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LONG-TERM LOAD FORECASTING USING ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM: A CASE STUDY OF 330KV MANDO TRANSMISSION STATION, KADUNA, NIGERIA

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ABSTRACT

Long-Term Load Forecasting Using Adaptive Neuro-Fuzzy Inference System: A Case Study of 330kV Mando Transmission Station, Kaduna, Nigeria is a research work which is aimed at predicting future energy demand, in Megawatt (MW), with the adaptive neuro-fuzzy inference system (ANFIS) method. Electric load forecasting (ELF) is an informed use of previous and current load demands in predicting load demand to come with high measure of reliability and accuracy. Load forecasting (LF), is a requirement for generation and or transmission expansion. The ANFIS method is a hybrid Artificial Intelligence (AI) method which consists of Artificial Neural Network, Fuzzy Logic and Fuzzy Inference System to develop a model which is intelligent in decision-making. Time series load demand data (in MW) for 2022, 2023 and 2024 were collected from the Mando Transmission Station, analyzed and collated into Peak and Average daily load demand. These 3 years load data were daily, half-hourly load demand data up to 56,560 data set and therefore used for the long-term electric load forecasting. With the use of feed forward back propagation training algorithm, in MATLAB/Simulink, these data were trained, tested

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and forecasting of load demand for 11 years to come was done: 2025 to 2035. Assessment of the performance accuracy of the data training was done with Root Mean Square Error (RMSE) assessment metric. The maximum prediction error for the Peak load demand was 0.07% while that of the Average load demand was 0.08%. This shows successful training and high-performance accuracy of the ANFIS model. Forecast made for the 11 years horizon showed the maximum peak daily load demand will be 592.7MW and will occur on 1st of December, 2031 while the corresponding maximum average daily load demand will be 262MW and will occur on 11th of November, 2031. Furthermore, the results show the peak daily load demand will rise by 69% in eleven years to come while the average daily load demand will rise by 81% in the same period.

INTRODUCTION

The certainty that Nigerian is becoming an economy to reckon with in Africa and the need to provide the energy requirements for its growing population underscores the need for generation and transmission expansion, thus it is imperative to forecast the future energy demand of the nation. This future energy demand prediction is known as electric load forecasting (ELF). Electric load forecasting is an informed use of previous and current load demands in predicting load demand to come with high measure of reliability and accuracy (Ade-Ikuesan et al., 2019; Airoboman & Idiagi, 2020; Alabi et al., 2022; Olabode et al., 2019).

Load forecasting is categorized as long, medium or short term. Olabode et al, (Olabode et al., 2019), broadly categorized load forecasting regarding the duration of the planning horizon to be short-term load forecasting (STLF), medium-term load forecasting (MTLF) and long-term load forecasting (LTLF). A horizon of 1 hour to 1 week for STLF: 1 week to 1 year for MTLF and more than 1 year for LTLF. Short-term load forecasting is very vital for the real-time control and the security performance of power system as well as electric power scheduling (Alabi et al., 2022)(Olabode et al., 2019). Short-term load forecasting is employed for the system security evaluation challenges, especially where there is higher penetration of renewable energy sources in power grids that are isolated. It can also provide useful information in sensing vulnerable situations very early. Long- and medium-term load forecasts are employed to design the fuel purchases plan, capacity of generation units, transmission or distribution system additions, together with the type of installations required in transmission expansion planning, yearly hydro and thermal maintenance planning, etc. (Alabi et al., 2022)(Olabode et al., 2019). Nikos Andriopoulos

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et al, (Andriopoulos et al., 2021), went further to identify a planning horizon duration of 5 minutes to 24 hours as very short-term load forecasting (VSTLF). The VSTLF is necessary for everyday operations of a power distribution company since it is used for unit commitment, energy transfer scheduling and load dispatch.

Many techniques have been used to carry out electric load forecasting each with their attendant drawbacks. For example, time series analysis is a good technique to form mathematical models for resolving a number of complicated problems (Ortiz-Arroyo et al., 2005). The mathematical models are employed to project the behaviour of an occurrence which is depicted with a series of observations. But forming a very correct model for such an occurrence is not easy at all (Ortiz-Arroyo et al., 2005). Models for electric load forecasting are majorly classified as statistical, Artificial Intelligence (AI) and hybrid (Olabode et al., 2019)(Sun et al., 2021). All forms of autoregressive and parametric approaches are categorized as statistical models whereas AI approaches include artificial neural networks (ANNs), support vector machine (SVM), fuzzy logic and expert systems (Olabode et al., 2019)(Sun et al., 2021). Many hybrid models combining different models were put forward. The hybrid model could be superior to the single model since the drawbacks of the single model could be overcome therein. In the hybrid models, ANN was given most attention and the ANN based forecasting techniques have been widely accepted in practice (Sun et al., 2021). Modern approaches now is to resolve human problems with the use of artificial intelligence (AI) ways (Alabi et al., 2022). One of the AI ways, which are the ANNs have been used with success to resolve a wide range of problems which contain linear processes as well as non-linear processes (Ortiz-Arroyo et al., 2005). The success of using the ANNs is because when they are correctly trained and configured, they can approximate any measurable function correctly.

