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FRAMEWORK BASED ON FUZZY EXPERT SYSTEM MODEL FOR PREDICTION OF ELECTRIC LOAD DEMAND-SUPPLY BALANCE

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Abstract

Fuzzy expert system model is a resilience approach in short term predicting of electricity load. In this study, the post privatisation electricity framework in Nigeria was examined and found that, load distribution was not based on the demand by the users which often led to underutilization of load transmitted to the distribution company despite the fact that, the available power is not sufficient. The contribution to the framework is to enable distribution of electricity that is based on location specific load requirement. To achieve this, fuzzy expert system is integrated to the post privatisation framework with temperature, humidity, rainstorm, time of the day, previous load history, standard of living and history of previous bill payment were used as the inputs parameter for the fuzzy expert system. The integration of the fuzzy expert model to the previous framework is to predict electricity that is affordable to the users thereby reducing the amount of the unused electricity as well as reducing the accumulated bill resulted from the inability of the users to pay for what it consume.

***Keyword*:** Fuzzy Expert System, Framework, load prediction, post privatization

1.0 Introduction

The stakeholders in electricity business in Nigeria are Nigerian Electricity Regulation Commission (NERC), Nigerian Bulk Electricity Trading (NBET), Generation Company (GenCos), Transmission (TCN), Distribution Company (DisCos) and the consumers themselves [1]. In an attempt to resolve the continue power epileptic situation in Nigeria, Federal government of Nigeria privatised National Electricity Power Authority (NEPA). As a results of the privatization by the Federal Government of Nigeria, In [2] stated that, PHCN was unbundled into six (6) Generation Companies (GenCos), one (1) independent power producer under the Niger Delta Power Holding Company (NDPHC), eleven (11) Distribution Companies (DisCos) and one (1) Transmission Company (TCN). Federal Government owns TCN completely, owns 20% of the GenCos and own about 40% of the DisCos [3].

However, the privatization of NEPA did not yield the needed results as the power availability in Nigeria is still a nightmare to it citizenry. The major causes of the continued epileptic power supply are a share responsibility of the TCN and the DisCos resulting from transmission of electricity without considering the load requirement of such location among other factors. It is a known fact that the total power generated by the combined Generation Companies is far below what is required to power Nigeria. To compound on the inadequacy of power generation, the TCN have severally failed to deliver power to the right location as might be required by the DisCos. Similarly, the DisCos sometime failed to deliver power to the needed customers because of inefficient distribution transformer. This is a result of the problem of transformer overload and vandalization [3].

Electric load prediction is the forecasting of future electric needs that is based on available past load records [4]. Load forecasting a necessary mechanism to effectively managing electricity distribution [5]. It significantly smoothing the

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operations of power management system such as unit commitment, schedule maintenance [6, 7]. The dependency on electrical energy required a thorough managerial decision to ensure the generated energy is fully utilized. As decision regarding where and when to drop electric power is characterised with lots of uncertainty and ambiguity, making such decision based on the past experience alone by human sometimes give undesirable results. To overcome the problem, a model for forecasting electric load and voltage control using step-2 Fuzzy logic was adopted by [8], the study succeeded to automatically regulating electric voltage control system in distribution setup and periodically forecast short term electric load demand in some selected location thereby providing a real time algorithm that provide instantaneous solution to problem such as unit commitment decision.

2.0 Method

2.1 The Proposed Fuzzy Logic Based Prediction Model Framework

The concept of this study is an adaptation of Nigeria post privatization power sector framework [9] with the fuzzy based predictive model being the contribution of this study to the framework as illustrated in Figure 1. In the privatization framework, power is distributed by Distribution Company (DisCos) to their customers without taking into consideration, the amount of electricity needs by group of customers. In a similar fashion, Transmission Company of Nigeria (TCN) may transmit electricity to DisCos at the time that their facility may have been damage by rainstorm as they adopts overhead transmission lines.

