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A Novel Fuzzy Inference System for Predicting Balanced Electricity Demand

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Abstract

In developing economies, reducing waste in hard-earned electricity generation has been a major problem. As a case of interest, the issues of unit of power commitment decision-making have befuddled the post-privatised electricity framework in Nigeria. This choice simply determines how many units of power should be provided to a certain location at a given time. To address this issue, a novel model known as the Automated Fuzzy Inference Engine (AFIE) was formulated that mathematically suggests the output in the fuzzy rules in the inference engine instead of relying on intuition and the ranking method of fuzzification to detect the output. Python was utilized in the AFIE model experiment. As a fallout of this, some algorithms were birthed in the process of formulating data sets. According to the model, every 5°C increase in temperature increases electricity consumption by 0.96%. The models support previous findings and the premise that electricity usage is related to temperature, humidity, and standard of living. It also confirms that rainfall has a negligible relationship con electricity use. However, this study discovered that electricity supply is inversely correlated to rainstorms and directly proportional to bill payment history and living standards. Applying the import of this model will put stakeholders in the vantage position to prevent mistakes caused by users setting output values intuitively. Furthermore, this approach may be applied to any fuzzy predictive model as long as the input parameters are correctly categorised and weighted in relation to the output.

Keywords: Automatic, Fuzzy, AFIE, Inference, Engine, Model, Expert

Introduction

Electricity management and its distribution rely heavily on electricity load prediction (Ali & Vasira, 2018), as decisions about where and when to drop electric loads must be made quickly. The variation in size, load demand, and living standards has necessitated the need to accurately determine ahead of time the unit of electricity to be committed to any given location. Konica and Hanelli (2016) view electric load prediction as the process of forecasting future electric needs based on the available past load information. Predicting electricity will enhance the operation and management of electricity in order to maximise profit is considered one of the most important parameters in unit commitment planning, as opined by Madrid and Antonio (2021). Furthermore, the electricity that is costly and is generated in Nigeria by the combined generation company GenCos and transmitted to the distribution company DisCos by the transmission company of Nigeria (TCN) is yet to be fully utilized, leaving substantial parts of it unused as opposed to the fact that it is even far below the demand (Federal Government of Nigeria Power Sector Recovery Plan 2018-2021). Both the TCN and the DisCos trade blame for this problem. The DisCos say that the TCN is not dropping power at the right place, while the TCN says that the DisCos do not have the right equipment to accept all the power sent to their substation (Okere, 2018).

The challenges faced by Discos that resulted in insufficient utilisation of TCN power are as a result of weak and inadequate network coverage and overloaded transformers (Onochie, 2015). Additionally, is to incorrectly drop electricity loads to locations that may have fewer demands for electricity or with no financial backup to pay for its consumption. Admittedly, Manoj and Shah (2015) addressed this problem by predicting ahead of time the unit commitment decision for a given location. More so, Oluwatoyin et al. (2015) established that the generation, transmission, and distribution of voltage in the right location and at the right time is a major challenge, retarding economic growth in most developing countries. Furthermore, Rizwan and Alharbi (2021) demonstrated that while performing short-term load prediction using the fuzzy logic method and only considering previous load history, the study was successful in predicting the hourly load of some selected locations and revealed that the fuzzy logic results were better than the neural network results. However, merely taking into account, the prior load history may impair the accuracy of the outcome. Similarly, Khadijah et al. (2021) used the fuzzy logic method to predict ahead of time the electric load demand of some shopping malls while investigating the weekly load requirements of those areas. The study also attempted to compare the accuracy of results using ARIMA and the fuzzy logic method. It discovered that holiday consumption is higher than non-holiday consumption, and the fuzzy logic technique surpassed the ARIMA method. This study, nevertheless, is confined to only three inputs, namely: time, temperature, and past load history.

This study is aimed at developing a model that automatically generates a fuzzy inference engine FIE by supplying the input variables with their respective variables as well as their weight or impact with respect to each variable. The weight for each variable is necessary because Ali et al. (2016) argue that temperature has a greater effect on load demand than humidity. More so, unlike temperature, which greatly determines the amount of electricity consumed, rainfall, in some cases, has minimal impact on power consumption, as observed by Jakuenoks and Laizāns (2016) while trying to intuit that "there is a strong correlation between weather parameters and power consumption." The study showed that there is an insignificant correlation between rainfall and power consumption. However, Jakuenoks and Laizns (2016) proved that there is a partial correlation between rainfall and the amount of sunshine and power consumption. In agreement with this, Penggunaan et al. (2019) identified five main climatic variables, average temperature, average rainfall, forest area, carbon dioxide emission, and arable land. The study showed that there is a unidirectional relationship between average temperature, average rainfall, and power consumption. However, Hernández et al. (2012) considered several climatic variables and discovered that average precipitation and average pressure have no correlation with power consumption. According to the study, while temperature, solar radiation, and average humidity have a much stronger relationship with power consumption, wind speed and direction have a negligible relationship with it. However, Audu, et al. (2021) evidently established that supply-required factors (SRF) such as standard of living and historical bill payment also affect electric demand and were used as factors that balanced demand and supply of electricity to customers. It is therefore worthwhile to consider the weight of each variable, as extant studies reveal varying degrees of impact each variable may have with respect to the output being the load prediction as represented in the FIE.