While some of the literatures used time series forecasting methods, some of them, especially (Ade-Ikuesan et al., 2019) and (Filippov et al., 2021), used the multi-factor forecasting methods. Factors like economic and demographic do affect the accuracy of such ELF outcome which is a research gap in itself (Hammad et al., 2020). Other literatures either worked on short-term load forecasting or medium-term load forecasting which do not meet the significance of this research work of using the results of the work for generation and transmission expansion planning. Again, there are problems associated with some of the single techniques used like Artificial Neural Network model, where training the network is time consuming, and if data is trained to extreme accuracy, it becomes rigid and may not be suitable for future forecasting. Another single technique used is the Fuzzy System, which has the problems of slow response due to serial data processing and that the fuzzy output can be interpreted in a number of ways which makes the analysis difficult (*BasuMillick, 2024*).

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However, ANFIS, being a hybrid AI method, can overcome these limitations because it can be used to model nonlinear connections between inputs and outputs which are mostly difficult for traditional methods to model. It can also handle noisy or incomplete data including missing values and outliers by the use of fuzzy logic to exhibit imprecision and uncertainty. Again, ANFIS learns from feedback and adjusts its rules, which makes it stronger and adaptable than static models. Additionally, ANFIS gives results that can be explained and interpreted, because the neural networks and fuzzy rules can be understood and even visualized by human beings (*Walker II, 2024)*. Furthermore, ANFIS does not require prior human expertise, it makes learning fast and accurate, and it has ease of implementation (Al-Hmouz et al., 2012). It is worth mention here that the ANFIS, as a time series forecasting method, is less difficult and faster (Hammad et al., 2020); (Nti et al., 2020).

Electric load forecasting is a very crucial part of electric power system operation through which decisions like generating capacity, reliability analysis and maintenance plan can be made. Hence, ELF result needs to be always accurate if not, it can lead to waste of energy or failure to serve the load demand. On the other hand, if the ELF result is accurate, power system operation will be safeguarded and energy utilization will also be improved (Sun et al., 2021).

LITERATURE REVIEW

There are a number of methods and techniques or models available for load forecasting (LF). In their comprehensive review work on methods and models for ELF, Mahmoud et al, (Hammad et al., 2020), averred that the ELF methods are classified into:

- Multi-factor techniques and
- Time series techniques.

According to (Hammad et al., 2020), the multi-factor technique pays attention to the relationship that exists between various factors (such as economic and demographic) which affect the LF and the LF outcomes. This however puts the multi-factor forecasting methods at a disadvantage because it is more difficult to forecast economic and demographic factors than just the LF (Nti et al., 2020). They (Hammad et al., 2020), however, asserted that the time series technique focuses on the historical sequence of the load. This could be why many researchers have grouped ELF methods into two, namely the multi-factor and time series forecasting methods and, at the same time, tend to be using the time series method so as to avoid those factors that will make the ELF much more complicated, thereby affecting the accuracy of the LF outcomes (Hammad et al., 2020)(Nti et al., 2020). So, the time series forecasting method is less difficult and faster, however, none of the methods is taken scientifically as better in all cases (Hammad et al., 2020)(Nti et al., 2020). Based on the most commonly and extensively used

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techniques, the time series techniques can be further classified into three (3) namely, statistical techniques, machine learning or artificial intelligence techniques and hybrid techniques (Hammad et al., 2020). The hybrid techniques are mixtures of techniques and methods which can give superior LF accomplishment than a single technique by combining the merits of different single LF techniques and hence, extensively used in various LF arenas. Hence, this research paper will use the ANFIS method which is a hybrid machine learning/AI technique. And therefore, the focus here will be on the ANFIS technique only.

ANFIS is a type of technique which uses neural networks, fuzzy logic and inference systems that creates decision-making models that are intelligent. It can carry out tasks like clustering, regression, control, classification, etc. ANFIS is advantageous because it can deal with incomplete and complicated data, and can also learn from experience, and adapt to changing environments (Walker II, 2024). It can easily model nonlinear connections between inputs and outputs which traditional methods cannot. It can handle noisy or incomplete data including missing values using fuzzy logic to exhibit imprecision and uncertainty. ANFIS has the ability to learn from feedback and use that to adjust its rules whenever necessary. This makes it stronger and adaptable than the statistical models. Furthermore, it has the ability to give results which can be explained and interpreted, because the neural networks and fuzzy rules can be understood and even visualized by human beings (Walker II, 2024).

The working procedures of the ANFIS are, (a) input data is fed into a neural network that has layers of artificial neurons which perform mathematical operations on the input data, (b) output of the neural network is then taken through an FIS. The FIS contains the fuzzy sets and the fuzzy rules which map its outputs to linguistic terms, (c) the FIS employs FL in handling uncertainty and imprecision in the data by allotting degrees of membership to each term based on how good they suit the output and (d) the end result comes out as a crisp value that best suits the input and the output as decided by the fuzzy rules and neural network (Walker II, 2024). Applications of the ANFIS are system behaviour prediction, prediction of events, medical diagnosis, image recognition, control system, artificial intelligence, etc. (Al, 2023; Kassem et al., 2017; Keshavarz & Torkian, 2018; Kumar et al., 2023; Walker II, 2024).

In their work, (Ade-Ikuesan et al., 2019) used the technique of linear regression analysis to carry out long-term load forecasting (LTLF) in Ogun State of Nigeria, and the population for a horizon of 10 years. Electric energy demand data for 2016 and 2017 were collected from Ibadan Electricity Distribution Company while the population data were collected from Nigeria's National Population Commission. The result obtained showed a rise in electricity consumption demand by 53% with a corresponding population growth rate of 3.35% per annum. The method used here is the multi-factor forecasting method and

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factors like economic and demographic do affect the accuracy of such ELF outcome which is a research gap in itself (Hammad et al., 2020).

