Sigma Journal of Engineering and Natural Sciences
Web page info: https://sigma.yildiz.edu.tr
DOI: 10.14744/sigma.2025.00100

Research Article

Load demand estimation and prediction models for effective planning and sustainability of microgrid project in rural community

Harrison Oyibo IDAKWO[1,2,*], Lanre OLATOMIWA[1,3], James Garba AMBAFI[1], Abubakar Sadiq AHMAD[1]

[1]*Department of Electrical and Electronics Engineering, Federal University of Technology Minna, Gidan Kwano, Minna, 920101, Nigeria*
[2]*Department of Electrical and Electronics Engineering, University of Maiduguri, Borno State, 600004, Nigeria*
[3]*Department of Electrical and Electronic Engineering Science, University of Johannesburg, Johannesburg, 2006, South Africa*

ARTICLE INFO

Article history
Received: 23 March 2025
Revised: 01 June 2025
Accepted: 01 July 2025

Keywords:
Artificial Intelligence; Community; Ensemble Learning; Machine Learning; Microgrid; Prediction

ABSTRACT

In Nigeria, where many rural areas lack proper electricity service, how to improve access to electricity becomes a significant challenge. The aim of this study is to improve the sustainability of the microgrids by developing special models for estimating and predicting the energy demands of rural households living in Gwam community in Niger State. The process involves reducing relevant identified (factors) input variables by Exploratory Factor Analysis, then applying Fuzzy Analytical Hierarchy Process (Fuzzy-AHP) to rank the reduced factors (input variables) according to importance and relevance where the topmost five (5) factors were selected, this was followed by data preprocessing to ensure data is of high quality. The study adopted the Ensemble Learning method to see if combining Adaptive Neuro-Fuzzy Inference Systems (ANFIS) with its optimized versions (ANFIS-PSO and ANFIS-GA) could improve the accuracy of load demand predictions. The results showed that the Ensemble Model delivers a better prediction than ANFIS-GA (MAPE: 19.8094%, RMSE: 3.3019, MSE: 10.9025), ANFIS-PSO (MAPE: 19.9320%, RMSE: 3.5462, MSE: 12.5755) and the standalone ANFIS model (MAPE: 20.9701 %, RMSE:3.9908, MSE: 15.93), achieving 14.6932% for MAPE, 2.4071 for RMSE and 5.8121 for MSE. Further statistical tests confirmed its superiority, with near-zero mean error (0.0097) and a narrow 95% confidence interval [-0.0656, 0.0851]. ANOVA ($F = 3842.1494$, $p<0.001$) and Tukey HSD tests ($p<0.001$) further validated its dominance. The study's novelty lies in its context-specific approach, integrating real load and climatological data with ensemble modeling to develop a tailored predictive model for rural microgrids. Findings demonstrate that ensemble learning improves microgrid sustainability, offering a viable solution for rural electrification in Nigeria.

Cite this article as: Idakwo HO, Olatomiwa L, Ambafi JG, Ahmad AS. Load demand estimation and prediction models for effective planning and sustainability of microgrid project in rural community. Sigma J Eng Nat Sci 2026;44(5):3077–3095.

***Corresponding author.**
*E-mail address: idakwoharrison@unimaid.edu.ng

This paper was recommended for publication in revised form by Editor-in-Chief Ahmet Selim Dalkilic

Published by Yıldız Technical University Press, İstanbul, Turkey
© Author. This is an open access article under the CC BY-NC license (http://creativecommons.org/licenses/by-nc/4.0/).

INTRODUCTION

Access to reliable electricity is a major problem for parts of the world facing global energy crisis. Almost 790 million people do not have a dependable power supply and more than three-quarters (75%) are in Sub-Saharan Africa. As a result, the goal set by the UN, to provide affordable, reliable and sustainable energy by 2030, is at stake [1-4]. Attributed to poor infrastructure and a full central grid, more than 43% of people in Nigeria (approximately 85 million of the total population) do not have electricity. Communities in rural areas find their economic and social development limited by recurrent power outages, hence the search for alternatives, with microgrid becoming a preferred choice [5-9]. In remote communities, microgrids supply secure electricity by making use of renewable energy, however, these systems depend largely on good Load demand estimation and prediction models (LDEPMs) to manage resources, lower expenses and maintain a steady supply of energy [10-14]. However, it is challenging to predict load because of poor data quality issues, also renewable energy supplies can vary, likewise seasonal changes affect demand and also how people use energy is hard to anticipate hence, prediction is made more difficult due to these factors and so it is important to take into cognizance these factors when designing the LDEPMs [15-23].

Various techniques including Long Short-Term Memory networks, Support Vector Machines (SVM), Artificial Neural Networks and their combination models, have been analyzed to boost the accuracy of load prediction [10, 23-38]. However, these approaches are limited by their over-reliance on urban and industrial microgrids, Insufficient methods for consideration of critical input variables that influence load demand, the lack of thorough risk assessment models and the difficulty of choosing a model that is not too simple or too difficult to learn from. Also, several numbers of techniques have difficulty achieving convergence in different situations, stressing the need for improved solutions specific to rural microgrids.

This study addresses these gaps through a novel comprehensive framework that enhances load prediction accuracy for rural microgrids. The study proposes a hybrid method for predicting short-term load in Gwam community microgrid, a rural microgrid in Niger State, Nigeria. To rank and choose critical input variables of load demand, the methodology applies factor analysis and Fuzzy analytical hierarchy process (Fuzzy-AHP). A reliable data preprocessing framework was then utilized to improve the quality of the data. Next, an Adaptive Neuro-fuzzy inference system (ANFIS-based) ensemble method was designed by combining it with its improved version and machine learning to achieve higher prediction accuracy and robustness.

For practical application and deployment of LDEPMs in real-world microgrid systems, more than algorithmic robustness is required, also real-time models suitable to run on embedded systems with constrained resources is required. Issues such as poor processing power, memory constraints, and sensor reliability have to be resolved. The load prediction models must thus be uncomplicated to implement with microgrid management hardware such as micro-powered embedded hardware, edge, or programmable logic controllers (PLCs) and must be computationally friendly.

This research helps achieve sustainable develop goal 7 (SDG 7) (affordable and clean energy) and SDG 11 (sustainable communities) by systematically reviewing what affects rural energy demand, constructing a prioritization framework with Fuzzy-AHP and introducing a hybrid ANFIS with Ensemble system for improved prediction accuracy. The findings will help improve microgrid operations and planning for regions in need, encouraging both access to electricity and economic growth.

The main focus of this research investigation consists of predicting energy consumption patterns for future rural microgrid projects. Here are the major contributions:

- Using exploratory factor analysis, to carefully identify and evaluate the various input variables that influence load demand. This method allows us to gain a clearer and deeper understanding of how energy is consumed in rural households.
- Developing a Fuzzy-AHP method that will determine which input variables hold the most significance. Model design decisions become more effective through the utilization of this method. This approach helps solve an essential missing aspect in current research while providing valuable support for decision-making when developing models.
- To build and develop a data preprocessing model that enhances quality as well as reliability. This method addresses missing values along with duplicate entries and normalizes data then detects isolated values.
- To implement a Load Demand Estimation and Prediction Models (LDEPMs) using Adaptive Neuro-Fuzzy Inference System (ANFIS) and its improved version I-ANFIS along with Ensemble Learning.

The manuscript is structured as follows: After a brief Background of the study in section 1, Section 2 dwelt basically on the literature review, section 3 of the manuscript covers methodology for choosing variables, refining the dataset and developing the prediction models; Section 4 analyses how the model performed and summarizes the main findings; and finally, Section 5 describes the research conclusions and future plans.

Literature Review

Theoretical review

Microgrids have become a game changer in the contemporary power grid, and within this innovation, it has provided a more resilient, sustainable, and efficient power generation and supply in a decentralized manner [39, 40]. Central to the successful state of operations of microgrid

lies the importance of proper Load Demand Estimation and Prediction Models (LDEPMs). These models gives room for perfect control of energy and energy resources, as well as grid stability due to their ability to predict electricity consumption patterns precisely [41, 42]. Effective LDEPMs are built in accordance with the theoretical plan that comprises several crucial steps. It starts with the broad data collection and preprocessing of historical measurements of the loads, weather parameters, and other temporal factors, which are preprocessed through cleaning and normalization [43, 44]. The next steps associated with feature selection and engineering involve determining which predictors are most effective, including temperature, humidity, the time-of-day effect, and social economic indicators, which facilitate the reach of model precision [45, 46]. This is then followed by model evaluation, to evaluate performance and generalizability [47]. Lastly, models are continually optimized and applied in practice so they can be flexible enough to adapt to the variable consumption and grid level [48, 49].

LDEPMs undergo various complexities which make's prediction challenging. Missing values, errors in measurements could significantly influence the model performance [15]. Sources of renewable energy are not always present, and consumer behavior is particularly random, which predetermines the existence of a rather high variability in the supply of renewable energy sources, and this uncertainty is further supplemented by external impacts of rare weather conditions and dynamics of the economy [50, 51]. In addition, the models used in the microgrid scalability must be flexible with the capacity to accommodate greater load and trends of change without loss of precision [40].

Generally, LDEPM methods can either be categorized into two broad categories based on time frame and method of analysis. Some are applied at various steps of the operation planning (during its lifetime), and some are highly short-term (minutes to hours) and others are long-term (years) [52, 53]. On a technical level, methods include classical time-series models (ARIMA, SARIMA), statistical methods, machine learning and hybrid systems [23]. Among these methods, Hybrid models, in particular, have demonstrated a particular success in resolving difficult non-linear features of loads with the inclusion of the beneficial properties of other methods [27, 28].

A number of crucial factors affect patterns of load demand and should be taken into consideration in predictive modeling. Time factors such as the diurnal patterns, weekly patterns and seasons set a base of consumption patterns [54]. The weather especially the temperature and solar radiation influences the cooling/ heating demands as well as the renewable energy generation directly [52]. The segmentation of consumers indicates differences in the use patterns at the residential, commercial, and industrial levels, and the economic parameters like energy prices or Gross Domestic Product (GDP) evolution change the general consumption situation [54-56]. Unforeseeable random disturbances like a piece of broken equipment or an extraordinary event add to factors necessitating strong model contingencies [57].