Materials and Methods

Proposed Fuzzy Logic Prediction Model

For example, given a temperature T, humidity H, rainstorm R, time t, previous load history p, standard of living S, and bill payment history B as the input parameters (antecedents) for a fuzzy model for the prediction of electric load demand-supply balance for a given location, with the consequence P being the predicted load. Fuzzy systems use the following criteria to divide antecedents and consequences into different language groups:

$$T = \left\{\begin{matrix}\text{Excessively Low, Very Very low, Very Low, Low, Normal, High, Very High} \\ \text{Very Very High, Excessively High}\end{matrix}\right\} \quad 1$$

$$\mathrm{H} = \{\text{Very Very Dry, Very Dry, Dry, Normal, Wet, Very Wet, Very Very Wet}\} \quad 2$$

$$\mathrm{R} = \{\text{No Rainstorm, Low Rainstorm, High Rainstorm}\} \quad 3$$

$$\mathrm{t} = \left\{\begin{matrix}\text{Mid Night, Torward Morning, Early Morning, Mid Morning, Noon} \\ \text{Afternoon, Early Evening, Night, Late Night}\end{matrix}\right\} \quad 4$$

$$\mathrm{p} = \left\{\begin{matrix}\text{Excessively Low, Very Very low, Very Low, Low, Normal, High, Very High} \\ \text{Very Very High, Excessively High}\end{matrix}\right\} \quad 5$$

$$\mathrm{S} = \{\text{Poorest, Fairly Poor, Moderate, Faily Rich Rich}\} \quad 6$$

$$\mathrm{B} = \{\text{Very Low, Low, Average, High, Very High}\} \quad 7$$

$$\mathrm{P} = \left\{\begin{matrix}\text{Excessively Low, Very Very low, Very Low, Low, Normal, High, Very High} \\ \text{Very Very High, Excessively High}\end{matrix}\right\} \quad 8$$

Table 1 defines the number of membership function MF and their corresponding upper bounds. It shows that whereas serial numbers 1–7 are the antecedents' part of the FIE, number 8 is the consequence. The number of their MF representing their associated linguistic variable is further elaborated as in (1) to (7). As illustrated in Table 1, the upper bound of each variable is equal to the number of MF.

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Table 1: Input and output variables, as well as the number of MF that correspond to them

S/N	INPUTS/OUTPUT VARIABLES	NUMBER OF MF	UPPER BOUND
1	Temperature	9	9
2	Humidity	7	7
3	Rainstorm	3	3
4	Time	9	9
5	Previous Load History	9	9
6	Standard of Living	5	5
7	Bill Payment History	5	5
8	Predicted Load	9	9

Let the upper bound for $T = u_1$ 9
Upper bound of $H = u_2$ 10
Upper bound of $R = u_3$ 11
Upper bound of $t = u_4$ 12
Upper bound of $p = u_5$ 13
Upper bound of $S = u_6$ 14
Upper bound of $B = u_7$ 15
Upper bound of $P = u_8$ 16
Where upper bound $\boldsymbol{u_i}$ is the number of linguistic variables or MF for T, H, R, t, p, S, B and P respectively.

Let the initial value of all the antecedents be $\boldsymbol{a}$

Let $R_{max} = u_1 \times u_2 \times u_3 \times u_4 \times u_5 \times u_6 \times u_7$ **17**

Where $\boldsymbol{R_{max}}$ is the size of the matrix of all possible combinations of the antecedents corresponding to their respective consequences represented as in (18?)

$$\begin{bmatrix} T_{(a)} & H_{(a)} & R_{(a)} & t_{(a)} & p_{(a)} & S_{(a)} & B_{(a)} \\ & & & \vdots & & & \\ T_{(u_1)} & H_{(u_2)} & R_{(u_3)} & t_{(u_4)} & p_{(u_5)} & S_{(u_6)} & B_{(u_7)} \end{bmatrix} = \begin{bmatrix} P_{(b)} \\ \vdots \\ P_{(u_8)} \end{bmatrix} \quad 18$$

For each row on the left-hand side (LHS) of the matrix, the corresponding output, **P(RHS)** is determined by some underlying computations as follows:

The ratio r is the weight or a factor representing the impact of each variable on the output P. r is defined intuitively as what may be perceived with respect to P.

Let $\boldsymbol{r_1}$ be the ratio of T
$\boldsymbol{r_2}$ be the ratio of H
$\boldsymbol{r_3}$ be the ratio of R
$\boldsymbol{r_4}$ be the ratio of t
$\boldsymbol{r_5}$ be the ratio of p
$\boldsymbol{r_6}$ be the ratio of S
$\boldsymbol{r_7}$ be the ratio of B

Then the total ratio $total\_r$ is defined as:

$$total\_r = r_1 + r_2 + r_3 + r_4 + r_5 + r_6 + r_7 \quad 19$$

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A fraction f is needed to generate the sequences (the equivalent of each linguistic variable in the FIE) and is defined as:

$$f = \left(\frac{r_i}{total\_r}\right) \times u_8 \qquad 20$$

The sequence which is equivalent to linguistic variables for each antecedent is obtained using the general formula for arithmetic progression defined as:

$$a_n = a + (n-1)d \qquad 21$$

Where is the term under consideration, a is the first term in the sequence, n is the number of sequences, and d is the difference.