Also, (Chika O. Ikaraoha & Adegoke O. Melodi, 2015) employed Artificial Neural Network model for a multifactorial short-term load forecasting (STLF) for Enugu Load Centre in Enugu State of Nigeria with the aim of improving the LF accuracy. The authors therefore introduced temperature, per capita income and customer load category into the LF model. They used historical load data, temperature data, per capita income and load category for the months of August 2012 to October 2012 to train the model. Mean Square Error performance metric was used to evaluate the model. The MSE gave an average of 0.013 when the trained network was analyzed over the data of one week. Averagely, this shows a good degree of accuracy in the LF, as reported by the authors. However, there are problems associated with this ANN model: beside being a single technique, training the network is time consuming, and if data is trained to extreme accuracy, it becomes rigid and may not be suitable for future load forecasting.

Again, (Hattab et al., 2017) made use of Particle Swarm Optimization (PSO) algorithm based on Least Square Regression (LSRM) technique to perform medium-term load forecasting (MTLF) for the Jordanian grid for one year, 2015. Prediction was done on a weekly or a monthly basis on historical peak load data and weather influence. Performance assessment was done using the least square error (LSE) for both the PSO and the LSRM models and, thereafter, a comparison of these two models was made with Auto Regressive (AR) model and the informed assumptions that the Jordanian National Electric Power Company (NEPCO) used to do. NEPCO actual load data was used to validate how these two models performed. Using average error analysis, the two models of PSO algorithm and LRSM gave better projection than the AR model and the informed assumptions that the NEPCO used to do. However, result of the MTLF used here did not meet the significance of this research work of using the results of the research work for generation and transmission expansion planning.

In another literature, (Dikio C. Idoniboyeobu et al., 2018) conducted long-term load forecasting (LTLF) in Nigeria with the use of modified form of exponential model for a 20 years horizon (2013 – 2032). The model was carried out in MATLAB environment with plots of residential, commercial and industrial load demands in MW. Data used for the analysis were obtained from the Nigerian Central Bank and the Nigerian Bureau of Statistics. The result showed that power from the generating stations was seriously insufficient which was a mismatch, which was problematic in power system. Deviation between projected power demand in 20 years to come and available power was also observed. The modified form of exponential model is not a hybrid method which can give clear merits especially in transformational adjustment of variation in the environment, training by example,

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allowance to noise and finding out new connections between variables like the ANFIS model (Srinivasan & Lee, 1995).

In their work, (Faysal et al., 2019) employed fuzzy system and carried out short-term load forecasting (STLF) for the power network of Bangladesh. The authors considered the parameters of day time, yearly seasons, humidity and temperature, which determine electrical load demand. Mamdani rule on membership functions was applied to get the output by the use of centroid method. The result obtained presented the actual behaviour of the load demand. The difference between the actual load and the output of the fuzzy system was between +1.65% to -13.76%. This showed that fuzzy system can be used for such an interconnected power network like the one in Bangladesh to mitigate power losses where the generation is more than what the load actually demands. The Fuzzy System is a single load forecasting technique which has the problems of slow response due to serial data processing and that the fuzzy output can be interpreted in a number of ways which makes the analysis difficult.

In another work, (Imani, 2019) combined the two techniques of long short-term memory (LSTM) and support vector regression (SVR) and carried out short-term electrical load forecasting (STLF). The author reported that using LSTM for feature extraction from the load and temperature time series, then the extracted features were then given to the SVR, forecasting results were obtained that are better compared to when only LSTM was used for the feature extraction and forecasting. That is to say, LSTM and SVR gave better forecasting results in terms of accuracy than the use of the LSTM alone. Even though the method used here is a hybrid method, it falls short of the significance of this research paper of using the results for generation and transmission expansion planning as it was used for STLF only.

According to the work by (Filippov et al., 2021), who carried out long-term load forecasting (LTLF) by the use of energy demand forecasting based on systems analysis (EDFS) for the social and economic development of Russia's economy. This EDFS technique disaggregated electric power consumers by economic sectors, country regions, energy carriers and their locations. Consequently, it was made possible to consider the prospects of future technological and structural changes in the economy, its differences in various regions, mutual replacements of energy carriers and energy saving. In forecasting the economic variables, a conditional and dynamic model of the relationships between the economy and energy was used while that of the energy variables were done on the basis of their links with the economic factors. Eventually, this separation of variables made it possible to, in essence, get better LTLF results because of considering differences in the variation trends of the economic and energy variables in the forecast horizon. Again, the method used here is the multi-factor forecasting method and, as highlighted earlier, the

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accuracy of such ELF is affected by some of the factors used which is a research gap in itself (Hammad et al., 2020).

METHODOLOGY

The ANFIS method is an easy method which makes use of Fuzzy Logic to change numerical inputs into a required output by the use of well interconnected ANN processing and information elements that are weighted to map such inputs into an output (Al-Hmouz et al., 2012; *Anon. (2024)*; Zakri et al., 2019). ANFIS is a hybrid method which combines FL and ANN. It uses ANN learning techniques to tune FIS parameters. Some of the characteristics that make ANFIS very successful include its not needing prior human expertise, making learning fast and accurate, ease of implementation, refining the fuzzy rules of IF-THEN in describing the behaviour of any complex system, ease of including numeric and linguistic knowledge for solving problems, and robust generalization capabilities, very good explanation ability through fuzzy rules, offering the needed data set and a better choice of membership functions to use (Al-Hmouz et al., 2012).

