11.

(vi.) if three of the input parameters are high and two are low then electric load consumption is characterized by L10.

(vii.) if two of the input parameters are high and two are mid and one is low then electric load consumption is characterized by L9.

(viii.) if three of the input parameters are mid and one is high and one is low then electric load consumption is characterized by L8.

(ix.) if two of the input parameters are high and three are low then electric load consumption is characterized by L7.

(x.) if three of the input parameters are mid and one is high and one is low then electric load consumption is characterized by L6.

(xi.) if three of the input parameters are mid and two are low then electric load consumption is characterized by L5.

(xii.) if four of the input parameters are low and one is high then electric load consumption is characterized by L4.

(xiii.) if three of the input parameters are low and two are mid then electric load consumption is characterized by L3.

(xiv.) if four of the input parameters are low and one is mid then electric load consumption is characterized by L2.

(xv.) if all the input parameters are low then electric load consumption is characterized by L1.

After identifying the input parameters to the system as well as output data from the system, the first stage in the system development is the fuzzification of the data. FL toolbox in Matlab have different type of membership functions but the triangular (trimf) and trapezoid (trapmf) membership functions were used. The fuzzy inference system (FIS) is created using FL toolbox in Matlab and it is named stlfnew1.

There are two types of fuzzy inference method; Mamdani and Sugeno. The FIS used is Mamdani because it is the most commonly seen fuzzy methodology and its output membership functions are fuzzy sets while that of Sugeno are either linear or constant. Figure 2 shows the Fuzzy Inference System (FIS) editor

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for STELF than other types of electric load forecasting.

2. Approaches to Load Forecasting

There are three major approaches to LF. These include manual, statistical, and artificial intelligence.

a. Manual approach: This is the approach in which the operator uses his or her experience and intuition to obtain a good guess of the load demand. This approach is inefficient, non-effective and time consuming. It is prone to too much error. These limitations render this method not appropriate for load forecasting in getting correct result.

b. Statistical approach: This is the approach that depends largely on historical data of electric load consumption. This approach usually requires a statistical model that represents load as function of different factors such as time of the day, weather, and customer class. It involves the use of historical data and produces instant result. Statistical packages are readily available, though expensive. The historical load data used by this approach may not always be available especially in the developing countries. Load behaviour experiences sudden change which statistical method cannot always cope with. Therefore, this approach is not most appropriate for use in STELF. Statistical approach includes multiple linear regression (MLP), Adaptive models, general exponential smoothing, stochastic time series and state-space methods.

c. Artificial Intelligence (AI) Approach: This is the approach which is used to study and design intelligent agents (a system that perceives its environment and takes actions which maximize its chances of success). In this work, this approach is subdivided into four major parts which includes:

i. Genetic Algorithm: Genetic Algorithms (GAs) have recently received much attention as robust stochastic search algorithm for various problems (EL-Naggar and AL-Rumaih, 2005). This method is based on the mechanism of natural selection and natural genetics, which combines the notion of survival of the fittest, random and yet structured, search and parallel evaluation of the points in the search space. GA accommodate all the facets of soft computing, namely uncertainty, imprecision, non- linearity, and robustness. GA can be used to provide a good set of initial weights for Neural Network (NN), or can be used to fully train the NN or to find the optimal network structure (Haque and Kashtiban, 2005).

ii. Neural network: This approach depends solely on data. Artificial Neural Network (ANN) or simply put Neural Network (NN) acquires input variables from the historical database and output the forecasted load.

When the ANN is in the learning stage (Feinberg and Genethliou, 2006), the database is used as training set and the errors are back propagated until satisfactory levels of accuracy are achieved. This approach is weak at generalization and if not well trained, it can over fit the data. ANN approach is not interactive in nature and cannot provide explanation to the operator on what he needs to know. NN though accurate in weekday load forecasting (Dash *et al*, 1995) is poor at forecasting peak loads and holiday loads. NN based load forecasts give large errors when the weather profile changes very fast.

iii. Rule-based approach: This approach entails using a set of assertions, which collectively form the 'working memory', and a set of rules that specify how to act on the assertion set. Rule-based systems are a good choice (Caudil, 1991) when one has only a few data samples, when one has experts that are readily available for consultation, or when one finds that an explanation for answer is essential. Rule-base is modular in nature, in that it allows for modification. New rules can be added and old ones can be deleted, since rules are independent of one another. An example of rule-based system is an expert system (ES). ES differs from other kinds of AI in that it deals with subject matter of realistic complexity that normally requires a considerable amount of human expertise; exhibits high performance in terms of speed and reliability (Jackson, 1999). This makes ES to be a useful tool, capable of explaining and justifying solutions or recommendations to convince the user that its reasoning is in fact correct. ES provides a number of benefits according to Beckman (1991) which include reduce costs; improved quality; increased revenue; retention of expertise and easy distribution of expertise.