The difference d is defined as:

$$d = \frac{f}{upper\ bound\ of\ the\ antecedent} = a \qquad 22$$

From (21), the sequence of all consequences can be computed in order to generate a matrix whose sum of its rows represents the value of the predicted load P in the FIE.

Working Illustration

$if\ u_1 = 9, u_2 = 7, u_3 = 3, u_4 = 9, u_5 = 9. u_6 = 5, u_7 = 5\ and\ u_8 = 9$

Also,

$$if\ r_1 = 3, r_2 = 1, r_3 = 10, r_4 = 1, r_5 = 2\ and\ r_6 = 5\ and\ r_7 = 5$$

$$total_r = 3 + 1 + 10 + 1 + 2 + 5 + 5 = 26$$

The sequence for T is computed using (21). However, in order to find the difference d as in (21), a fraction f is required.

Where $f = \frac{r_i}{total_r} \times u_8$

$r_i = 3, total_r = 26\ and\ u_8 = 9$

$$f = \frac{3}{26} \times 9 = 1.04$$

$$d = \frac{f}{u_1} = \frac{1.04}{9} = 0.12 = a$$

Thus:

$T_1 = 0.12, T_2 = 0.24, \quad T_3 = 0.36, T_4 = 0.48, T_5 = 0.60, T_6 = 0.72, T_7 = 0.84, T_8 = 0.96\ T_9 = 1.08$

To compute the sequence for H using (21)

From (20),

$$f = \frac{1}{26} \times 9 = 0.35$$

$$d = \frac{f}{u_2} = \frac{0.35}{7} = 0.05 = a$$

Thus:

$$H_1 = 0.05, H_2 = 0.10,\ H_3 = 0.15,\ H_4 = 0.20\ H_5 = 0.25,\ H_6 = 0.30,\ H_7 = 0.35$$

To compute the sequence for R using (21)

From (20),

$$f = \frac{10}{26} \times 9 = 3.46$$

$$d = \frac{f}{u_3} = \frac{3.46}{3} = 1.15 = a$$

Thus:

$$R_1 = 1.15, R_2 = 2.30,\ R_3 = 3.45$$

However, since R is inversely proportional to the supply of electricity,

$$R_1 = 3.45, R_2 = 2.30, \quad R_3 = 1.15$$

To compute the sequence for t using (21)
From (20),

$$f = \frac{1}{26} \times 9 = 0.35$$
$$d = \frac{f}{u_4} = \frac{0.35}{9} = 0.03 = a$$

Thus:

$t_1 = 0.04, t_2 = 0.08, \quad t_3 = 0.12, \qquad t_4 = 0.16\ t_5 = 0.20, \qquad t_6 = 0.24, \qquad t_7 = 0.28, t_8 = 0.32,$ $t_9 = 0.36$

To compute the sequence for p using (21)
From (20),

$$f = \frac{2}{26} \times 9 = 0.69$$
$$d = \frac{f}{u_5} = \frac{0.69}{9} = 0.08 = a$$

Thus:

$p_1 = 0.08, p_2 = 0.16, \quad p_3 = 0.24, \ p_4 = 0.32\ p_5 = 0.40, \ p_6 = 0.48, \ p_7 = 0.56, p_8 = 0.64, \ p_9 = 0.72$

To compute the sequence for S using (21)
From (19),

$$f = \frac{5}{26} \times 9 = 1.73$$
$$d = \frac{f}{u_6} = \frac{1.73}{5} = 0.35 = a$$

Thus:

$S_1 = 0.35, S_2 = 0.70, \quad S_3 = 1.05, \ S_4 = 1.40\ S_5 = 1.75$

To compute the sequence for B using (21)
From (20),

$$f = \frac{5}{26} \times 9 = 0.96$$
$$d = \frac{f}{u_7} = \frac{1.73}{5} = 0.35 = a$$

Thus:

$B_1 = 0.35, B_2 = 0.70, \quad B_3 = 1.05, \ B_4 = 1.40\ B_5 = 1.75$

Thus, the matrix representing the inference engine is as represented in (23), being all possible combinations of the input variables.