Due to the further proliferation of microgrids, improvement in LDEPMs becomes critical in the realization of their potential. Future trends will focus on making adaptive learning systems that constantly integrate streams of real-time data, in addition to more advanced uncertainty quantification to enhance reliability. The synergy between artificial intelligence and IoT should facilitate more precise, real-time load forecasting, which will finally promote the intelligent management of energy and faster transition to sustainable power systems.

Review of related works

A comprehensive review of existing studies was conducted to understand the current advancements and limitations in load prediction for microgrid. Some of the works reviewed are presented as follows;

The work of Arkhangelski et al. [58] addressed the problem of finding an optimal urban microgrid with the LSTM-based load and renewable-storage integration to reduce the cost and enhance stability through their EFM algorithm. The model was not however validated on rural systems. In analyzing early failures of rural microgrids in the Global South, Derks and Romijn [24] focused on the off-grid electrification challenges in terms of governance and sustainability. Although their policy-driven approach made them expose the critical trade-offs between system expansion and service quality, such important factors as predictive load modeling as a possible failure prevention strategy were not mentioned in the work. The work reported by Zhang et al. [28] designed a hybrid model of DA-SVM to forecast the short-term load in an offshore microgrid based on past load, temperature, and weather records. The normalized-input model gave better results than PSO-SVM, GA-SVM, and BP neural networks with RMSE of 1.5 per cent and a computation time that was 50 per cent faster. The study however failed to justify its choice of input variables. GCA-MEABP model of Yang et al. [25] with similar-day selection and neural network optimization yielded a mean relative error (MRE) of 2.09 by reducing microgrid load prediction error. Although it outperformed BPNN/RBFNN, it lacked the justification of the input factors, preprocessing processes and risk analysis. Comparing ANN and GMDH used in day-ahead load forecast in a microgrid of a commercial bank, Izzatillaev and Yusupov [59] found ANN more superior by assessing the regression and MSE calculations. The study was however limited by the fact that its dataset was very limited as it only spanned 9 days and, although experts were used to narrow down items to be inputted, they did not use systematic criteria in doing so. Such methodological short-comings notably limit the reliability of the findings and its generalizability relative to more comprehensive research studies within the area. The work of Yao et al. [60] proposed a two-layer feature selection technique (uncorrelated/redundant pruning)

with neural networks and evolutionary algorithms to build a microgrid load forecasting system of university buildings. Although their methodology showed superior results in terms of accuracy and stability compared to the alternatives, the study did have its limitations: vague data preprocessing approach, lack of risk estimation of the model predictor, and rural applicability of the approach was not tested. Furthermore, Tayab et al. [10] proposed a hybrid SWPT-HHO-FFN model of microgrid load forecasting that incorporates 3-level wavelet decomposition of historical/weather data and neural networks which was optimized by the Harris Hawk algorithm. When applied to the Queensland market data, it decreased the MAPE by 33-61 percentages compared to the PSO-ANN, PSO-LSSVM, and BP-NN benchmarks. Nevertheless, the study lacks justification of the input variable selection and data preprocessing, which reduces reproducibility. Moradzadeh et al. [23] proposed a hybrid SVR-LSTM model to forecast short-term loads of rural microgrid in Africa considering the pattern of household and commercial loads. The model performed better than standalone SVR (R=0.9770) and LSTM (R=0.9809) in terms of correlation coefficient (0.9901) indicating improved pattern recognition ability in the behaviors of the loads. The complexity of the model as well as the absence of risk assessment of the error in the prediction of loads was a major limitation although results were much better than traditional techniques and those that had been previously studied. The work of Ma and Tang [61] suggested a combination approach Chaos-PSO-LSSVM to improve the accuracy in short-term load forecasting. They incorporated the chaos theory into PSO to foil the convergence of local optima and enhancement of learning ability by optimizing LSSVM parameters. The model incorporated the load profiles, meteorological and special loads as input for better prediction performances. Nevertheless, the research did not justify the choice of input variables and failed to provide information about data preprocessing, which partially restricts replicability. The work of Muzumdar et al. [27] trained a hybrid model by using RF-SVR-LSTM to forecast short-term loads, which utilizes several algorithms to cope with various consumption profiles. The inputs used were categorical and numerical (such as time intervals, day/month, season, etc.), which were pre-prepared through label encoding and min-max normalization. By testing on diverse consumer profiles, RMSE decreased by 3.46 percent and MAE decreased by 2.53 percent, which confirms that this is effective in microgrid energy management. The methodology of input selection was not clear however, and this limited reproducibility. Furthermore, the work of Moradzadeh et al. [62] suggested a Bi-LSTM-based load forecasting model in the context of rural microgrids in Sub-Saharan African with drops to the socioeconomic (levels of income, the number of households) and commercial (water pumps, schools, clinics) lines. The model was significantly accurate (R=99.34%, RMSE=0.3243) with learning the consumption behaviour every hour and compared to the comparable methods. Although there was strong predictive performance, the study did not advance a methodical approach of the input variable selection even though it placed a lot of importance in terms of capturing the load profile characteristics.

From the review, the following research gaps emerged: (1) Insufficient justification for input variable selection and lack of transparent preprocessing methodologies across multiple studies; (2) Neglect of socioeconomic factors and risk analysis in predictive modeling, despite their critical importance for rural electrification; (3) Persistent methodological limitations including small datasets and untested generalizability that undermine practical implementation; (4) Most of the studies carried out dwelt mostly on the load profile of urban or industrial microgrid with limited studies on the load profile of rural microgrid. These gaps collectively highlight the need for more context-sensitive, reproducible, and holistic approaches to microgrid load prediction.

MATERIALS AND METHODS

Research Framework

The research process commenced with a thorough literature search to identify input variables influencing load demand as presented in Table 1. Exploratory factor analysis, a technique presented in Figure 1 (suitable for identifying underlying pattern, and reducing dimensionality) was selected for dimensionality reduction, to reduce the large number of identified input variables in Table 1 to a more manageable subset of eight (8) using their communalities and factor loadings, where variables with communalities greater than 0.5 and factor loadings greater 0.7 where retained and others below this threshold value discarded as

Table 1. Identified factors influencing load demand

Variable	Description	Values
Previous hour load	V1	Hourly load (kWh)
Hour of the day	V2	1 to 24
Weekdays	V3	Binary (o or 1)
Weekends	V4	Binary (0 or 1)
Season of the year	V5	1, 2 and 3
Temperature	V6	Degree celcius
Humidity	V7	Percentage
Solar radiation	V8	Watts per square meter
Customer time of electricity usage	V9	Hourly usage pattern
Educational level	V10	1,2,3
Special events	V11	Binary 0 or 1
Holidays	V12	Binary 0 or 1
Unemployment status	V13	Binary 0 or 1
Customers' ability to pay	V14	1,2,and 3

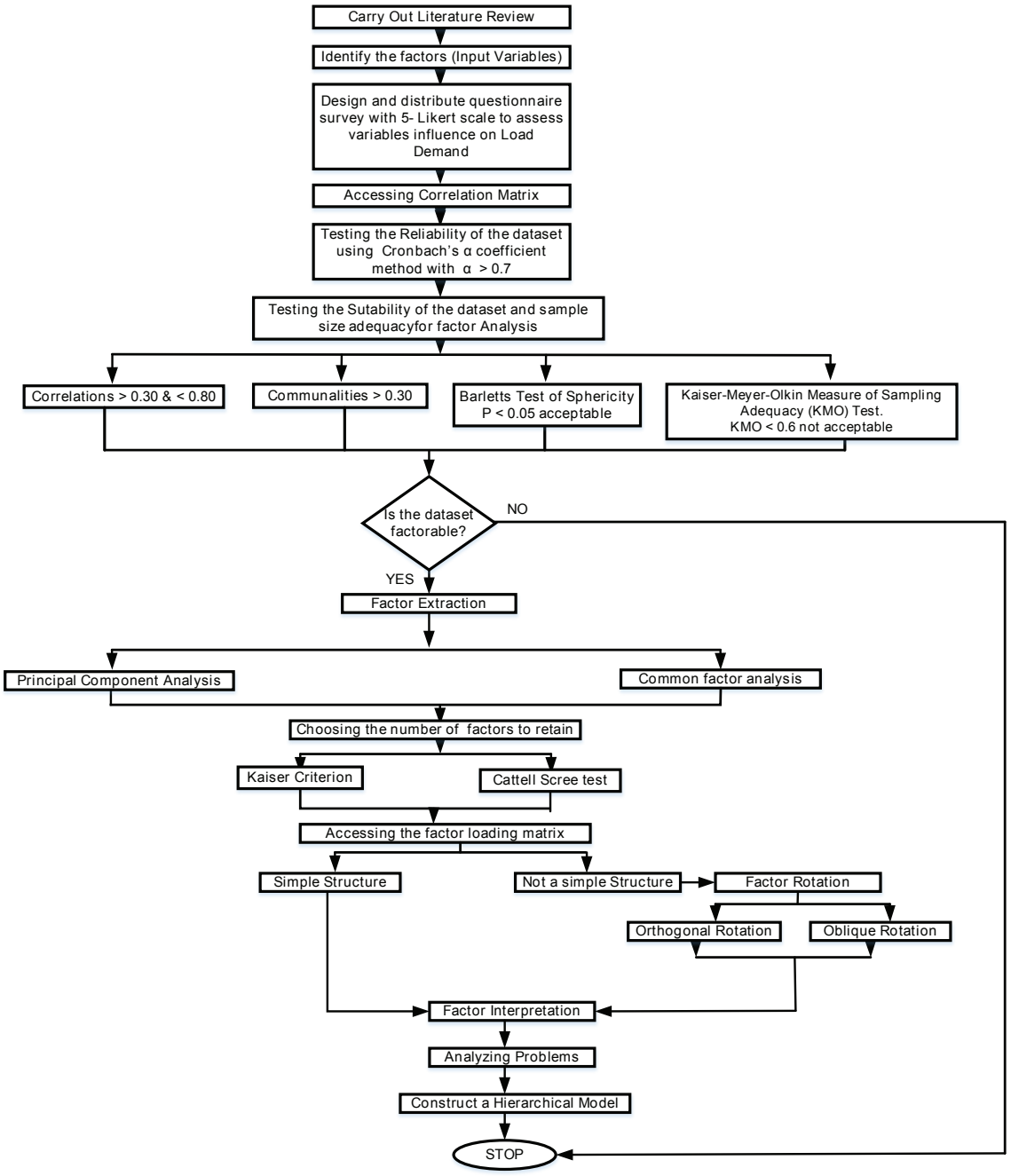


Figure 1. Exploratory factor analysis.