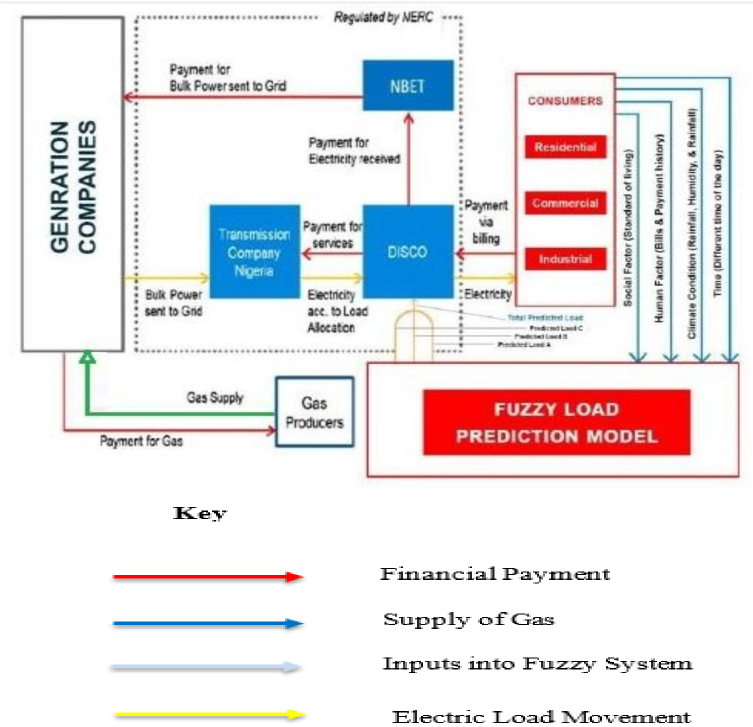

Figure 1: Overview of Nigerian Electricity Framework with Integrated Fuzzy Logic Based Electricity Load Transmission Framework.

2.2 Contribution to the existing framework

A Fuzzy Logic Controller (FLC) can be modelled either as Mamdani type or the Sugeno type. Additionally, a Fuzzy Control System can be model in form of a Mathematical Modelling like the K Means Clustering (Type-1 Fuzzy System) or it can be model based on Fuzzy Inference Rules (FIR) or Fuzzy Logical Rules like Fuzzy Decision Support System (Type-2 Fuzzy System) [10]. This study is model based on Mamdani Type Fuzzy Inference Rules because both inputs and output variables are assigned linguistic variables

The works of some researchers revealed that Fuzzy logic system or fuzzy inference system (FIS) has four major components [10, 11, 12, 13] namely: Fuzzification, Rule Base, Inference Engine and Defuzzification as shown in Figure 2. It shows the flow of control in the development of the proposed contribution to the framework.

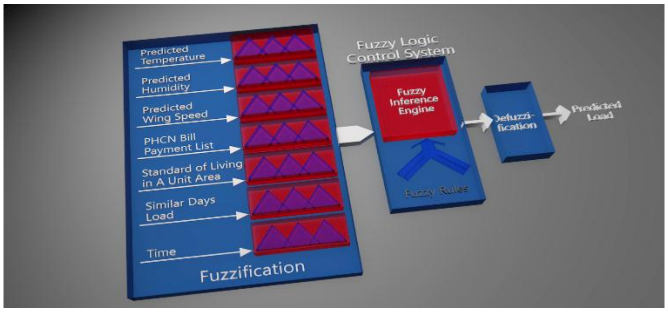

Figure .2: the Proposed Fuzzy Logic System Architecture

2.3 Conceptual Architecture

The conceptual architecture is shown in Table 1 and consist of seven (7) modules. Embedded in the modules as illustrated in Figure 3.2 are electric load prediction processes such as Fuzzification, knowledge base which comprises of the rule base and the inference engine and the centroid method for the Defuzzification which are the building block for fuzzy expert system.