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$$\begin{bmatrix} T_1 & H_1 & R_1 & t_1 & p_1 & S_1 & B_1 \\ T_1 & H_1 & R_3 & t_1 & p_1 & S_1 & B_1 \\ T_2 & H_1 & R_2 & t_2 & p_1 & S_2 & B_2 \\ T_2 & H_2 & R_2 & t_3 & p_2 & S_2 & B_3 \\ T_3 & H_3 & R_1 & t_4 & p_3 & S_3 & B_2 \\ T_3 & H_4 & R_1 & t_5 & p_4 & S_3 & B_3 \\ T_4 & H_4 & R_2 & t_4 & p_5 & S_4 & B_2 \\ T_6 & H_5 & R_3 & t_5 & p_6 & S_2 & B_3 \\ T_4 & H_6 & R_1 & t_4 & p_7 & S_3 & B_4 \\ T_6 & H_5 & R_3 & t_6 & p_7 & S_4 & B_5 \\ T_8 & H_7 & R_1 & t_8 & p_5 & S_1 & B_2 \\ T_7 & H_3 & R_1 & t_7 & p_6 & S_5 & B_5 \\ T_6 & H_6 & R_3 & t_8 & p_5 & S_2 & B_4 \\ T_2 & H_2 & R_2 & t_2 & p_2 & S_2 & B_2 \\ T_3 & H_3 & R_3 & t_3 & p_3 & S_3 & B_3 \\ T_4 & H_4 & R_1 & t_4 & p_4 & S_4 & B_4 \\ T_5 & H_5 & R_1 & t_5 & p_5 & S_5 & B_5 \\ T_5 & H_5 & R_2 & t_2 & p_5 & S_5 & B_5 \\ T_5 & H_5 & R_3 & t_5 & p_5 & S_5 & B_5 \\ T_6 & H_6 & R_1 & t_6 & p_6 & S_1 & B_1 \\ T_6 & H_6 & R_2 & t_6 & p_6 & S_2 & B_2 \\ T_6 & H_6 & R_6 & t_6 & p_6 & S_3 & B_3 \\ T_7 & H_7 & R_1 & t_7 & p_7 & S_4 & B_4 \\ T_7 & H_7 & R_2 & t_7 & p_7 & S_5 & B_5 \\ T_7 & H_7 & R_3 & t_7 & p_7 & S_1 & B_2 \\ T_8 & H_6 & R_1 & t_8 & p_8 & S_2 & B_3 \\ T_9 & H_7 & R_3 & t_8 & p_9 & S_4 & B_3 \\ T_9 & H_7 & R_2 & t_8 & p_9 & S_2 & B_5 \\ T_9 & H_7 & R_1 & t_9 & p_9 & S_3 & B_3 \\ T_9 & H_7 & R_1 & t_9 & p_9 & S_5 & B_5 \\ & & & \vdots & & & \\ T_9 & H_7 & R_3 & t_9 & p_9 & S_5 & B_5 \end{bmatrix} = \begin{bmatrix} P_{(b)} \\ \vdots \\ P_{(u_8)} \end{bmatrix}$$

Substituting the value of $T_1, T_2, \dots T_9, H_1, H_2, \dots H_7,$ $R_1, R_2, R_3, t_1, t_2, \dots, t_9, p_1, p_2, \dots p_9, S_1, S_2, \dots S_5$ *and* $B_1, B_2, \dots B_5$ in (23), the sequences produced for each input variable result in:

$$P_{(1)} = 0.12 + 0.05 + 3.43 + 0.04 + 0.08 + 0.35 + 0.35 = 4.42$$
$$P_{(2)} = 0.24 + 0.05 + 1.15 + 0.08 + 0.08 + 0.35 + 0.35 = 2.303$$
$$P_{(2)} = 0.24 + 0.05 + 2.30 + 0.08 + 0.08 + 0.70 + 0.70 = 4.07$$
$$P_{(3)} = 0.24 + 0.10 + 2.30 + 0.12 + 0.16 + 0.70 + 1.05 = 4.67$$
$$P_{(4)} = 0.36 + 0.15 + 3.45 + 0.16 + 0.24 + 1.05 + 0.70 = 6.11$$
$$P_{(5)} = 0.12 + 0.20 + 3.45 + 0.20 + 0.32 + 1.05 + 1.05 = 6.39$$
$$P_{(6)} = 0.48 + 0.20 + 2.30 + 0.16 + 0.40 + 1.40 + 0.70 = 5.64$$
$$P_{(7)} = 0.72 + 0.25 + 1.15 + 0.20 + 0.48 + 0.70 + 1.15 = 4.65$$
$$P_{(8)} = 0.48 + 0.30 + 3.45 + 0.16 + 0.56 + 1.05 + 1.40 = 7.40$$
$$P_{(9)} = 0.75 + 0.30 + 3.45 + 0.16 + 0.56 + 1.40 + 1.75 = 8.37$$
$$P_{(10)} = 0.84 + 0.35 + 3.45 + 0.32 + 0.40 + 0.35 + 0.75 = 6.46$$
$$P_{(11)} = 0.84 + 0.15 + 3.45 + 0.28 + 0.45 + 1.75 + 1.75 = 7.31$$
$$P_{(12)} = 0.72 + 0.30 + 1.15 + 0.32 + 0.40 + 0.70 + 1.40 = 4.99$$
$$P_{(13)} = 0.24 + 0.10 + 2.30 + 0.08 + 0.16 + 0.70 + 0.70 = 4.28$$
$$P_{(14)} = 0.36 + 0.15 + 1.15 + 0.12 + 0.24 + 1.05 + 1.05 = 4.12$$
$$P_{(15)} = 0.48 + 0.20 + 3.45 + 0.16 + 0.32 + 1.40 + 1.40 = 7.41$$
$$P_{(16)} = 0.60 + 0.25 + 3.45 + 0.20 + 0.40 + 1.75 + 1.75 = 8.00$$