iv. Fuzzy Logic: Fuzzy logic is a generalization of the usual Boolean logic used for digital circuit design (Feinberg and Genethliou, 2006). An input under Boolean logic takes on a truth-value of "0" or "1". Under fuzzy logic, an input has associated with it a certain qualitative ranges. Fuzzy logic allows one to (logically) deduce outputs from fuzzy inputs. In this sense, fuzzy logic is one of a number of techniques for mapping inputs to outputs (i.e. curve fitting). Among the advantages of fuzzy logic are the absence of a need for a mathematical model mapping inputs to outputs and the absence of a need for precise (or even noise free) in- puts. With such generic conditioning rules, properly designed fuzzy logic systems can be very robust when used for forecasting.

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2.1 *Related Work*

Sun *et al.* (2004) presented fault diagnosis of electric power systems using fuzzy Petri nets (FPN) as a modeling Tool. The validity and feasibility of this method is illustrated by simulation examples which shows from seven cases that the faulted system elements can be diagnosed correctly by use of these models, and a satisfying result can also be achieved even in the situation with large amount of incomplete and uncertain alarm information. Also, the merits of easy reasoning, fast diagnosing speed and strong practicability of fault diagnosis models based on FPN were demonstrated..

Wu (1998) presented a Petri net algorithm for multiple contingencies of Distribution system operation by combining with a new restoration approach. This approach is performed by releasing some loads required to maintain the rest system in safe operation in overload cases and opening all of the switches in the out-of-service areas for fault cases, and then closing proper switches to restore the isolated areas. Heuristic rules and valuation functions were presented for the best first search in the Petri nets (PN). A practical Taiwan power (Taipower) distribution system was simulated to demonstrate the effectiveness of the proposed method. Combining with the proposed restoration algorithm, the Petri net and its inference processing are efficiently implemented using C++. It was concluded that multiple contingencies of distribution systems could be solved by the proposed method effectively.

Iyanda *et al*. (2011) presented a short-term electric load forecasting in uncertain domain using fuzzy decision tree approach. The fundamental requirement for the proposed model is the production of robust and accurate performance with minimal computational and data resources. Solution strategy was developed around a computational intelligence method which exploits knowledge using fuzzy logic and decision tree based techniques. The model was developed and evaluated using three years data (i.e. 2004, 2005 and 2006) on electric loads obtained from the National Control Centre (NCC) Osogbo, Nigeria and was implemented using the Fuzzy Decision Tree software (FID 4.2). The data was supported by knowledge elicited from experienced power monitoring staff at NCC. The results showed that the average fractional forecast errors for the proposed model on selected data from the three years was 0.17 while that of the conventional multiple regression model was 0.80.

3. Methodology

3.1 *System Design*

The interaction between the system and user is designed using coloured Petri nets (CPN). Petri nets are graphical and mathematical tools that provide a uniform environment for modelling, formal analysis, and design of discrete event systems (such as industrial automated systems, communication systems, and computer-based systems). One of the major advantages of using Petri net models is that the same model is used for the analysis of behavioural properties and performance evaluation, as well as for systematic construction of discrete event simulators and controllers. Petri nets can be used to model properties such as process synchronization, asynchronous events, concurrent operations, and conflicts or resource sharing (Zurawski, 1994). Tokens are used in these nets to simulate the above properties. CPNs allow tokens to have a data value attached to them. Petri nets contain places which symbolise states or conditions that need to be met before an action can be carried out and transitions that may be connected by directed arcs which symbolise actions. The proposed model contains nine *places* (P_1 to P_9) and two *transitions* (T_1 and T_2), In order to simulate the dynamic behaviour of this system, a state or marking in a Petri nets is changed according to the following transition (firing) rule: A *transition*, t is said to be enabled if each input *place*, p of t is marked with at least w(p,t) tokens, where w(p,t) is the weight of the arc from p to t. For this system, the initial markings are 3,2,2 for temperature, humidity and wind-speed respectively. An enabled transition may or may not fire, depending on whether or not the event actually takes place (Iyanda *et al*., 2014). A Petri net is a 5-tuple;

$$PN = \langle P, T, F, W, M_0 \rangle \quad (1)$$

P is a finite set of place, i.e., $P = \{P_1, P_2, P_3, P_4, P_5, P_6, P_7, P_8, P_9\}$