presented in Table 2, and Table 3 respectively. Subsequently, a Fuzzy-AHP model (due to its ability to handle uncertainty maintain consistency and reflect real world complexities) as presented in Figure 2 was selected to rank the reduced variables (from EFA) based on their importance and relevance, ultimately selecting the top five (5) variables (previous hour load, temperature, humidity, hours of the day, holidays) which was used to design the LDEPMs. Data collection was then carried out based on the selected five (5) variables. All the required climatological data for this research were source from the database of National Aeronautics and Space Administration for the period of 2021 to 2023. Data loggers connected to a stable power source and also to a wireless modem to collect hourly load demand data stream from the microgrid was sourced from the database of Solemenz engineering Nigeria limited (company responsible for managing the microgrid at Gwam community) for the period of 2021 to 2023 as these were the available datasets as at the time of conducting this study. Weekdays and weekends dataset were represented using a binary format (0/1), whereas the holiday

Table 2. (14) variables communalities

	Initial	Extraction
V1	1.000	.660
V2	1.000	.776
V3	1.000	.715
V4	1.000	.726
V5	1.000	.611
V6	1.000	.578
V7	1.000	.684
V8	1.000	.485
V9	1.000	.711
V10	1.000	.625
V11	1.000	.699
V12	1.000	.775
V13	1.000	.492
V14	1.000	.723

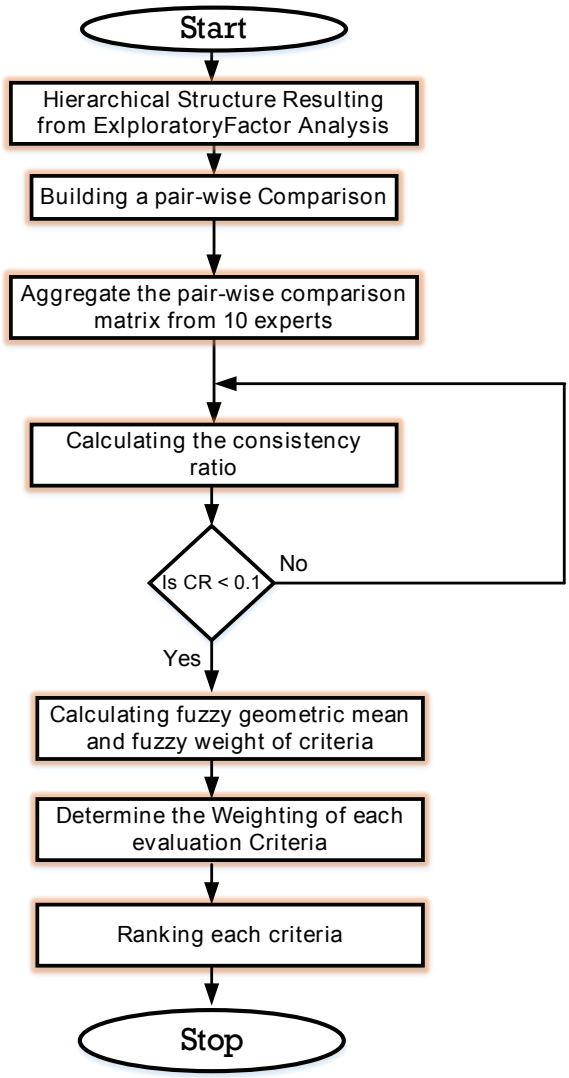


Figure 2. Fuzzy-AHP.

Table 3. Factor loadings showing 8 retained variables

	Component				
	1	2	3	4	5
V1	.117	.289	.810	-.223	.085
V2	.868	-.119	.113	-.026	-.089
V3	.076	.254	.489	.503	.373
V4	.347	.727	-.175	.232	.088
V5	.627	.218	-.116	.357	.139
V6	.051	.148	.003	.843	-.147
V7	.075	.013	-.033	-.062	.900
V9	-.087	-.173	.784	.221	-.128
V10	.747	.170	-.002	.054	.208
V11	.378	.064	.111	.590	.506
V12	-.147	.845	.122	.051	-.060
V14	.379	.574	.343	.160	.197

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
Rotation converged in 6 iterations.

datasets were compiled from a Nigerian calendar, capturing all national and regional holidays in Nigeria. Days with holidays were represented using binary format (0/1). An integrated data preprocessing framework in Figure 3 that combines interpolation, min-max normalization, z score method, K-means clustering was implemented to clean and prepare the collected data and the result of the processed data was further utilized to develop the LDEPMs presented in the subsequent section. This was followed by model evaluation using standard evaluation metric like mean absolute percentage error (MAPE), mean squared error [63] and root mean squared error (RMSE).

Model Formulation

Traditional ANFIS model

The development of the ANFIS prediction model followed a structured approach, as highlighted in Figure 4 and Equations 1 to 4, using the selected input variables resulting from EFA and Fuzzy-AHP. In a similar fashion, the structure of the conventional ANFIS model is given by Figure 5.

Layer 1: Fuzzification Layer

Nodes in this layer convert crisp inputs to fuzzy sets using Gaussian membership functions.

$$O_{A_1} = \mu_{A_1}(x_1) \tag{1}$$

where μ_{A1} is the membership function.

Layer 2:

Nodes in this layer apply fuzzy logic AND/OR operators to generate fuzzy rules, yielding outputs that represent the firing strength of each rule, as calculated in Equation 2.

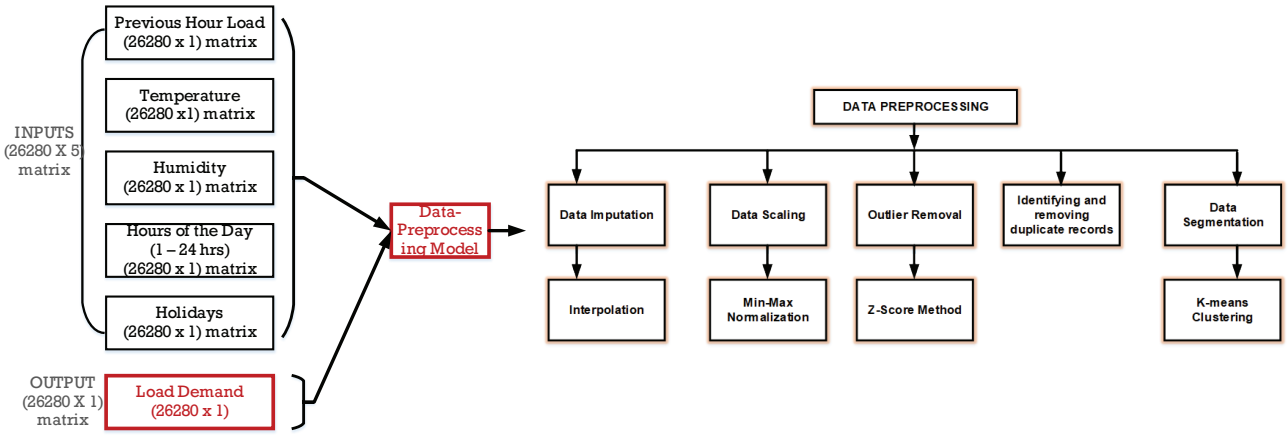


Figure 3. Integrated data-preprocessing model.

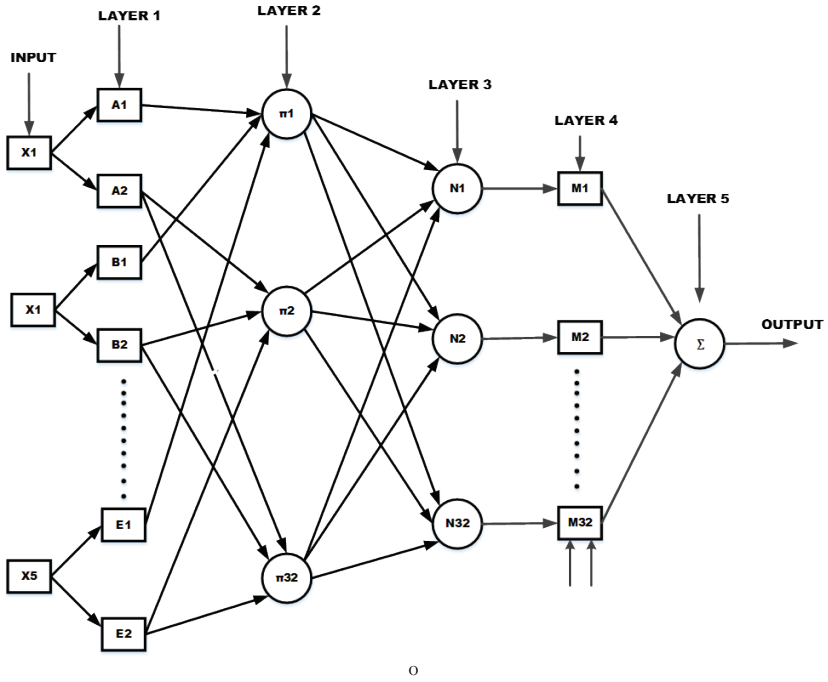


Figure 4. Five (5) inputs two (2) membership function ANFIS structure.

$$O_{\Pi_1} = \mu_{A1}(x_1) I \mu_{B1}(x_2) I \ldots\ldots\ldots I \mu_{E_1}(x_5) \quad (2)$$

Where, the notation $\bigcap$ denotes the AND operator, which is realized by using the product function.