$$P_{(17)} = 0.60 + 0.25 + 2.30 + 0.08 + 0.40 + 1.75 + 1.75 = 713$$
$$P_{(18)} = 0.60 + 0.20 + 1.15 + 0.20 + 0.40 + 1.75 + 1.75 = 6.05$$
$$P_{(19)} = 0.72 + 0.30 + 3.45 + 0.24 + 0.48 + 0.35 + 0.35 = 5.89$$
$$P_{(20)} = 0.72 + 0.30 + 1.15 + 0.24 + 0.48 + 1.15 + 1.15 = 5.19$$
$$P_{(21)} = 0.84 + 0.35 + 3.45 + 0.28 + 0.56 + 1.40 + 1.40 = 8.28$$
$$P_{(22)} = 0.84 + 0.35 + 2.30 + 0.28 + 0.56 + 1.75 + 1.75 = 7.47$$
$$P_{(23)} = 0.84 + 0.35 + 1.15 + 0.28 + 0.56 + 0.35 + 0.70 = 4.23$$
$$P_{(24)} = 0.96 + 0.30 + 3.45 + 0.32 + 0.64 + 0.70 + 1.05 = 7.42$$
$$P_{(25)} = 0.96 + 0.30 + 3.45 + 0.32 + 0.64 + 1.05 + 1.05 = 7.77$$
$$P_{(26)} = 1.05 + 0.35 + 1.15 + 0.32 + 0.72 + 1.40 + 1.05 = 7.74$$
$$P_{(27)} = 1.05 + 0.35 + 2.30 + 0.32 + 0.72 + 0.70 + 1.75 = 6.19$$
$$P_{(28)} = 1.05 + 0.35 + 3.45 + 0.36 + 0.72 + 1.75 + 1.75 = 9.43$$

$$P_{(m)} = 1.05 + 0.35 + 1.15 + 0.36 + 0.72 + 1.75 + 1.75 = 7.13$$

The sum of $P_{(1)}, P_{(2)\dots\ P_{(bm)}}$ (each row) after approximation to the nearest integer gives the value p in the FIE. Each row represents a single line in the FIE based on linguistic variables as described in (1) … (7). Thus (23) and the resulting summation will give the FIE as attached Appendix A.

Inference Engine

The inference engine constitutes the entire rule set for the system and is responsible for selecting the appropriate rules from the rule based on the knowledge base. The first part of the development of the inference engine for this work was the generation of combination values for all input variables with respect to the number of linguistic terms for each input variable. The study succeeded in formulating a mathematical model that automatically assigned the value of the predicted load for each rule formed from the combination of all possible rules. A total of about 347,000 combinations were generated, which were subsequently used in generating the fuzzy rules for this study. The combination algorithm is as shown in algorithm 1.

Algorithm 1: The algorithmm for generating all possible combinations of inputs in data set generated using recursive approach

def combination (store, items, start_index):

1. If **start_index** is greater or equal to length of **items**, return from recursive call
2. Set **i** to 0 and repeat the following until **i** is less than length of **items**
3. Set **j** to 1 and repeat until **j** equals **item** at position **i**
4 Copy all the elements in **items** to a new list **tmp**
5 Set the **i**th element of the new list **tmp** to the value of **j**
6 Add the modified list **tmp** to **store**
7 ***Recurse*** with **i + 1** as the starting index
8 Delete list **tmp**

Furthermore, in determining the predicted load for each variable, each variable was assigned a ratio representing its impact on the result. This study created a relationship between input variables and the corresponding output. This was achieved by assigning different weights to the input variables depending on their prevailing consequence on the output. Rainstorm R has the highest weight, followed by the supply-required factors: standard of living (SoL) and bill payment history (BPH). Temperature T has the highest weight among the demand-required factors. Whereas Algorithm 2 depicts the establishment of the relationship between input and output variables, Algorithm 3 puts all the algorithms together to give the fuzzy predicted model.

Algorithm 2: Algorithm for computing the relationship between all variables with respect to the output

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Def compute(upper_bound, output_upper_bound, inverse = False):
1. create a new list **of data**
2. divide **output_upper_bound** by **upper_bound** and store the quotient in **diff**
3. if **inverse** is set to false
4. loop from 0 to **upper_bound** with **i** as the loop counter
5. set element in **data** at position **i** to **(i + 1)** x **diff**
6. else if **inverse** is set to true
7. loop from 0 to **upper_bound** with **i** as the loop counter
8. set element in **data** at position **i** to **output_upper_bound - ((i + 1) x diff)**
9 return **data**

Algorithm 3: Algorithm for the load demand-supply balance predictive model
1. Create and Initialize the antecedents to hold universe variables
2. Create and initialize the consequent object
3. Create membership functions for all antecedents' objects
4. Create an empty list **rules**
5. Read generated dataset for fitting from external comma separated values file
    a. For each row in the data
    b. Create a rule from the columns in the current row
    c. Add the rule to **rules** list
6. Create a control system using the **rules** list above
7. Create a simulation object for simulating the system
8. Simulate the control system with some sets of input
9. Visualize result

Results

Inputs were supplied to the model, and the corresponding output in graphical and numeric value is shown in Figures 1 and 2 respectively.