T is a finite set of transition, i.e., $T = \{T_1, T_2\}$

$F \subseteq (P \times T) \cup (T \times P)$ is the set of arcs (flow relation)

$W : F \rightarrow \{1, 2, 3, ...\}$ is a weight function, i.e., W = w(p, t), tokens on the arc

$M_0 : P \rightarrow \{0, 1, 2, 3, ...\}$ is the initial marking i.e., $M_0 = 3, 2, 2$

$P \cap T = \varphi$ and $T \cap P = \varphi$

The model is shown in Figure 1. T represents temperature and it has three tokens (hot, mild and cold). H represents humidity and it has two tokens (yes and no). WS represents wind-speed and it has two tokens (true and false). S represents season (combination of T, H and WS). P represents population and it has two tokens (high and low). DT represents Day-type and it has three tokens (high, mid and low). SE represents social-event and it has three tokens (high, mid and low). UT represents user-type and it has three tokens (high, mid and low). LF represents load forecast. Any of the token on each of the *place* can be fired.

T1 fires only when it receives tokens from T, H and WS to produce season. T2 fires only when it receives tokens from P, DT, SE, UT and S to produce the forecast. The forecasted electric load has been categorized with number ranging from 0 (for the minimum) and 15 (for the maximum) depending on the combination of the fired tokens. In this research minimum load used was 2000MW and the maximum was 4000MW.

3.2 *System Implementation*

The fuzzy inference engine converts the input fuzzy set into an output fuzzy set through an inference process which includes rule block formation, rule composition, rule firing, implication and aggregation. The rule block consists of a number of rules which are interrelated and normally operate based on certain set criteria. The number of rules is determined in line with the complexity of the associated fuzzy system. A fuzzy rule is composed of two parts, namely an IF part and a THEN part. Unlike the conventional rule-

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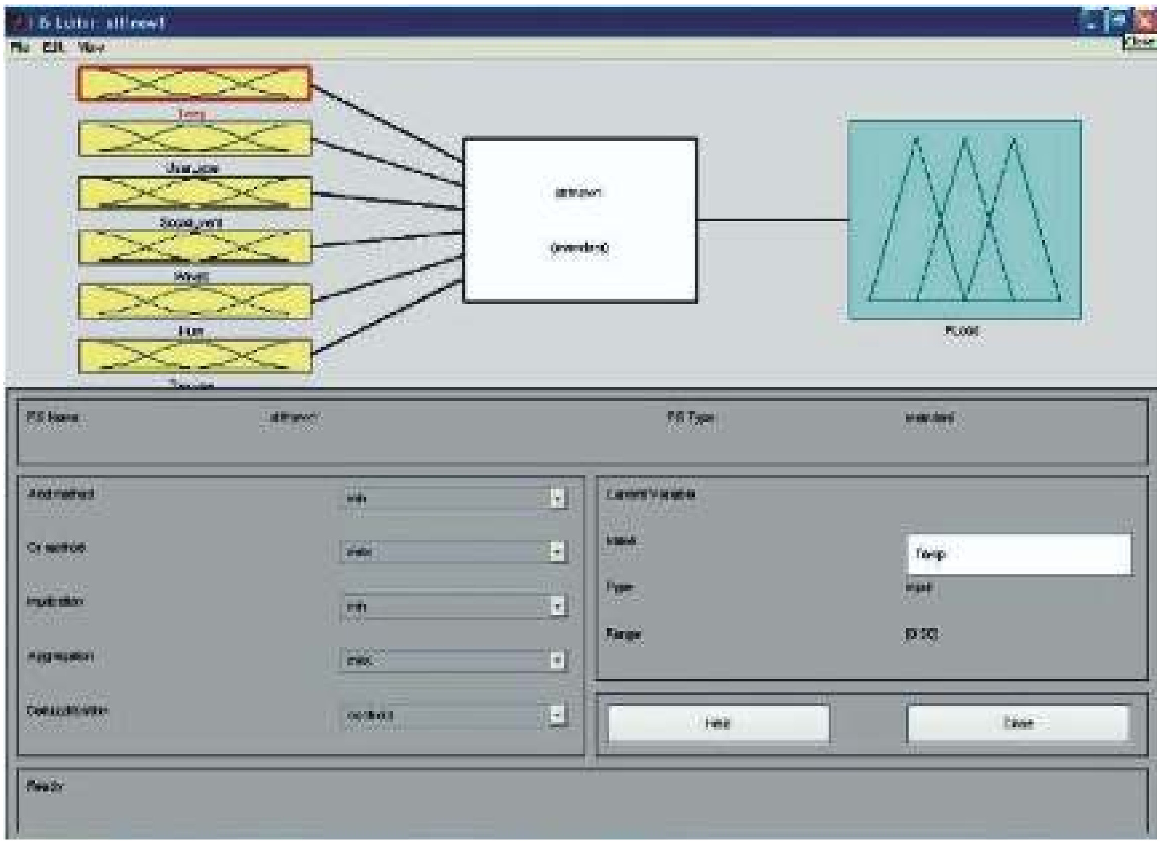