In ANFIS, rules that are not the same do not share similar output membership function, because the number of membership functions must be the same with the number of rules. Based on Takagi-Sugeno (TS) Model, two fuzzy IF-THEN rules are presented in the ANFIS architecture as follows (Al-Hmouz et al., 2012).

$\text{Rule}_{(1)}$: IF x is A_1 AND y is B_1, THEN

$$f_1 = p_1x + q_1y + r_1. \quad (1)$$

$\text{Rule}_{(2)}$: IF x is A_2 AND y is B_2, THEN

$$f_2 = p_2x + q_2y + r_2. \quad (2)$$

Where: x and y are the inputs, A_i and B_i are the fuzzy sets, f_i are the outputs within the fuzzy rule, and p_i, q_i and r_i are the design parameters that are determined during the training process.

The above TS Model process is as shown in Figure 1. It is the foundation for the ANFIS model for implementing $\text{Rule}_{(1)}$ and $\text{Rule}_{(2)}$. As can be seen from the Figure, a circle shows a fixed node while a square shows an adaptive node. The ANFIS architecture has five layers namely: Layer 1, Layer 2, Layer 3, Layer 4 and Layer 5. These layers can be explained as follows (Al-Hmouz et al., 2012).

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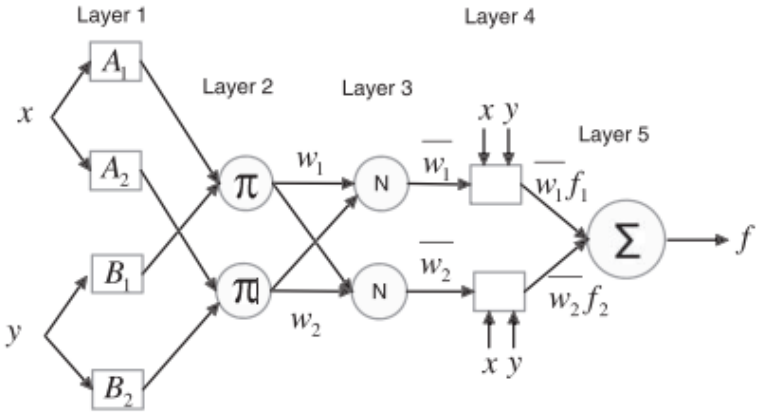

Fig. 1. ANFIS architecture based on TS Model (Al-Hmouz et al., 2012)

Layer 1: it consists of adaptive nodes whose outputs are the fuzzy membership form of the given inputs as shown in equations (3) – (6);

$$O_{1,i} = \mu A_i(x), \quad i = 1, 2, \tag{3}$$

$$O_{1,i} = \mu B_{i-2}(y), \; i = 3, 4, \tag{4}$$

where: x and y are inputs to node i, A_i and B_i are the linguistic labels (high, low, etc.) related with performance of this node, $\mu A_i(x)$ and $\mu B_{i-2}(y)$ can take any fuzzy membership function.

"For example, if the bell-shaped membership function is employed, $\mu A_i(x)$ is given by

$$\mu A_i(x) = \frac{1}{1+\left[\left(\frac{x-c_i}{a_i}\right)^2\right]b_i}, \; i = 1, 2, \tag{5}$$

or the Gaussian membership function by

$$\mu A_i(x) = exp\left[-\left(\frac{x-c_i}{a_i}\right)^2\right], \tag{6}$$

where a_i , b_i , and c_i are the parameters of the membership function" (Al-Hmouz et al., 2012).

Layer 2: this layer has fixed nodes and contains fuzzy operators. It makes the use of **AND** operator in fuzzifying the inputs. The operators are symbolized with π to show that they simply carry out multiplications. Layer 2 output is expressed by equation (7);

$$O_{2,i} = w_i = \mu A_i(x) * \mu B_i(y), \; i = 1, 2. \tag{7}$$

These operators are known as the firing strength of the rules (Al-Hmouz et al., 2012).

Layer 3: this layer also has fixed nodes, which are symbolized by the letter *N*, to show that they carry out normalization of the firing strengths from the preceding layer. Layer 3's output is expressed by equation (8);

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_{1+w_2}}, \; i = 1, 2. \tag{8}$$

The outputs of this layer are known as normalized firing strengths (Al-Hmouz et al., 2012).

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Layer 4: this layer also has adaptive nodes. Each node output here is the product outputs of layer 3 and a first order polynomial (in a case of first order TS Model). Layer 4 output is given by Equation (9);

$$O_{4,i} = \overline{w_i}\, f_i = \overline{w_i}\,(p_i\, x + q_i y + r_i),\ i = 1, 2. \qquad (9)$$

where: $\overline{w}$ is the output of layer 3 and p_i, q_i, and r_i are the consequent parameters (Al-Hmouz et al., 2012).

Layer 5: this is the only fixed node which is symbolized by $\sum$. This is where the sum of all the incoming signals from layer 4 is done. Equation (10) gives the final output of the system (Al-Hmouz et al., 2012);

$$O_{5,i} = \sum_i \overline{w}\, f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}, \qquad (10)$$

The following Figure 2 shows flowchart for the LTLF model.