Table 1 Modular approach to Fuzzy Expert Model for electric load prediction

Modules	Description
Module 1	Convert crisp input to fuzzy input (linguistic variables)
Module 2	Assigned fuzzy scale to the linguistic variables
Module 3	Implementation of Fuzzification processes
Module 4	Formulation of fuzzy rules
Module 5	Enhance Fuzzy Inference System development by adding rule(s)
Module 6	Implementation of Defuzzification
Module 7	Integrating load prediction model

Module 1: This module involve classification of fuzzy input variable such as predicted temperature, predicted Humidity, Rainstorm, time into their corresponding linguistic variable and the number of membership was determine.

Module 2: In this module, trigonometric membership was adopted because of it flexibility as well less processing time as against the non-linear MF such as the singleton MF or generalise bell MF. Three point are assigned crisp value such as temperature in the interval $40^{\circ}C\ a, 45^{\circ}C\ b\ and\ 50^{\circ}C\ c$ is converted into Extremely High linguistic variable. The algorithm in this module takes as input, the crisp input and converts it into linguistic variable. The process was repeated until all membership function was exhausted.

Module 3: module 1 and module 2 were repeated for all variables such as Predicted Temperature, predicted Humidity, and all the variables that are required to build the fuzzy expert system for electric load prediction model.

Module 4: Rules were created by logically ANDing all or some linguistic variables from each of the input variable.

Module 5: The strength of the algorithm that determine the action that resulted from the consequences is enhanced as more rules were created. This action was repeated until the algorithm is able to predict the best possible result

Module 6: Centroid method is called to determine the best output as well as conversion of fuzzy input to the formant understandable by human.

Module 7: All components of fuzzy system were integrated to form the complete model that predict a balanced electric load for a given location.

The proposed model development is further explained in Figure 3 as described by the modular fuzzy development process in Table 1.