$T = 38, H = 80, R = 5, t = 17, p = 20, S = 10, B = 15$ and P=19.23466254

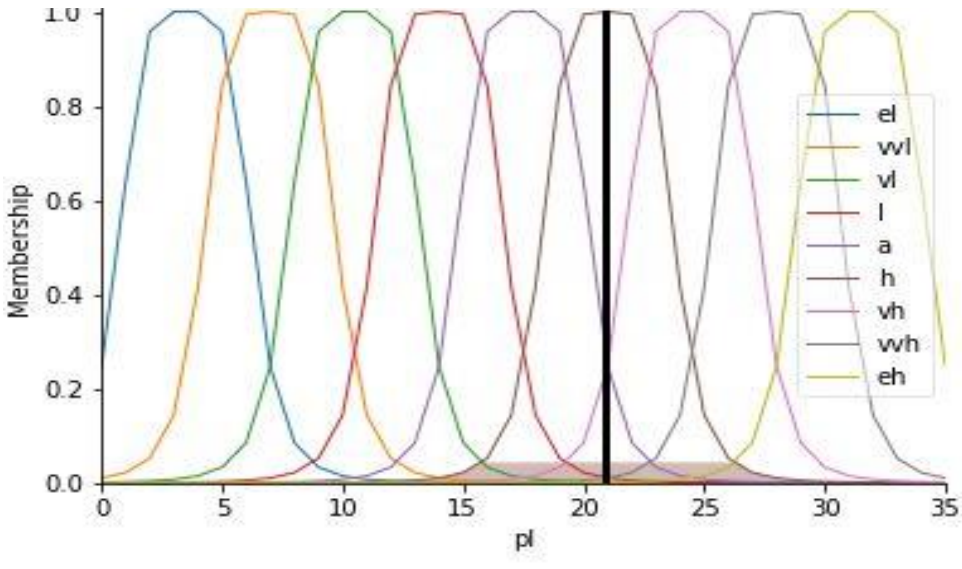

Figure 1: Non-Linear Model Predicted Results for a

$T = 38, H = 80, R = 45, t = 17, p = 20, S = 10, B = 15$ and P=10.68016271

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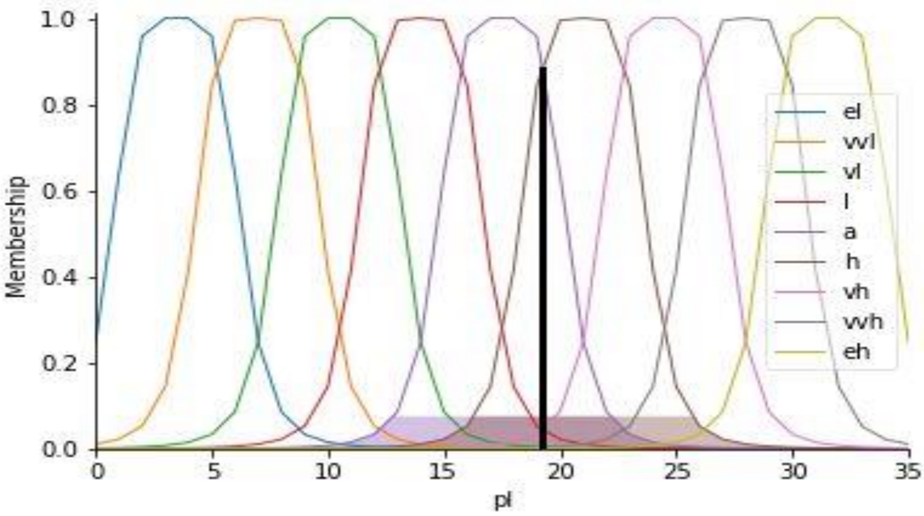

Figure 2: Non-Linear Model Predicted Results for b

In Table 1, more information about the results and how they relate to the inputs are presented. The linear relationship between the input variables and the outputs is further shown in Figure 3.