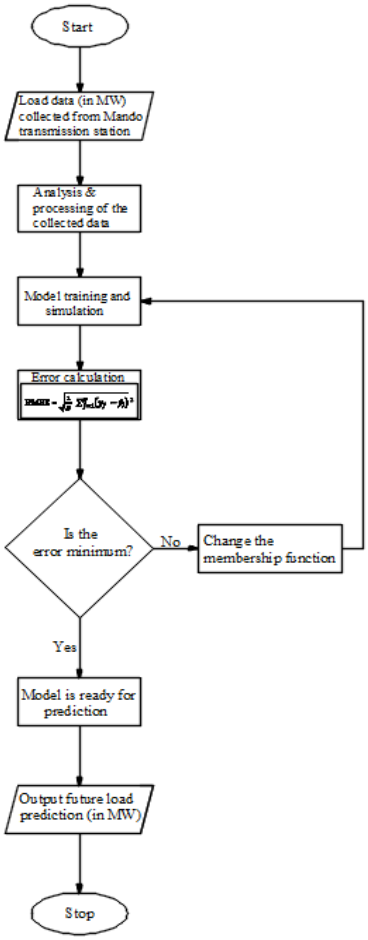

Fig. 2. Flowchart for the LTLF model

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Time series load demand data from the Mando Transmission Station were collected for 36 months, from January 2022 to December 2024. These 36 months load data were daily, half-hourly load demand data that amounted to 56,560 data set and therefore used for the long-term electric load forecasting of 11-year horizon. These load data, in megawatt (MW), were analyzed based on peak and average daily load. Feedforward back propagation network architecture was used because it is a good ANN topology for pattern recognition while back propagation is a good ANN training algorithm which can learn by example. This architecture is also efficient for analysis of a large set of data (Alabi et al., 2022). Hence, it is very suitable for long-term electric load forecasting.

This time series data set was then split into four columns using time delays of x(t-3), x(t-2) and x(t-1) then x(t+1) was used as output thus forming a three input, one output ANFIS structure. The data set was then partitioned into training data (50%) and checking and testing data (50%). This is necessary for the ANFIS inbuilt validation mechanism to work. Figure 3 shows a triangular membership function (MF) for the three inputs and one output. The membership functions (MFs) determine the extent to which every input value belongs to a specific set of fuzzy. Each linguistic label is characterized by a membership function which determines to what extent an input value belongs to a particular label (*Anon. (2025). Fuzzy Logic Toolbox-for Use with MATLAB [Online]. Available: Https://Www.Mathworks.Com/Help/Fuzzy/Logic-Toolbox-for-Use-with-Matlab.Html*, 2025). This is called membership grade μ, a number between 0 and 1. Many functions can be used as MFs; however, the triangular and trapezoidal MFs are popular and sufficient for most control purposes.

The first step in the design is to choose number and the distribution of membership functions (MFs) for the inputs and the output. In this work, seven normalized membership functions with triangular shapes are considered. Each of the variables in the input and output spaces are partitioned into a number of overlapping regions to cover the range of the variable and each partition is given a linguistic label such as positive big (PB), positive medium (PM) positive small (PS), negative big (NB), negative medium (NM), negative small (NS), and zero (ZE). Seven membership functions with triangular shapes and range of discourse –1 to 1 are used. They are NB, NM, NS, ZE, PS, PM, and PB shown in Figures 3 and 4 for error e, error dot $\dot{e}$ and output u.

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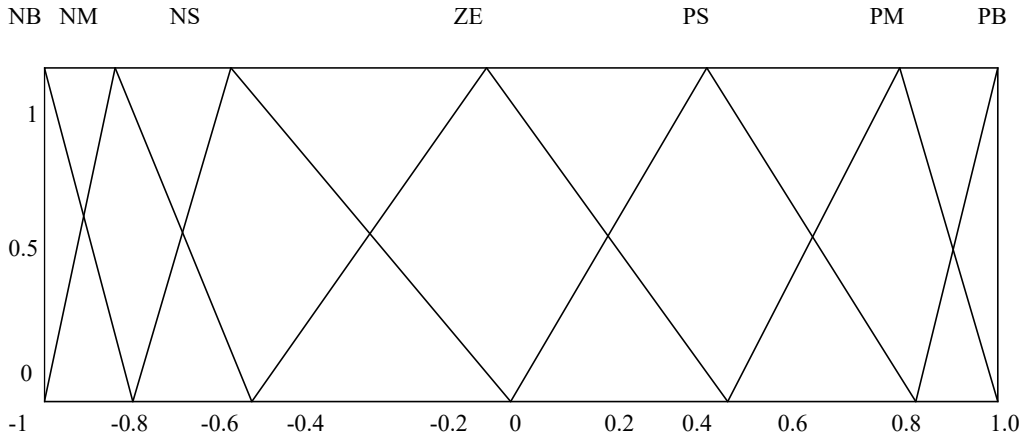