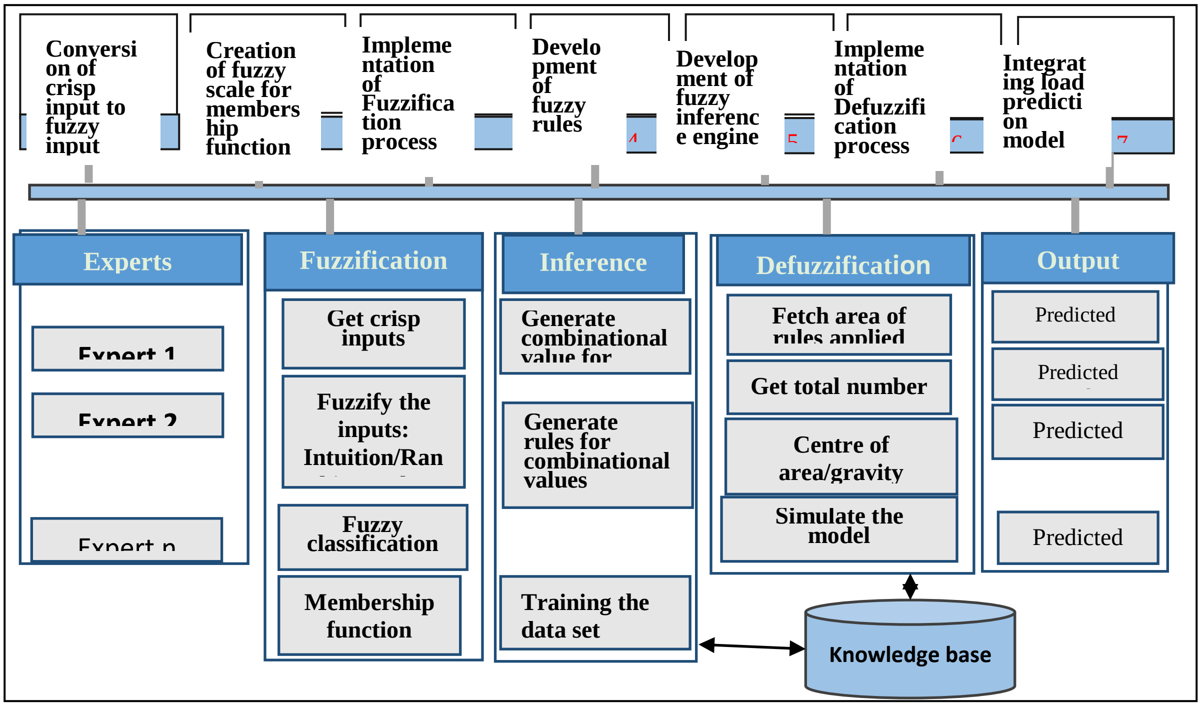

Figure 3: fuzzy expert system development

2.4 Fuzzification

This is the first phase in the development of a Fuzzy Inference System [10] and it is the process that involves converting crisp input(s) or crisp quantities such as the temperature of 38^{oc} or 90% level of compliance in the payment bill level into a fuzzier set or linguistic variable such as very hot or normal temperature or very high compliance level. Admittedly, there are two distinct method of Fuzzification: the first is Support Fuzzification (s-Fuzzification) methods expressed mathematically thus:

$$\tilde{A} = \mu_1 Q(x_1) + \mu_2 Q(x_2) + \mu_3 Q(x_3) + \mu_n Q(x_n) \qquad (1)$$

In this Fuzzification algorithm, μ_i is kept constant while x_i is transformed to a fuzzy set Q(x_i) which is refers to as kernel of Fuzzification. The second is grade Fuzzification (g-fuzzification) which is the same with the s-fuzzification with the distinction only on the two parameters used. In this method, x_i is kept constant while varying the μ_i as it now indicates the fuzzy set [14].The proposed contribution to [9] adopts the grade fuzzification as the approach varied the MF function and keeps the fuzzy set constant.

Admittedly, identification of inputs to the fuzzy system is very important as unit commitment decision depends on the inputs variables. Some studies availed that only exogenous parameters such as temperature [15, 16, 17, 18, 19, 20, 21]. Also humidity, rainfall, time of the day, previous load history, weekend, weekdays and holidays were used. However this contribution to the framework is intended to in addition to some of the exogenous parameters, add standard of living as well as inputs to the model. The standard of living is aimed at balancing demand of electricity with it supply while the rainstorm is to check the availability of Discos' critical infrastructure that is needed proper utilization of electricity received from the TCN. Fuzzification process for this research involves classification and assigning fuzzy scale to the selected inputs as well as creation of fuzzy membership function (MF).

2.5 Inference Engine

After assigning MF and linguistic variables to all the selected inputs variables using intuition method and the ranking order method of MF assignment, rules are needed in order to build the knowledge base. FRBS is built using the IF-THEN rules which consist of the antecedent and the consequences. The antecedents and consequences consists of fuzzy logic statement rather than the classical logical statement. Tripathi, Shukla, and Poonam (2012) [22] outlined that, the application of FRBS in Fuzzy Modelling, Fuzzy Control and Fuzzy Classification have greatly improved the decision making of fuzzy control system. Obviously, FRBS is used in representing expert knowledge as well as modelling the relationship between the variables used in the load prediction model and to handle the uncertainty that exit in this research work.