Layer 3:

The output of each node is the ratio of its firing strength to the sum of all rule's firing strength. For example, for a 32 rules, the firing strength of the i^{th} rule is as expressed in Equation 3.

$$\overline{O_{\Pi_1}} = \frac{O_{\Pi_i}}{O_{\prod_1} + O_{\prod_2} + \ldots\ldots\ldots\ldots + O_{\prod_{32}}} \quad (3)$$

Layer 4:

Each node in this layer has an output as expressed in Equation 4.

$$\overline{O\Pi_i}(p_i x_1 + q_i x_2 + \ldots\ldots\ldots + t_i x_5 + u_i) \quad (4)$$

Where (p, q.....t, u)are the parameter set, i = 1.....249. These parameters can also be referred to as consequence parameters.

Layer 5:

Contains a node that sums up the overall output X_0 of all incoming signals from the previous layer.

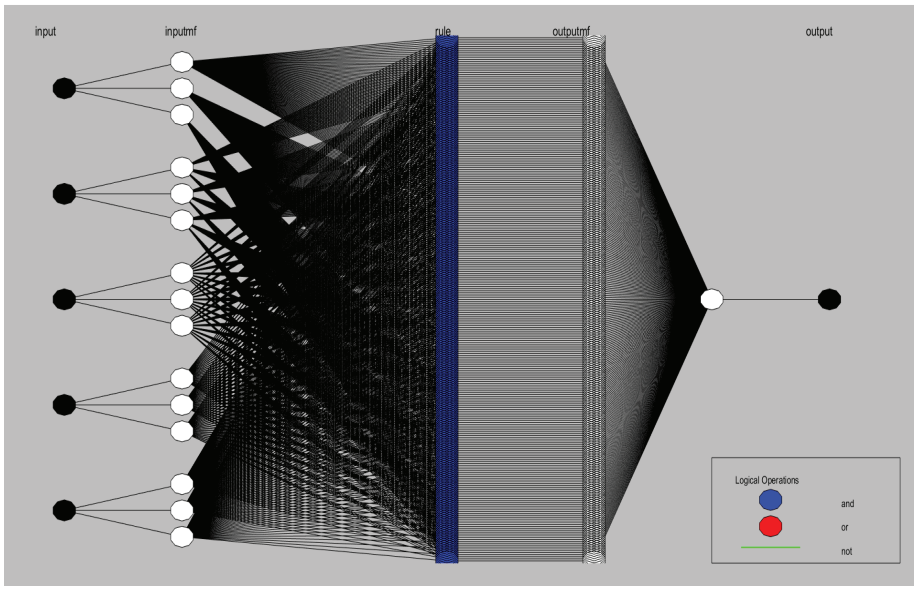


Figure 5. Five (5) inputs three (3) membership function structure of conventional ANFIS.

Improved ANFIS model

To further improve ANFIS's abilities to make predictions, an Improved Adaptive Neuro-Fuzzy Inference System (I-ANFIS) was developed by integrating ANFIS with Particle Swarm Optimization (PSO) and Genetic Algorithm (GA). In this way, the approach adjusts membership functions and adaptive rules to enhance the system's ability to learn and become more effective. The flow chart of these models is presented in Figure 6 and Figure 7 respectively.

Ensemble Learning model

The output prediction from the ANFIS and I-ANFIS base models were combined by ensemble learning to achieve better accuracy and strength. The final meta-model was developed using stacking an ensemble learning method benefiting from the strengths of each ANFIS, ANFIS-PSO and ANFIS-GA method and trained using Random Forest, to help in predicting load demand. Equations 5 to 10 shows the mathematical model for the process.

$$\hat{Y}_{ANFIS} = f_{ANFIS}(X) \tag{5}$$

$$\hat{Y}_{ANFIS\text{-}PSO} = f_{ANFIS\text{-}PSO}(X) \tag{6}$$

$$\hat{Y}_{ANFIS\text{-}GA} = f_{ANFIS\text{-}GA}(X) \tag{7}$$

Where

$f_{ANFIS}(X)$ is the prediction function of the standard ANFIS model

$f_{ANFIS\text{-}PSO}(X)$ is ANFIS optimized with Particle Swarm Optimization

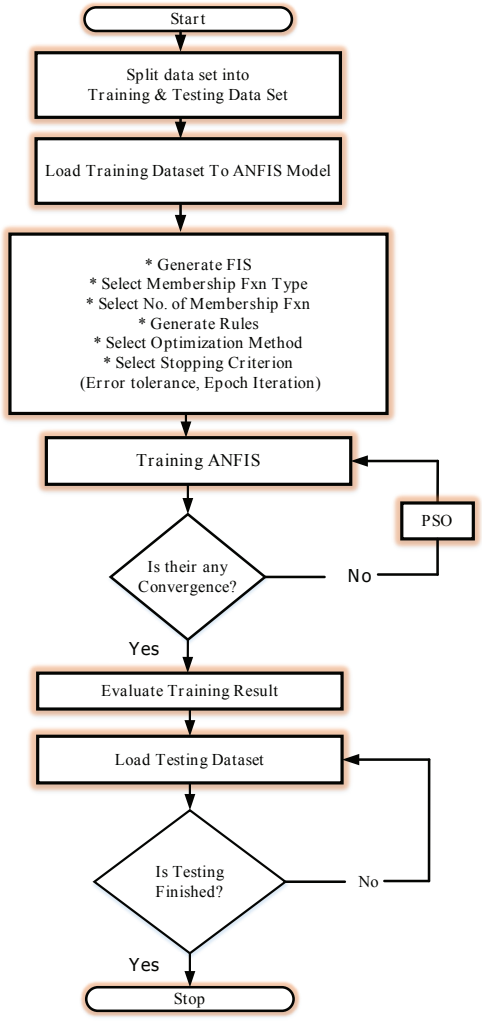


Figure 6. ANFIS-PSO.

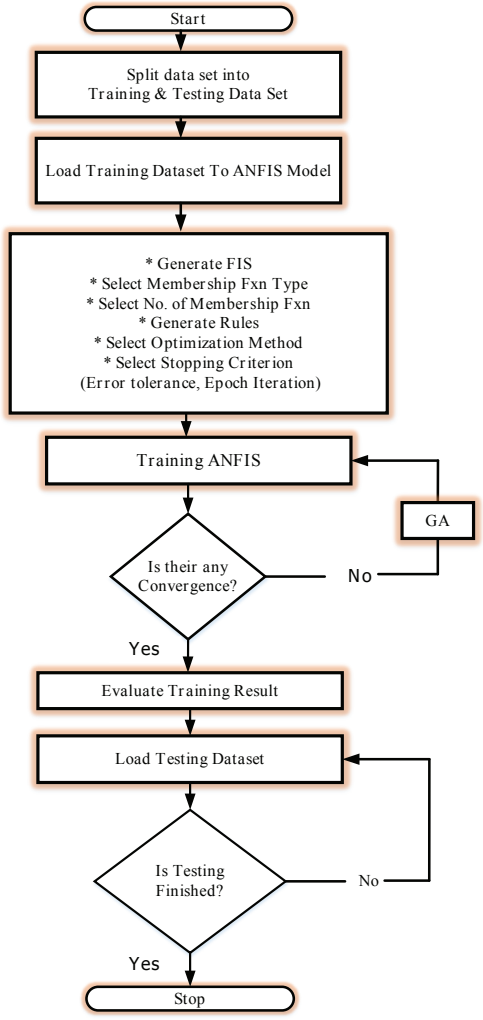


Figure 7. ANFIS-GA.

$f_{ANFIS\text{-}GA}(X)$ is ANFIS optimized with Genetic Algorithm

The outputs from these models form a new feature set as given by Equation 8 and Equation 9.

$$Z=[\hat{Y}_{ANFIS}, \hat{Y}_{ANFIS\text{-}PSO}, \hat{Y}_{ANFIS\text{-}GA}] \quad (8)$$

$$\hat{Y}_{final} = g_{RF}(Z) = g_{RF}\ ([\hat{Y}_{ANFIS}, \hat{Y}_{ANFIS\text{-}PSO}, \hat{Y}_{ANFIS\text{-}GA}] \quad (9)$$

A Random Forest regression model g_{Rf} implemented using TreeBagger is then trained using Z as input to predict the final output as given by Equation 10

$$\hat{Y}_{final} = g_{RF}(Z) = g_{RF}\ ([\hat{Y}_{ANFIS}, \hat{Y}_{ANFIS\text{-}PSO}, \hat{Y}_{ANFIS\text{-}GA}] \quad (10)$$

Ensemble learning is applied last to produce base models that are trained with Random Forest to boost how accurately they predict. A diagram of the Ensemble Learning process is shown in Figure 8.

Model Parameter Selection

Parameter selection for ANFIS, ANFIS-PSO, and ANFIS-GA models prioritized predictive accuracy and computational efficiency. Key parameters were chosen based on their ability to optimize performance: ANFIS utilized 5 inputs (previous hour load, temperature, humidity, time of day, holiday effects) for their critical impact on energy consumption patterns, and employed Sugenotype and Gaussian membership functions for effective prediction and smooth representation of nonlinear relationships. Also the number of membership function per input variable (Guassian with three membership function per variable), were set based on preliminary experiments and domain knowledge. The ANFIS rule based was constructed using grid partitioning, with the number of rules determined. Regarding data splits, the dataset was randomly partitioned into training (70%), validation (15%) and testing (15%) subsets, ensuring that the distribution of load demand was preserved across splits. ANFIS-PSO used a swarm size of 50 particles to balance exploration and computational efficiency, with a maximum iteration of 50 to facilitate thorough search without excessive processing time, and parameters of inertia weight 0.5 and cognitive component 1.5 to ensure stable convergence and responsiveness to new information. ANFIS-GA incorporated a crossover rate of 0.8 and mutation rate of 0.17 to enhance solution diversity and exploration capabilities, with elitism, tournament selection, and real value encoding to retain high-quality solutions and streamline convergence. Finally, the Ensemble model using Random Forest was trained with 50 trees to maintain a balance between reducing variance and controlling computational cost.