Table 1. Model development outcomes

S/N	**Pred. Temp.**	**Pred. Humidity**	**Pred. Rainstorm**	**Time**	**Previous Load History**	**Living Standard**	**Bill Payment**	**Predicted Results**
1	20	40	10	14	16	40	50	19.85078435
2	22	70	5	24	18	45	55	23.91980779
3	30	90	50	16	19	80	85	19.24331729
4	17	38	3	10	22	60	69	25.88611553
5	24	68	40	12	14	20	15	11.0137814
6	30	55	7	14	17	65	70	25.78306812
7	18	85	52	20	27	80	85	20.47487798
8	18	85	52	20	27	30	25	12.36601134
9	40	90	1	15	28	90	95	27.83583489
10	43	85	45	15	28	90	90	20.98546185
11	39	70	58	16	26	95	95	20.92479465
12	38	80	5	17	20	10	15	19.23466254
13	38	80	45	17	20	10	15	10.68016271
14	23	75	4	18	21	80	76	26.02712201
15	17	45	55	19	20	95	75	17.29651328
16	17	45	7	19	20	95	75	26.09108875
17	17	45	7	19	20	10	15	18.01319542
18	15	50	20	1	15	30	35	19.25156917
19	23	59	16	4	10	70	60	22.68209429
20	19	22	2	7	17	28	45	19.27917309

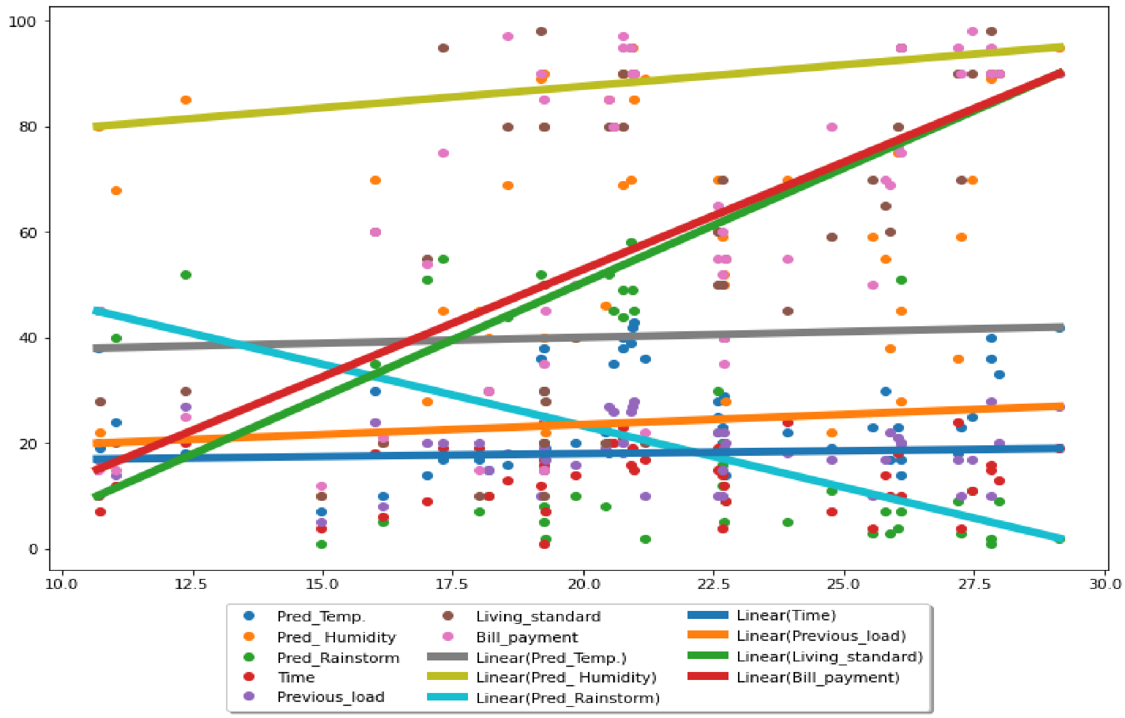

Figure 3: Relationship between Antecedents and the Consequence in Load Balancing Prediction Based on Gbell

Discussion

The results show that electricity increases by 0.96% for every 5℃ increase in temperature, as opposed to an increase of 0.26% for every 5℃ increase in temperature as outlined by Salehizade et al. (2015). The increased electricity consumption in this study is a result of the higher temperature that is associated with the study area as compared to the study by Salehizade et al. (2015). Furthermore, some algorithms were developed to generate datasets for experimentation to test the model. Additionally, this study further revealed that the consumption of electricity is directly proportional to the standard of living and the history of bill payment. This method will reduce errors resulting from users' intuitively assigning output values in the fuzzy inference engine development procedure.

Conclusion

This research proposed a model that takes temperature T, humidity H, rainstorm R, time t, previous load history P, standard of living S, and bill payment history B as the input parameters (antecedents) as well as the weight or the impact of each input variable as may be defined or perceived by the users in order to automatically generate a FIE for any given fuzzy predictive model or the prediction of electric load demand-supply balance for a given location. The results affirmed the linear relationship that exists between load consumption and temperature and humidity. However, it was revealed that load supply is inversely proportional to rainstorms. This is a result of the overhead distribution of electricity in the study area (Nigeria), which is easily affected by rainstorms, resulting in a minimal supply of electricity during heavy rainstorms. Furthermore, this model can be applied to any fuzzy predictive model as long as the input parameters are properly classified and assigned their weight with respect to the output.

Recommendations

The results affirmed the linear relationship that exists between load consumption and temperature and humidity.

1. This paper recommends that in considering the load consumption there is a need to consider the temperature and humidity of the area.
2. These factors need to be looked into very well. There is a need for more research in this field so that the weaknesses can be addressed as other factors may have a serious impact on load consumption. Similar locations should be used to test the prediction of electric load demand-supply balance.