Fig. 3. Membership function of inputs e and *ė*

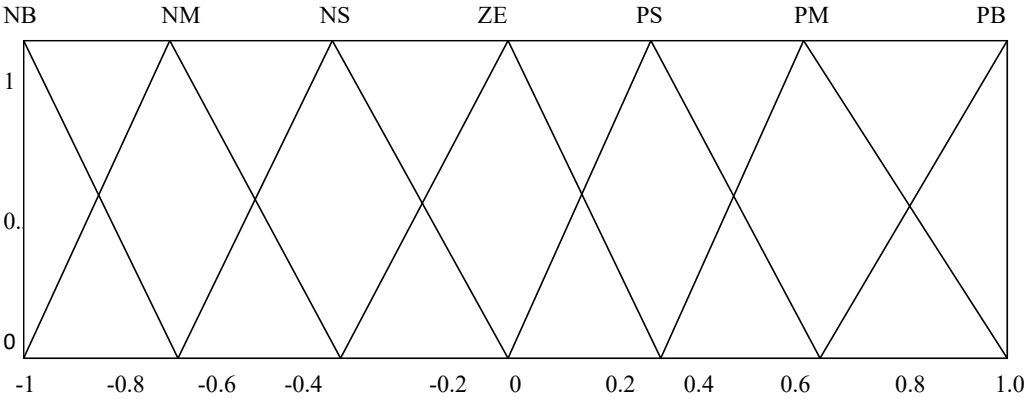

Fig. 4. Membership function of output u

MATLAB/Simulink R2015a was used for data training. In training a fuzzy system with neuro-adaptive technique, the input/output training data was collected using simulation of the Load Forecasting model and defining it in the MATLAB workspace (Anon, 2024). The forecasting accuracy was evaluated using Root Mean Square Error (RMSE), in this work (Olabode et al., 2019). The error values obtained from results of the ANFIS model training determine how good the model is: where smaller RMSE values imply a good model (Solichin & Hana Saputri, 2021). The RMSE is described by equation (11) as follows (Al-Hmouz et al., 2012):

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{j=1}^{N}\left(y_j - \hat{y}_j\right)^2} \qquad (11)$$

Where N is the total number of predictions, $\hat{y}_j$ is the predicted time series, and y_j is the original series.

Furthermore, the acceptance of any given load forecasting model is done by comparing the error between the actual and the predicted values, and the smaller the RMSE, the more accurate the model will be (Nti et al., 2020).

RESULTS AND DISCUSSION

Figure 5 shows input membership functions for the peak daily loads' training data, which was obtained from the Mando Transmission Substation in form of time series load demand data. Input 1, input 2 and input 3 graphs respectively represent the 12 months, daily, half-hourly peak load data membership functions for 2022, 2023 and 2024. From the three (3) input graphs in the Figure, all the three input membership functions are between 1 and 0 which shows a good degree of membership function of a fuzzy input.

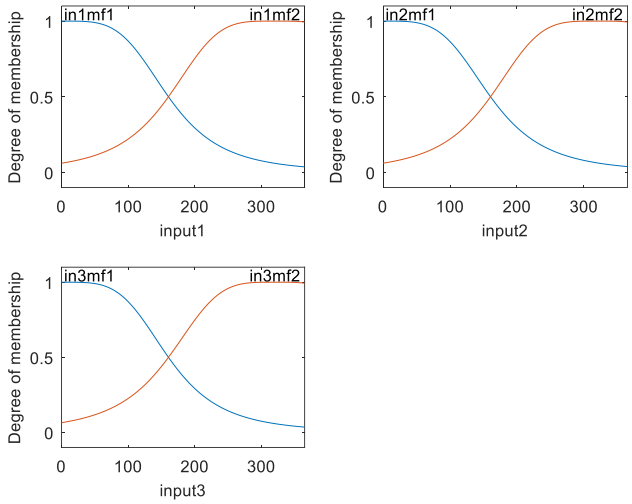

Fig. 5. Input membership function for the peak daily load data of 2022 – 2024

Figure 6 shows the peak daily load data training error curve. The ANFIS prediction cycle ran for 10 epochs which gave the maximum error of about 0.08 for the check data. As shown on the graph, error 1 is the training data error while error 2 is the check data error.

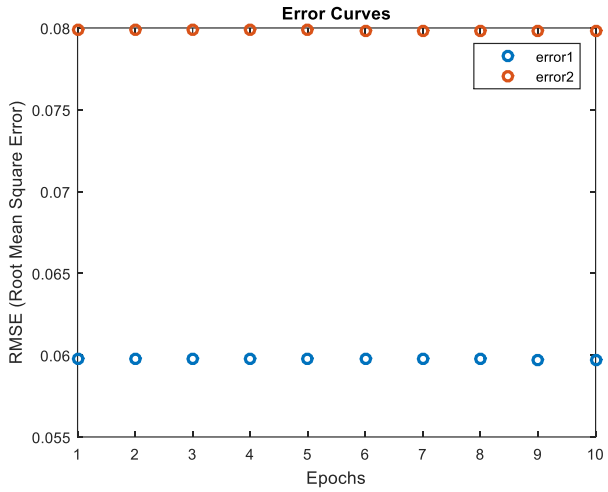

Fig. 6. Training error curve for the peak daily load data of 2022 – 2024

The graph in Figure 7(a) shows results of 36 months (January, 2022 – December, 2024) ANFIS peak load data training while that of Figure 7(b) shows results of the corresponding prediction error. Figure 7(a) actually contains 2 graphs: the peak load, which is in blue colour, and the predicted values, which is in reddish brown colour. It can be seen from the graph that the extent of correlation between the two graphs makes them look the same. However, Figure 7(b) shows graph of the prediction error, which gave the maximum error of 0.2395MW at 365.2MW of the peak daily load. In terms percentage, the maximum error was 0.07% which is very small. This shows successful training and good prediction accuracy of the ANFIS model.