Given that the inputs variables to the contribution are defined as follow:

$$T = \begin{Bmatrix} \text{Excessively Low, Very Very low, Very Low, Low, Normal, High, Very High} \\ \text{Very Very High, Excessively High} \end{Bmatrix} \quad (2)$$

$$\text{H} = \{\text{Very Very Wet, Very Wet, Wet, Normal, Dry, Very Dry, Very Very Dry}\} \quad (3)$$

$$\text{R} = \{\text{No Rainstorm, Low Rainstorm, High Rainstorm}\} \quad (4)$$

$$\text{t} = \begin{Bmatrix} \text{Mid Night, Torward Morning, Eraly Morning, Mid Morning, Noon} \\ \text{Afternoon, Early Evening, Night, Late Night} \end{Bmatrix} \quad (5)$$

$$\text{plh} = \begin{Bmatrix} \text{Excessively Low, Very Very low, Very Low, Low, Normal, High, Very High} \\ \text{Very Very High, Excessively High} \end{Bmatrix} \quad (6)$$

$$\text{sol} = \{\text{Poorest, Fairly Poor, Moderate, Faily Rich Rich}\} \quad (7)$$

$$\text{bph} = \{\text{Very Low, Low, Average, High, Very High}\} \quad (8)$$

$$\text{pl} = \begin{Bmatrix} \text{Excessively Low, Very Very low, Very Low, Low, Normal, High, Very High} \\ \text{Very Very High, Excessively High} \end{Bmatrix} \quad (9)$$

Samples rules are as follow:

Rule1: IF (temp['high'] & humid['normal']|& rainstorm['low'] & time['afternoon'] & pdlh['very_high'] & sol['moderate'] & bph['very_good'], THEN predicted_load['high'])

Rule2: IF (temp['high'] & humid['dry']|& rainstorm['no']& time['afternoon'] & pdlh['high'] & sol['ave'] & bph['very_good'], THEN predicted_load['very_ high'])

Rule3: IF (temp['very_low'] & humid['very_dry']|& rainstorm['no']& time['afternoon'] & pdlh['low'] & sol['high'] & bph['very_good'], THEN predicted_load['very_ high'])

2.6 Defuzzification

Inference engine constitute the entire rules for the system and is responsible for selecting the appropriate rules from the rule base based in the knowledge base. Inference engine get richer and more effective as the rules increasing thereby increasing the decision making of the fuzzy control system. The first part in the development of the inference engine for this work was the generation of combination values for all inputs variables with respect to the number of linguistic term for each inputs variable. Total of about 340, 000 combination was generated which was subsequently used in generating the fuzzy rules for this work. The centroid method of Defuzzification will be used to compute the predicted electricity load that will be affordable to the consumers thereby reducing the wastage arises from the customers' inability to pay for the electricity consume by the users.

3.0 Conclusion

The post privatisation electricity framework of Nigeria comprises of the Generation Company (GenCos) which is responsible for generating the combine electricity need of Nigeria. The Transmission Company of Nigeria (TCN) has the needed facilities to transmit electricity from the point of generation to the third components of electricity distribution system being the Distribution Company (DisCos). DisCos are responsible for distribution of electricity directly to consumers. However, DisCos are expected to purchase electricity from Nigerian Bulk Electricity Trade (NBET) being the only organ that have the sole right to purchase electricity from the GenCos and resale to the DisCos. DisCos did not put into consideration, the load needs of a given location as well as the facilities that may have been damage by natural disaster such as rainstorm before accepting load from the TCN for onward transmission to the customers in the post privatization framework.

Undoubtedly, the contribution to the post privatisation electricity framework is aimed at predicting a day ahead using fuzzy expert system model, the unit requirement of a given location that is based on some climatic variables such as temperature, humidity as well as time of the day which determine electricity need of individuals and by extension, electricity need of a given location. Rainstorm is chosen as inputs parameter because of the overhead nature of power transmission lines in developing countries (Nigeria). Overhead transmission of electricity is easily damage by rainstorm which if not predicted may result to DisCos being transmitted with electricity that they may have no facilities to distribute to their customers. The standard of living as well as the bill payment history is chosen to ensure customers are given electricity load that is affordable to them.

The integration of the model to the post privatisation electricity framework is to predict ahead of time, the electricity load that will be affordable to consumers thereby reducing the huge debt owe by customers resulting from consuming electricity beyond their means. This will address the limitation of the previous work that is based on consumers need only without considering if they can afford their needs.

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