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Appendix A

Rule1= If T(excessively_low) & H(very_very_wet) & R(very_high_rainstorm) & t(mid_night) & p(excessively_low) & S(poorest) & B(very_low) then P(very_very_low)

Rule2= T(excessively_low) & H(very_very_wet) & R(no_rainstorm) & t(mid_night) & p(excessively_low) & S(poorest) & B(low) then P(average)

Rule3= T(very_very_low) & H(very_very_wet) & R(high_rainstorm) & t(toward_morning) & p(very_very_low) & S(poor) & B(average) then P(low)

Rule4= T(very_very_low) & H(very_wet) & R(high_rainstorm) & t(early_morning) & p(very_very_low) & S(moderate) & B(low) then P(low)

Rule5= T(very_low) & H(wet) & R(very_high_rainstorm) & t(mid_morning) & p(very_low) & S(poor) & B(low) then P(high)

Rule6= T(very_low) & H(normal) & R(very_high_rainstorm) & t(noon) & p(very_low) & S(moderate) & B(average) then P(high)

Rule7= T(low) & H(wet) & R(high_rainstorm) & t(mid_morning) & p(average) & S(rich) & B(low) then P(high)

Rule8= T(high) & H(wet) & R(no_rainstorm) & t(noon) & p(very_high) & S(poor) & B(average) then P(avearge)

Rule9= T(very_low) & H(very_wet) & R(very_high_rainstorm) & t(mid_morning) & p(very_very_high) & S(moderate) & B(high) then P(very_high)

Rule10= T(high) & H(wet) & R(no_rainstorm) & t(afternoon) & p(very_high) & S(fairly_rich) & B(very_high) then P(very_very_high)

Rule11= T(very_very_high) & H(very_very_wet) & R(very_high_rainstorm) & t(night) & p(average) & S(poorest) & B(low) then P(high)

Rule12= T(very_high) & H(dry) & R(very_high_rainstorm) & t(early_evening) & p(high) & S(rich) & B(high) then P(very_high)
Rule13= T(high) & H(very_wet) & R(no_rainstorm) & t(night) & p(average) & S(poor) & B(very_high) then P(average)
Rule14= T(very_very_low) & H(very_dry) & R(high_rainstorm) & t(toward_morning) & p(very_very_low) & S(poor) & B(low) then P(very_low)
Rule15= T(very_low) & H(dry) & R(no_rainstorm) & t(early_morning) & p(very_low) & S(moderate) & B(average) then P(low)
Rule16= T(low) & H(normal) & R(very_high_rainstorm) & t(mid_morning) & p(low) & S(faily_rich) & B(high) then P(very_high)
Rule17= T(average) & H(very_wet) & R(very_high_rainstorm) & t(noon) & p(low) & S(rich) & B(high) then P(very_very_high)
Rule18= T(average) & H(wet) & R(high_rainstorm) & t(toward_morning) & p(average) & S(rich) & B(high) then P(very_high)
Rule19= T(average) & H(wet) & R(no_rainstorm) & t(noon) & p(average) & S(rich) & B(poorest) then P(very_high)
Rule20= T(high) & H(wet) & R(very_high_rainstorm) & t(afternoon) & p(high) & S(rich) & B(high) then P(high)
Rule21= T(high) & H(very_wet) & R(very_high_rainstorm) & t(afternoon) & p(high) & S(poorest) & B(very_low) then P(high)
Rule22= T(high) & H(very_wet) & R(high_rainstorm) & t(afternoon) & p(high) & S(faily_poor) & B(very_low) then P(average)
Rule23= T(high) & H(very_wet) & R(no_rainstorm) & t(afternoon) & p(high) & S(moderate) & B(average) then P(very_very_high)
Rule24= T(very_high) & H(very_very_wet) & R(very_high_rainstorm) & t(early_evening) & p(very_high) & S(faily_rich) & B(high) then P(very_high)
Rule25= T(very_high) & H(very_very_wet) & R(no_rainstorm) & t(early_evening) & p(very_high) & S(poorest) & B(low) then P(low)
Rule26= T(very_very_high) & H(very_wet) & R(very_high_rainstorm) & t(night) & p(very_very_high) & S(faily_poor) & B(average) then P(very_high)
Rule27= T(extremely_high) & H(very_very_wet) & R(no_rainstorm) & t(night) & p(extremely_high) & S(faily_rich) & B(average) then P(very_very_high)
Rule28= T(extremely_high) & H(very_very_wet) & R(high_rainstorm) & t(night) & p(extremely_high) & S(poor) & B(very_high) then P(high)
Rule29= T(extremely_high) & H(very_very_wet) & R(very_high_rainstorm) & t(late_night) & p(extremely_high) & S(moderate) & B(average) then P(extremely_high)
Rule = **Rule30**= T(extremely_high) & H(very_very_wet) & R(very_high_rainstorm) & t(late_night) & p(extremely_high) & S(rich) & B(avery_high) then P(very_high)

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