Model Evaluation

Performance of all models was then evaluated using Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and Mean Squared Error [63] given by equations 11, 12 and 13 respectively.

$$MAPE=\frac{1}{N}\sum_{m=1}^{N} abs\left(\frac{Load_{forecast}(m)-Load_{actual}(m)}{Load_{actual}(m)}\right)\times 100 \quad (11)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{M=1}^{N}(A_M - F_m)^2} \quad (12)$$

$$MSE=\frac{1}{N}\sum_{M=1}^{N}(A_M - F_m)^2 m^{th} \quad (13)$$

Where N represents the total number of hours in the dataset, A_m the actual load for the m^{th} hour and F_m the predicted load for the m^{th} hour.

RESULTS AND DISCUSSION

Exploratory factor analysis and Fuzzy-AHP method were used to assess, reduce and rank the factors that affect

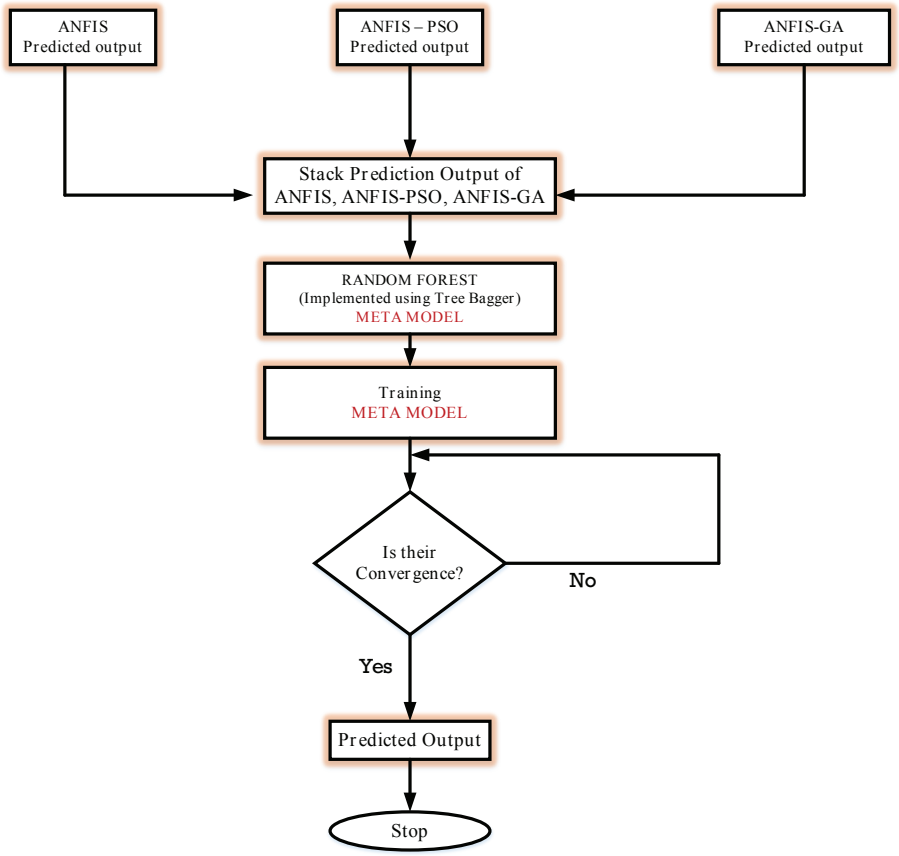


Figure 8. Ensemble model of ANFIS, ANFIS-PSO and ANFIS-GA.

load demand the most. The most influential factors out of fourteen (14) initially studied factors found from Table 1 were reduced to eight (8) as presented in Figure 9, and the Fuzzy-AHP ranked the reduced factors as previous hour load (0.3149), temperature (0.2298) and humidity (0.1790), hours of the day (0.0904) as well as holidays (0.0669) as presented in Figure 10 were the topmost five (5) factors were selected. Collected datasets based on the five (5) topmost

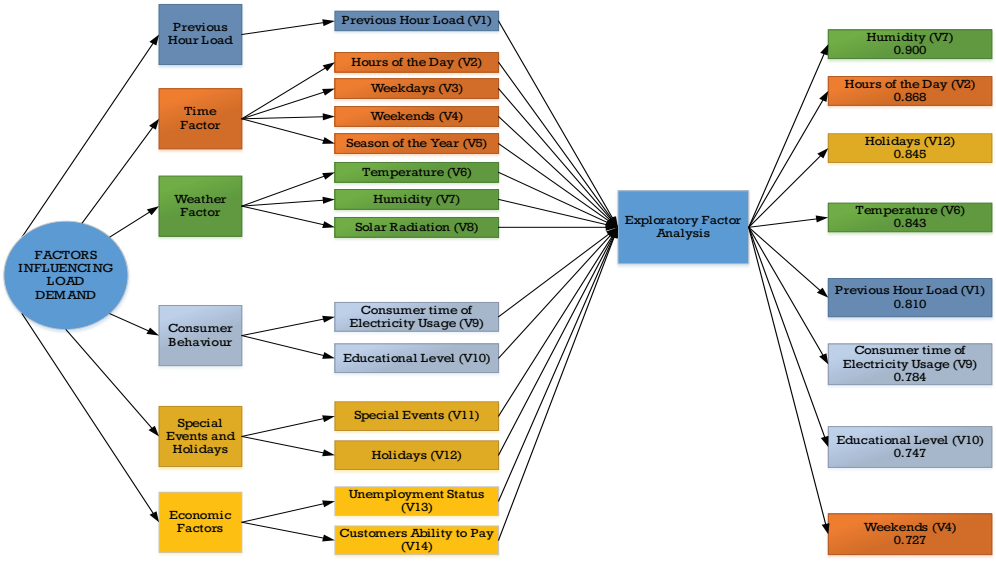


Figure 9. Exploratory factor analysis.

factors was preprocessed and the output of the preprocessed dataset presented in Figure 11. Using the preprocessed dataset, ANFIS, I-ANFIS and ensemble models of ANFIS and I-ANFIS were developed, trained and evaluated using MAPE, RMSE and MSE and a comparison was made to determine which of the models performed better for microgrid projects in Gwam rural community.

Figure 12-14 shows the results of the training and optimization for the ANFIS, ANFIS-PSO and ANFIS-GA models. From Figure 12, there was a noticeable fall in rmse from about 0.225 at the beginning to 0.2220 after 50 epochs, demonstrating that the ANFIS model learned quickly in the first 30 epochs and reached its converging point. The ANFIS-PSO model showed that, using the PSO to optimize

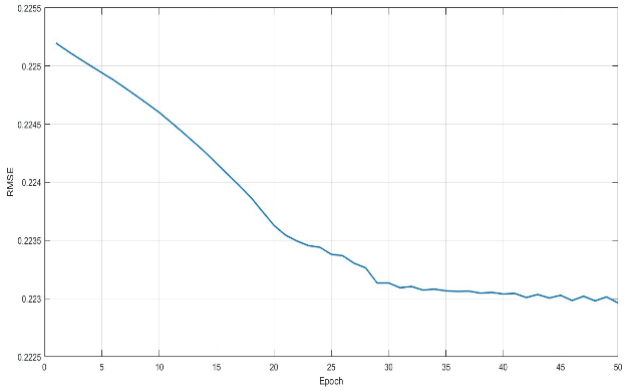


Figure 12. ANFIS training plot.

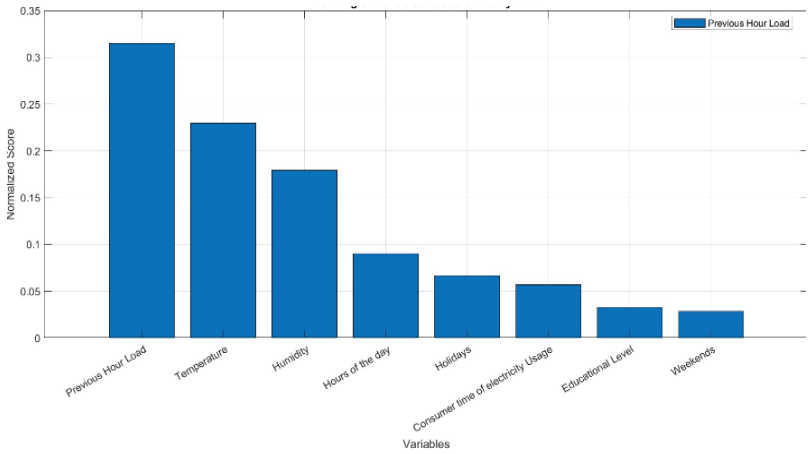


Figure 10. Fuzzy-AHP ranking of variables.

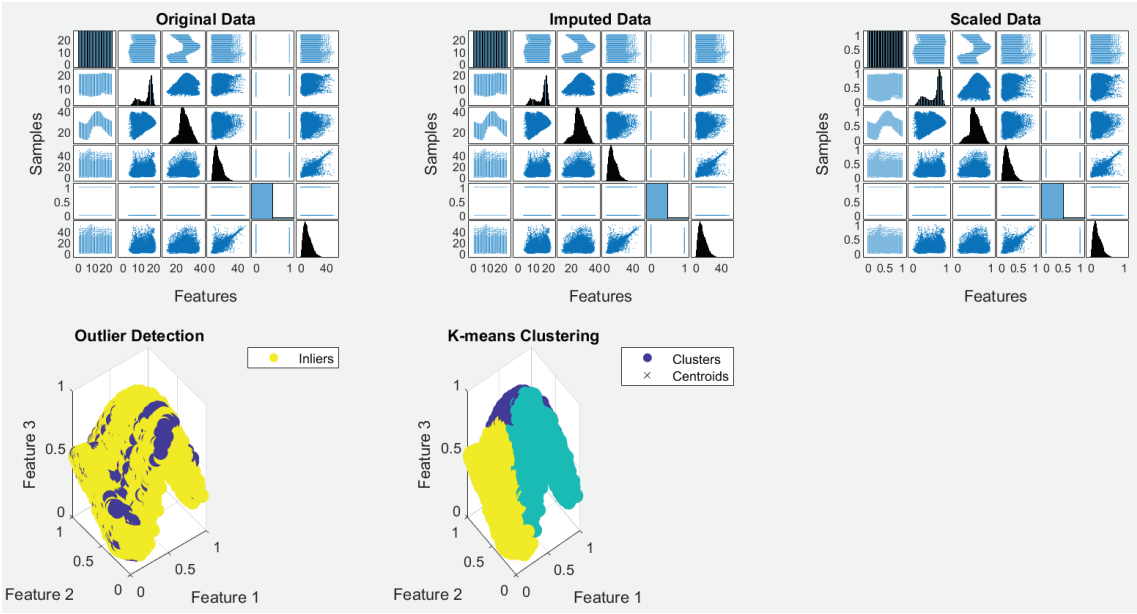


Figure 11. Preprocessed dataset.