Figure 2: FIS Editor

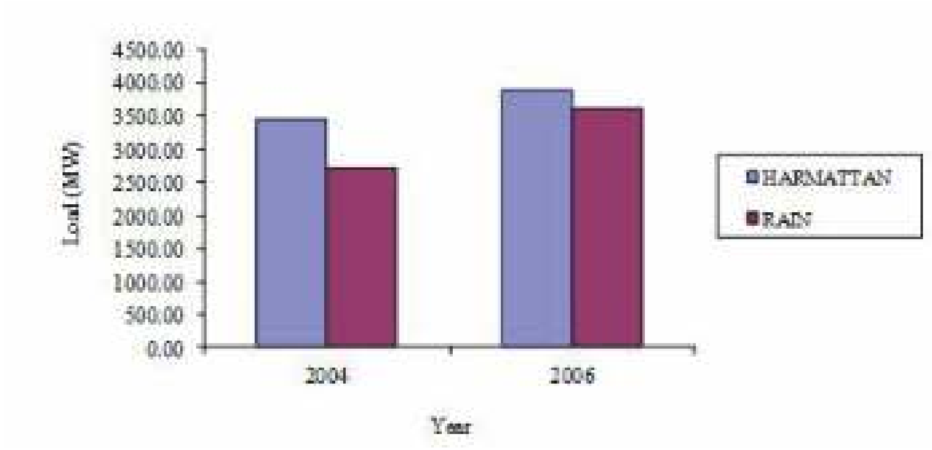

Figure 3: Average Load comparison for both harmattan and rain in 2004 and 2006

based mechanism, fuzzy rules allow the use of imprecise, uncertain and ambiguous terms (Jeng *et al.*, 1997).in which the MFs for both the input and output variables were defined for the STELF system.

4 Result

Table 1 shows the sample in general, the actual electric load consumption against the forecasted (conventional and proposed) electric load. It was established that the percentage fractional error is the conventional model is higher than that of the proposed model. In Table 2, the average electric loads forecasted in the year 2004 were 3440.56MW for January 1st (harmattan) and 2730.56 MW for June 5th (rain). Result established that the electric load consumed during the dry season (harmattan) is usually greater than that of the rainy season. Two different months specifying the two seasons have been used to establish this fact. The average electric loads forecasted in the year 2006 were 3896.98MW for January 1st (harmattan) and 3613.33 MW for September 6th (rain). This data is shown graphically in Figure 3.

5 Conclusion

The 24-h ahead forecasting results were presented (Table 1). Our model predicts 24-h ahead load for the two seasons (Rain and Harmattan) experience in Nigeria. The result showed that percentage electric load consumption for rain is lower than that consumed in harmattan. The results conclude that more focus should be given to generating more power during harmattan than during rain.

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If such factors as poor and insufficient power infrastructure due to poor funding, mismanagement of the available power resources (both human and material), vandalism, etc contribute to the above problem are adequately addressed and there is an accurate forecast of the available electric load, this will yield an increase in the kinds of investments in the country, as power is a crucial component of sustainable development. Therefore, in the next 50 years, Nigeria will experience stable power supply, which will produce a greater sustainable development of the citizens and Nigeria as a country.

Related aspects for the Short-term electric load forecasting are described in detail in our previous work (Iyanda *et al*., 2011) which presents the application of fuzzy decision tree (FDT) technique in the computational modelling and simulation of the STLF problem in an uncertain domain.

Table 1: 24-hour ahead electric load orecasted in MW of actual versus conventional model (F) and proposed model (FLoad)

[illegible]	[illegible]	[illegible]	[illegible]

Table 2: 24-hour ahead electric load forecasted in MW for both harmattan and rain seasons

[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

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