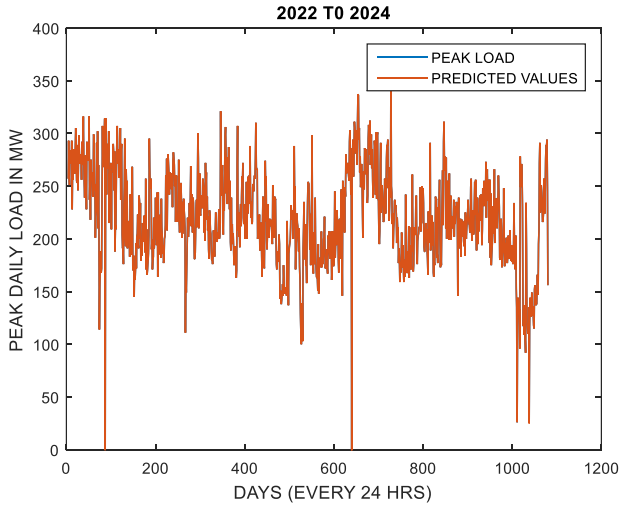

Fig. 7(a). Graph of ANFIS peak daily load data training

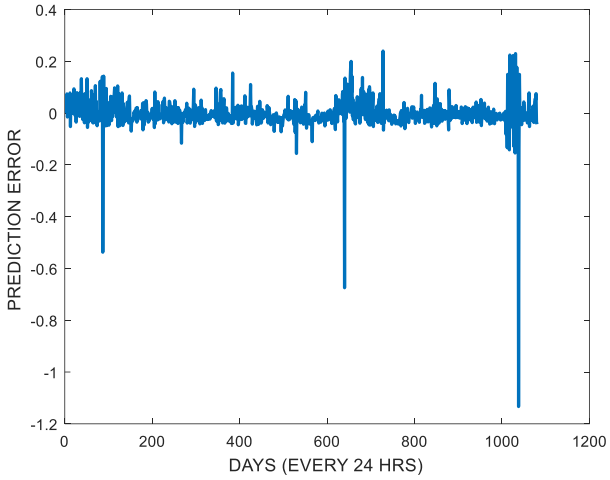

Fig. 7(b). Graph of ANFIS peak daily load data prediction error

After the successful training of the ANFIS model on the peak daily load data, it was used to predict the peak daily load for eleven (11) years to come: 2025 to 2035. The results obtained are summarized and presented in Table 1. The results showed a rise in peak daily load demand in 11 years to come by 69%.

Table 1. Summary of 2025 – 2035 peak daily load demand predictions

S/N	Year	Predicted maximum peak daily load demand (MW)	Date of occurrence	Predicted minimum peak daily load demand (MW)	Date of occurrence
1	2025	287.3	07.10.2025	162.2	15.06.2025
2	2026	287.3	01.07.2026	84.88	19.11.2026
3	2027	337.3	03.12.2027	84.88	11.08.2027
4	2028	337.3	24.08.2028	84.88	02.05.2028
5	2029	337.3	17.05.2029	84.88	23.01.2029
6	2030	337.3	06.02.2030	178	16.01.2030
7	2031	592.7	01.12.2031	6.11	18.11.2031
8	2032	300.5	16.05.2032	151.8	23.01.2032
9	2033	299	06.02.2033	153.3	19.11.2033
10	2034	425.7	01.12.2034	112.7	04.11.2034
11	2035	274.3	25.08.2035	161.7	03.05.2035

Figure 8 shows input membership functions for the average daily loads' training data, which was obtained from the Mando Transmission Substation in form of time series load

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demand data. Input 1, input 2 and input 3 graphs respectively represent the 12 months, daily, half-hourly average load data membership functions of 2022, 2023 and 2024. From the three (3) input graphs in the Figure, all the three input membership functions are between 1 and 0 which shows a good degree of membership function of a fuzzy input.

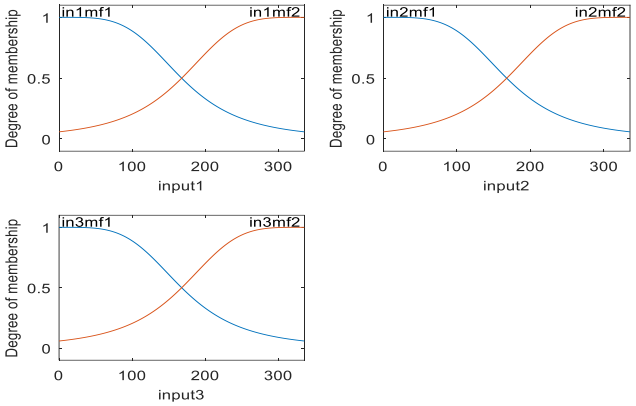

Fig. 8. Input membership functions for the average daily load data of 2022 - 2024

Figure 9 shows the average daily load data training error curve. The ANFIS prediction cycle ran for 10 epochs which gave the maximum error of about 0.03 for the check data. As shown on the graph, error 1 is the training data error while error 2 is the check data error.