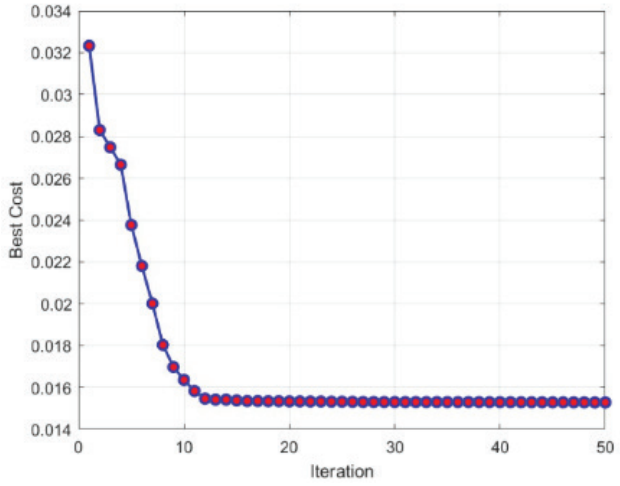


Figure 13. PSO optimization plot.

ANFIS decreased cost from 0.034 to 0.0153 within 50 iterations as shown in the plot of Figure 13, indicating improved performance from the model, in addition, showing that the PSO algorithm can enhance the results of the ANFIS model, as shown by the 55% boost. Improvement in prediction accuracy and low prediction error are shown by the ANFIS-GA model's best fitness value of 0.00475. Also, the GA enables ANFIS to find good solutions due to the low mean fitness score of 0.004876 as shown in Figure 14. Generally, all the models' learning curves were steady, had a reasonable learning rate and performed well to the data, making them suitable for correct load prediction in rural microgrid applications.

The plots of actual load demand (blue) versus the predicted load demand (orange) shown in Figure 15-18 for ANFIS, ANFIS-PSO, ANFIS-GA and Ensemble models shows that there exist characteristic performance differences

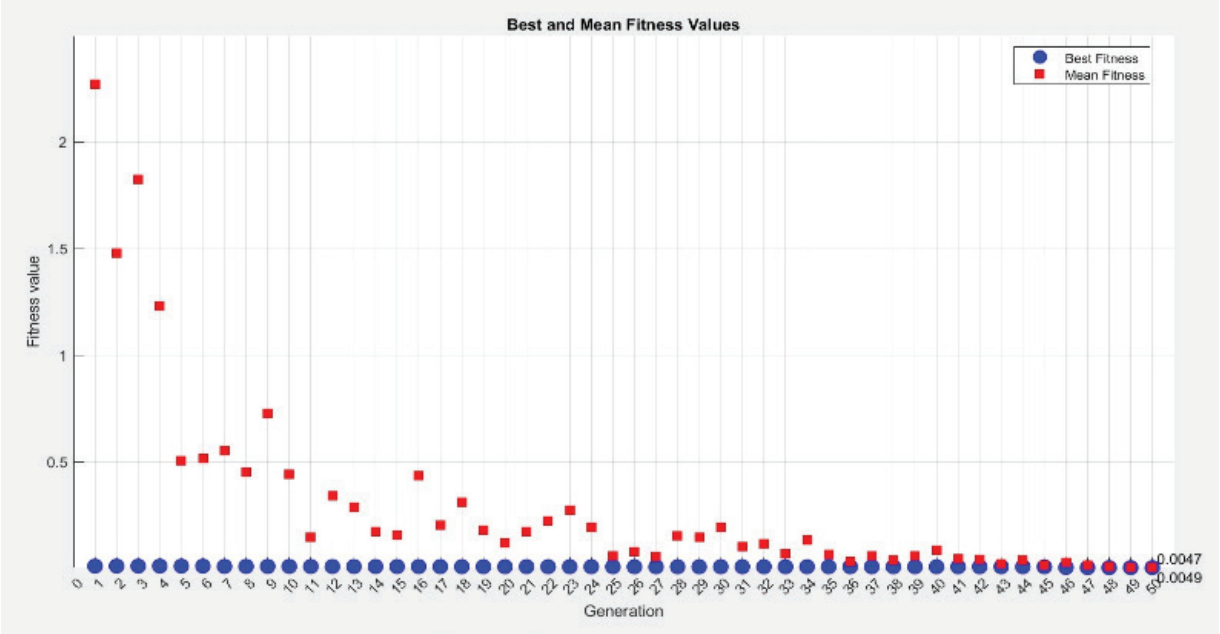


Figure 14. GA-optimization plot.

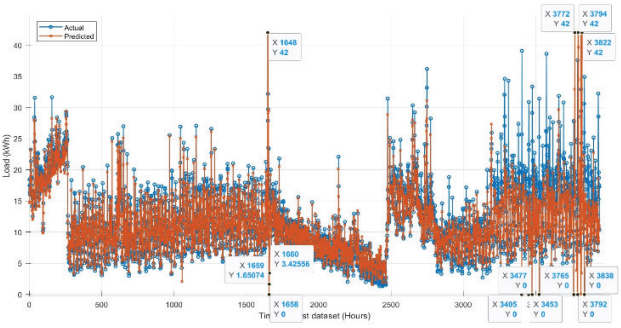


Figure 15. ANFIS actual vs. predicted load.

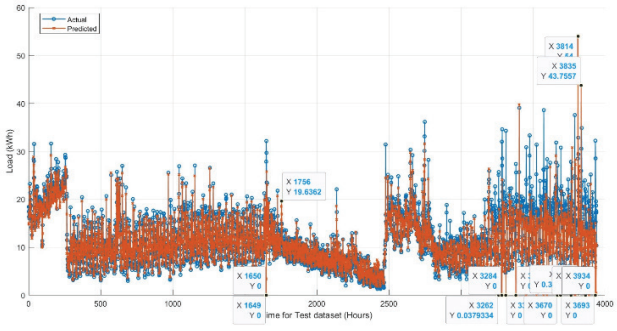


Figure 16. ANFIS-PSO actual vs. predicted load.

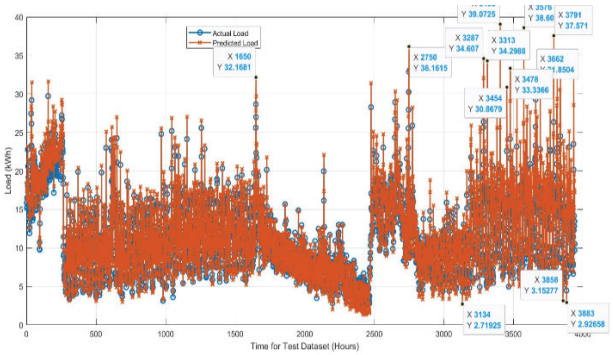


Figure 17. ANFIS-GA actual vs. predicted load.

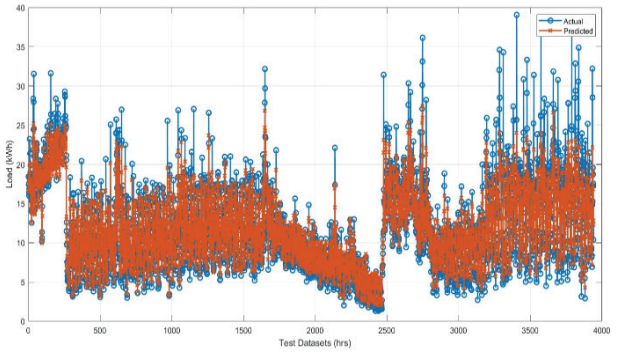


Figure 18. Ensemble actual vs. predicted load.

between the models on entire test dataset of 3,942 hours. Although the ANFIS model had a decent fit to real load trends in Figure 15, there were little discrepancies, sharp spikes and deviations in cases of high demand variability and sudden peaks (where the load demand was extremely high) revealing its limitations in predicting sudden surges as can be seen in the hours of 1648, 1658, 1659, 1660, 3405, 3453, 3477, 3765, 3772, 3792, 3794, 3822 and 3838 from the plot. Using the ANFIS model together with Particle Swarm Optimization (PSO) performance improved. Generally, the oranges cross (representing predicted load) closely aligns with the actual load, but there's still notable discrepancies during rapid changes as can be seen in the hours of 1649 ,1650,1756,3262,3284,3670,3693,3814,3835 and 3934 in Figure 16. The ANFIS-GA model predicted values closely tracked the actual load across the entire test dataset (3942) as presented in Figure 17, effectively managing rather sharp variations with fewer significant deviations. The Ensemble model's performance in capturing load dynamics is evident in its actual versus predicted load plot shown in Figure 18. Even with a range of actual loads, the predictions really match up nicely and effectively capture underlying trends. Notably, compared to more conventional models, this model minimizes errors. While minor deviations persist, the Ensemble model generally tracks actual load more accurately than standalone models, showcasing enhanced generalization, reduced overfitting, and improved adaptability.