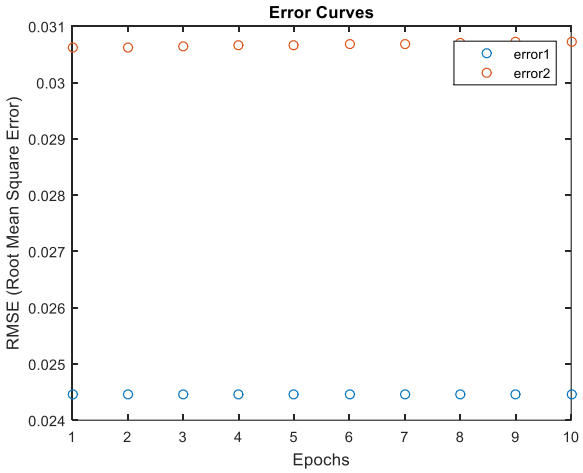

Fig. 9. Training error curve for the average daily load data of 2022 – 2024

The graph in Figure 10(a) shows results of 36 months (January, 2022 – December, 2024) ANFIS average load data training while that of Figure 10(b) shows results of the corresponding prediction error. Figure 10(a) actually contains 2 graphs: the average load, which is in blue colour, and the predicted values, which is in reddish brown colour. It can be seen from the graph that the extent of correlation between the two graphs makes

them look the same. However, Figure 10(b) shows the graph of the prediction error, which gave the maximum error of 0.1952 at 235.9MW of the average daily load. In percentage form, the maximum error was 0.08% which is very small. This shows successful training and good prediction accuracy of the ANFIS model.

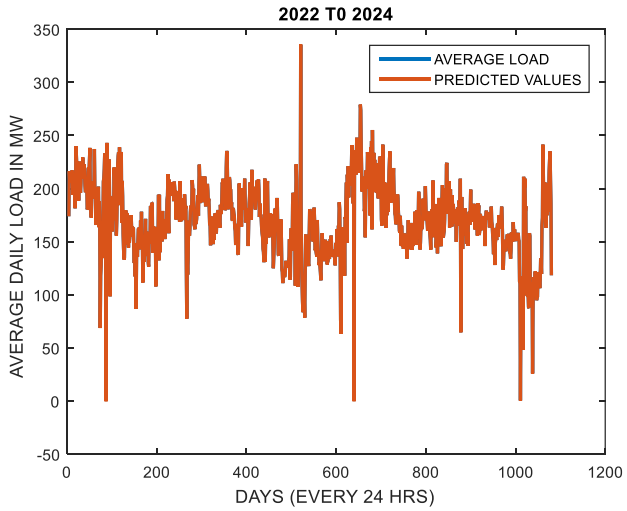

Fig. 10(a). Graph of ANFIS average daily load data training

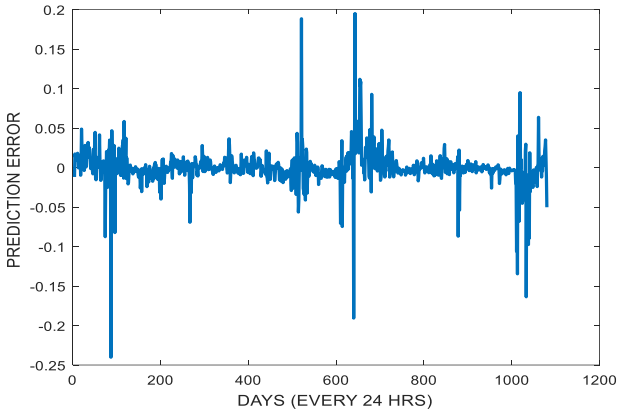

Fig. 10(b). Graph of ANFIS average daily load data prediction error

After the successful training of the ANFIS model on the average daily load data, it was also used to predict the average daily load for eleven (11) years to come: 2025 to 2035. The results obtained are summarized and presented in Table 2. The results showed a rise in average daily load demand in 11 years to come by 81%.

Table 2. Summary of 2025 – 2035 average daily load demand predictions

S/N	Year	Predicted maximum average daily load demand (MW)	Date of occurrence	Predicted minimum average daily load demand (MW)	Date of occurrence
1	2025	203.8	11.09.2025	113	20.02.2025
2	2026	203.8	03.06.2026	84.44	17.11.2026
3	2027	218.8	07.11.2027	40.57	06.12.2027
4	2028	224.8	06.10.2028	40.57	27.08.2028
5	2029	224.8	29.06.2029	40.57	20.05.2029
6	2030	226.3	05.10.2030	40.57	09.02.2030
7	2031	262	26.11.2031	71.66	07.12.2031
8	2032	205.8	24.06.2032	140	19.05.2032
9	2033	206.1	17.03.2033	111.7	09.02.2033
10	2034	232.5	26.11.2034	85.01	06.12.2034
11	2035	209.1	31.07.2035	112.6	28.08.2035

As at January 2025, the total capacity of the 330kV Mando Transmission Station was 690MVA, which comprised of 4 x 150MVA and 1 x 90MVA 330/132/33kV transformers. For this Substation to accommodate a 69% rise in peak daily load demand and a corresponding 81% rise in average daily load demand, the total capacity of the Substation needs to be upgraded. Similarly, the thermal capacities of the transmission lines need to be equally upgraded.

CONCLUSION

An ANFIS model was developed, which was used for LTLF. Using the relevant data obtained from Mando Transmission Station Kaduna in Nigeria, the case study substation, the ANFIS model was developed, MATLAB/Simulink software was used to carry out simulations and, based on the simulation results, predictions of future load demands were made with good accuracy. This implies that this work is a useful ingredient for generation expansion planning and or network expansion planning. However, this work is limited to the available time series load demand data obtained from the case study Substation. Further work can be done by incorporating factors like economic and demographic but with utmost caution. This is so because such factors can affect the accuracy of the LF outcomes due to the complex nature of forecasting the factors as established by some literatures.

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