A comparison of the prediction models shows different error distributions as presented in Figure 19-22. The ANFIS model has a normal distribution of errors with 0 kWh as the mean, and more of the errors within ±20 kWh of the mean, with a wider error width, and most errors near zero as shown in Figure 19, suggesting high prediction certainty and low systematic error. Although large errors occur, they are not frequent. Better performance came from ANFIS-PSO which produced errors that distributed symmetrically on both sides of 0 kWh while maintaining unbiased predictions. The frequency of prediction errors as shown in Figure 20 shows a concentration band centered at ±10 kWh near the mean value thus indicating improved accuracy and precision compared to ANFIS results. The ANFIS-GA model error band result shown in Figure 21 showed a very steep error distribution suggesting greater prediction precision and lower bias. Few extreme errors

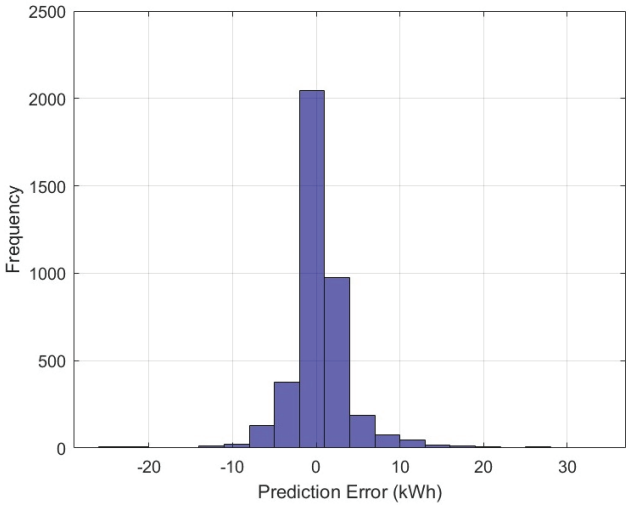


Figure 19. ANFIS model error plot.

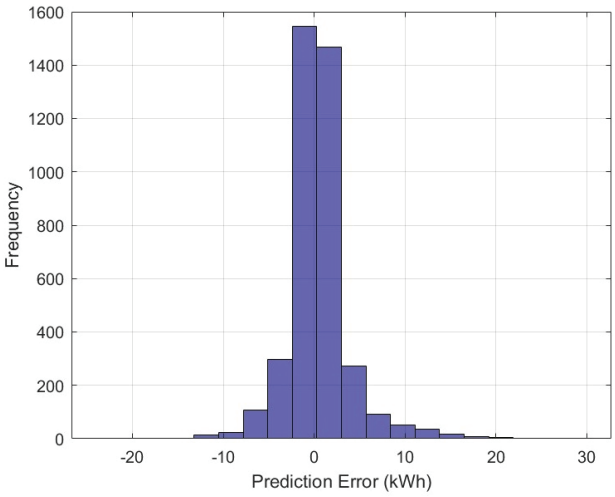


Figure 20. ANFIS-PSO model error plot.

occur more than ±10 kWh, which indicates a better control over the large errors. A comparison between ANFIS-PSO and ANFIS-GA, showed the latter has a smaller error width and more errors of moderate size at 0 kWh and less severe deviations. The Ensemble model in Figure 22 showed better performance when compared with the individual models as the error distribution concentrated around 0 kWh and the error width was smaller. Errors in the prediction were reduced to the minimum and happen very infrequently more than ±5 kWh, making the ensemble model a more reliable choice for load demand prediction.

The visualizations from Figure 23-25 shows the interaction patterns between hourly humidity, hourly temperature and predicted normalized load demand through surface viewer plots for ANFIS, ANFIS-PSO and ANFIS-GA models. The ANFIS plot in Figure 23 shows an undulating surface indicating that the model struggles to learn the behaviour of the dataset presented to it. The ANFIS-PSO model in Figure 24 produces better undulations which enhance its ability to detect changes in system inputs and adapt to variations while delivering uncertain results in periods of extreme demands. The ANFIS-GA in Figure 25 model produces the most sophisticated plot representation through its smooth undulating features that accurately depict system connections during load prediction operations.

Comparative performance evaluation for the load prediction models is presented in Table 4. The analysis based on Table 4 demonstrates that all these models were efficient in load demand prediction. The Ensemble model outperformed the rest, landing a remarkable MAPE of 14.6932%, RMSE of 2.4071 and MSE of 5.8121 which demonstrates a firm grasp in representing load demand fluctuations. The ANFIS-GA model trailed not too far behind with a MAPE of 19.8094%, RMSE of 3.3019, and an MSE of 10.9025 indicating reasonable generalization skills. Similarly, the ANFIS-PSO model also improved prediction accuracy with MAPE, RMSE, and MSE of 19.9320%, 3.5462, and 12.5755 respectively. However, the standalone ANFIS model had the most errors out of the models, accounting for a MAPE of 20.9701%, RMSE of 3.9908, and MSE of 15.93% displaying its limitation to tackle intricate load demand behaviors.

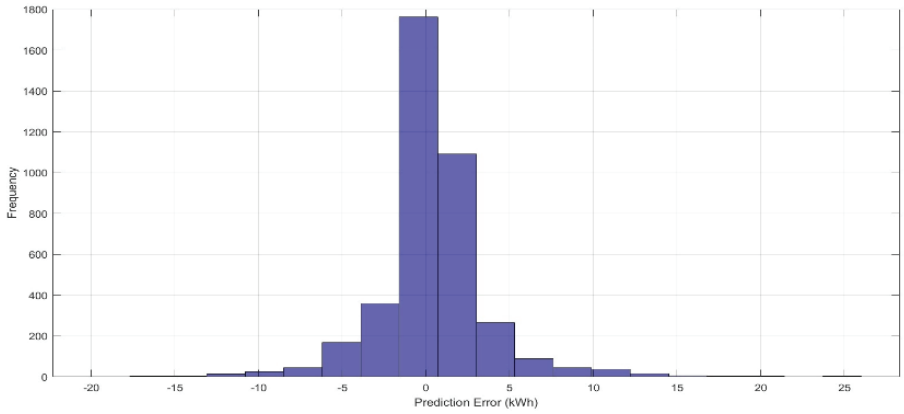


Figure 21. ANFIS-GA model error plot.

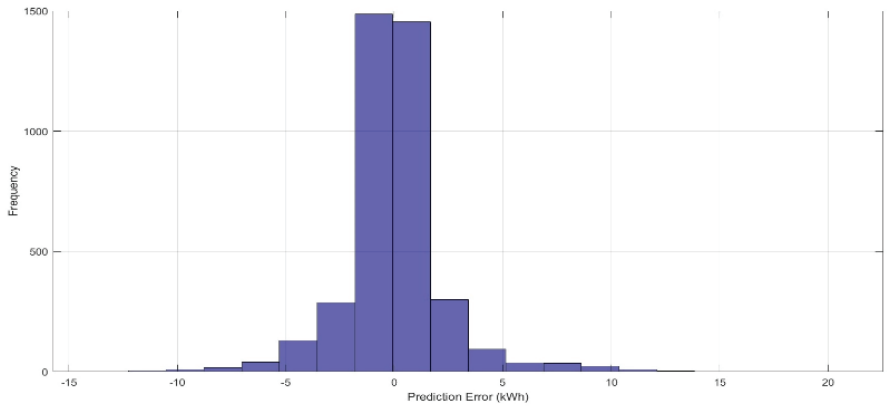


Figure 22. Ensemble model error plot.

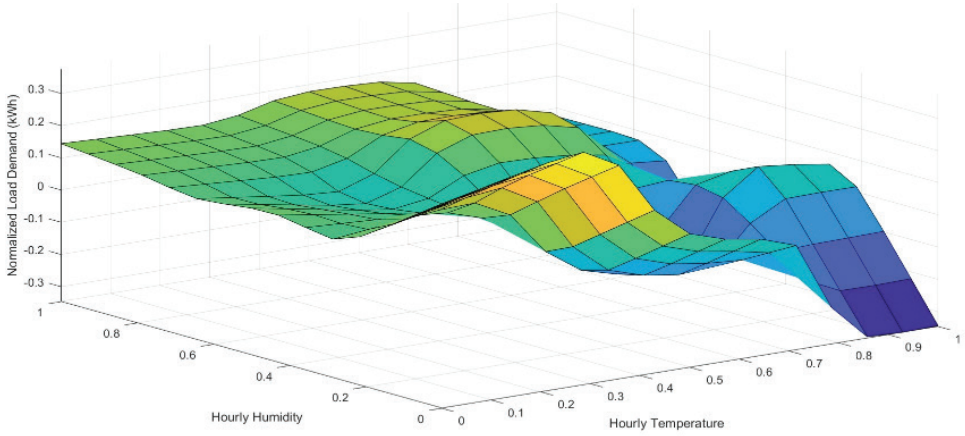


Figure 23. ANFIS model surface plot.

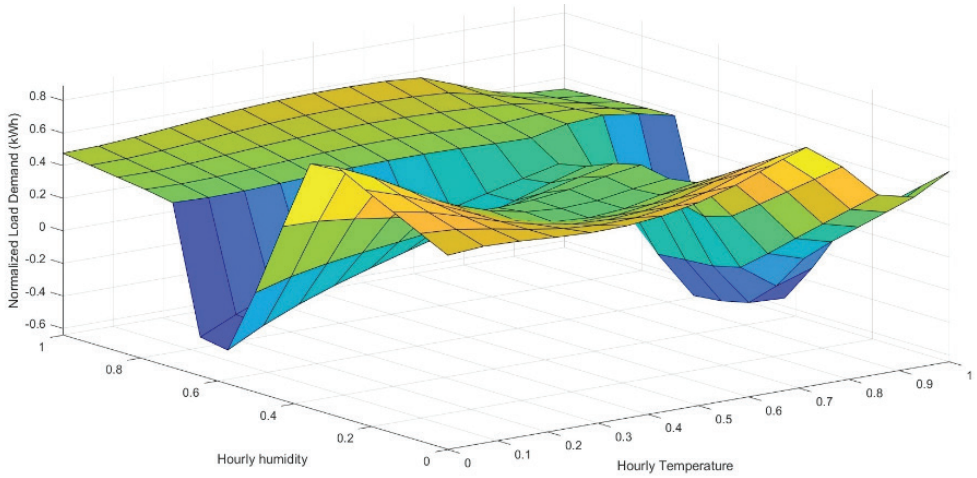


Figure 24. ANFIS-PSO surface plot.

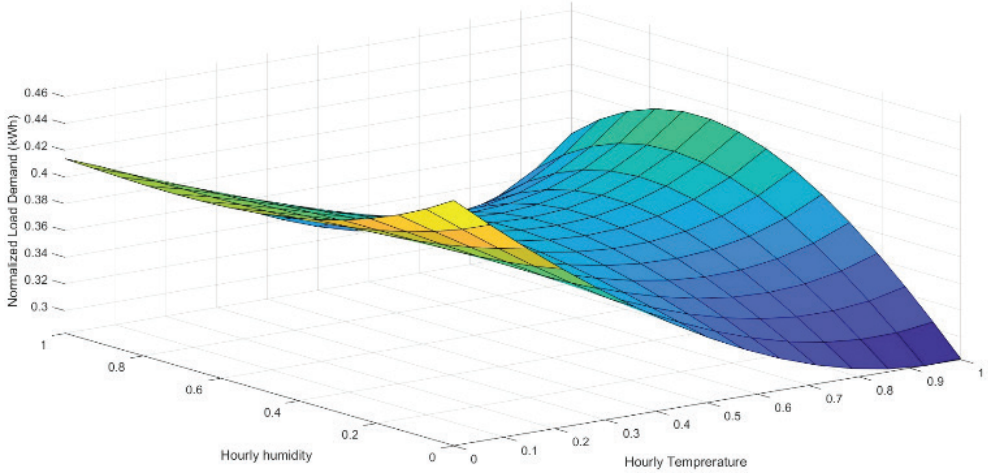


Figure 25. ANFIS-GA surface plot.

Table 4. Comparative analysis of ANFIS, ANFIS-PSO ANFIS-GA and ensemble models

T.DS	ANFIS			ANFIS-PSO			ANFIS-GA			Ensemble Model		
	Mape (%)	rmse	Mse	Mape (%)	rmse	Mse	Mape (%)	rmse	Mse	Mape (%)	rmse	Mse
O.TD	20.97	3.99	15.93	19.93	3.55	12.58	19.81	3.30	10.90	14.69	2.41	5.81
WD	20.68	3.90	15.24	19.71	3.47	12.03	19.68	3.24	10.51	14.64	2.40	5.78
WKND	21.70	4.20	17.66	20.50	3.73	13.93	20.14	3.45	11.87	14.83	2.43	5.90

Key: T.DS = Testing Data Set OTD = overall Testing Data, WD = Weekdays, WKND = Weekends

Furthermore, comparison was done on the performance of the four models based on their mean prediction error and 95 percent confidence intervals (CI), the ensemble model was the best performing model with a nearly zero mean error (0.0097) and its 95 percent CI [-0.0656, 0.0851] which included zero, showing that the model has a small bias and very high precision relative to the other three models.

In contrast, ANFIS, ANFIS-PSO and ANFIS-GA exhibited mean error: 0.4775, CI: [0.3538,0.6013], PSO (mean error: -8.1138, CI: [-8.3132, -7.9145]) and ANFIS-GA (mean error: -8.0076, CI: [-8.2023, -7.8129]) respectively.ANOVA analysis ($F = 3842.1494$, $p<0.001$) further revealed that the results were significant in each of the four models according to one-way ANOVA. Since ANOVA scores are significant, post-hoc tests (Tukey HSD) was carried out to determine which two groups are different. Post-hoc Tukey HSD analyses showed that the Ensemble technique has significantly better results compared to all other models, with very high mean differences (7.4411 more than ANFIS-PSO and 7.3059 more than ANFIS-GA) and very significant p-values ($p<0.001$). Thus, the Ensemble approach is not only qualitatively preferable but also quantitatively distinct in its superiority.

The findings were benchmarked against existing studies [31, 64-68] reinforcing the conclusion that integration of ANFIS with GA and PSO and also the Ensemble model of ANFIS, outperforms the traditional ANFIS in handling complex, nonlinear load demand.

On the whole, the results of this study provide practical application in the area of increasing the accuracy of load prediction in rural microgrids available to energy stakeholders around the world, which can assist policymakers and development agencies in creating data-driven energy policies to improve energy access, infrastructure investments planning, and the implementation of smart management systems that support optimized energy management and provide cost-efficiency and resilience.

CONCLUSION

This study has established that an integrated hybrid ensemble learning technique can be efficient to make adequate predictions concerning load demands in rural microgrids. Using both EFA and Fuzzy-AHP, we systematically reduced and ranked the most powerful variables that are influential in predicting load demand, namely previous hour load, temperature, humidity, and hours of the day, and holidays. Development and comparisons of multiple models showed that the ensemble model integrating ANFIS and both PSO and GA optimizations performed well compared to individual models, recording an impressive MAPE, RMSE, and MSE of 14.69 %, 2.41 and 5.81 respectively. Futhermore, statistical comparison based on mean prediction error and 95% confidence intervals confirmed the ensemble model's robustness, showing a near-zero mean error (0.00097) and a CI of [-0.0656, 0.0851], indicating minimal bias and high precision. The statistical significance of these results was validated using one-way ANOVA ($F = 3842.1494$, $p<0.001$), confirming significant differences across the four models. Subsequent post-hoc Tukey HSD tests revealed that the Ensemble model was statistically superior to all other models with highly significant mean differences.

These findings reveal that the selection of variables and methods of hybrid modeling are significant in predictive accuracy, which is more relevant in resource restricted rural conditions. The findings confirm that the suggested approach could provide a useful decision-support tool to microgrid operators to handle effective load management and sustainable energy planning addressing the specificities in rural regions. Furthermore, the integrated framework in addition proves to be robust and adaptable implying that it might be applicable to any other rural or off-grid energy system.

While this study provides valuable insights, it is not without limitations. These include potential constraints related to data availability, limitations in risk assement of prediction models, the scope of the selected variables, and the generalizability of the findings to other contexts. These limitations may impact our findings by limiting the range of analysis, neglecting some key variables, and limiting generalizability to other contexts. Regardless of these shortcomings, the study demonstrates the potential of the proposed method in enhancing load demand prediction within rural microgrids.

Future directions of research should include other variables like social- economic factors and look at deep learning methods of modeling such as Long short term memory (LSTM) and come up with a predictive model that is adaptable and run in real-time. In addition, upgrading the prediction framework with elements of a risk assessment

and the modules that would be employed in developing an operational decision would further render this framework practically viable in supporting the demands of rural microgrid operators. Furthermore, future study should also be extended beyond the Gwam microgrid to include other rural microgrid locations, ensuring broader applicability of the developed models.

ACKNOWLEDGEMENTS

The author wants to express special appreciation to the Federal University of Technology Minna (FUTMinna) for the research-friendly environment and access to the necessary databases, Solemenz Engineering for kindly providing the load data utilized in this study, and the National Aeronautics and Space Administration (NASA) for providing access to the weather data utilized in this study through their web portal.

AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

STATEMENT ON THE USE OF ARTIFICIAL INTELLIGENCE

Artificial intelligence was not used in the preparation of the article.

REFERENCES

[1] Kwakwa PA, Adusah-Poku F, Adjei-Mantey K. Towards the attainment of sustainable development goal 7: What determines clean energy accessibility in sub-Saharan Africa. Green Finance 2021;3:268–286. [CrossRef]

[2] Panos E, Densing M, Volkart K. Access to electricity in the World Energy Council's global energy scenarios: An outlook for developing regions until 2030. Energy Strateg Rev 2016;9:28–49. [CrossRef]

[3] Shobayo O, Abayomi-Alli O, Odusami M, Misra S, Safiriyu M. Modeling and simulation of impedance-based algorithm on overhead power distribution network using MATLAB. In: Advances in Electrical and Computer Technologies: Select Proceedings of ICAECT 2019; 2020. p. 335–345. [CrossRef]

[4] Gözüoğlu A, Ozgonenel O, Gezegin C. Modeling and implementation of demand-side energy management system. Sigma J Eng Nat Sci 2024;42:1628–1645. [CrossRef]

[5] Udoakah YO, Khalaf S, Cipcigan L. Blackout and black start analysis for improved power system resilience: The African experience. In: 2020 IEEE PES/IAS PowerAfrica; 2020. p. 1–5. [CrossRef]

[6] Hartvigsson E, Ahlgren EO. Comparison of load profiles in a mini-grid: Assessment of performance metrics using measured and interview-based data. Energy Sustain Dev 2018;43:186–195. [CrossRef]

[7] Chawrasia SK, Hembram D, Chanda CK. Impact analysis of EV load on distribution system. In: 2022 2nd Odisha International Conference on Electrical Power Engineering, Communication and Computing Technology (ODICON); 2022. p. 1–6. [CrossRef]

[8] Mylonas E, Tzanis N, Birbas M, Birbas A. An automatic design framework for real-time power system simulators supporting smart grid applications. Electronics 2020;9:299. [CrossRef]

[9] Hamoodi SA, Hamoodi AN, Mohammed RAN. Design and Simulation of Smart Grid Based on Solar Photovoltaic and Wind Turbine Plants. J Eur Syst Autom 2024;57:953. [CrossRef]

[10] Tayab UB, Zia A, Yang F, Lu J, Kashif M. Short-term load forecasting for microgrid energy management system using hybrid HHO-FNN model with best-basis stationary wavelet packet transform. Energy 2020;203:1–11. [CrossRef]

[11] Alaraj M, Alsaidan I, Kumar A, Rizwan M, Jamil M. Advanced intelligent approach for solar PV power forecasting using meteorological parameters for Qassim region, Saudi Arabia. Sustainability 2023;15:1–16. [CrossRef]

[12] Lin S, et al. MatPSST: A Matlab/Simulink-based power system simulation toolbox for research and education. IET Gener Transm Distrib 2023;17:2272–2288. [CrossRef]

[13] Benaissa OM, Hadjeri S, Zidi SA. Modeling and simulation of grid connected PV generation system using Matlab/Simulink. Int J Power Electron Drive Syst 2017;8:392. [CrossRef]

[14] Ahmad M, Kirmani S. Simulation and analysis of a grid integrated distribution system based on LMS algorithm for hybrid types of load. Int J Syst Assur Eng Manag 2022;13:1082–1092. [CrossRef]

[15] Nespoli A, Ogliari E, Pretto S, Gavazzeni M, Vigani S, Paccanelli F. Electrical load forecast by means of lstm: The impact of data quality. Forecasting 2021;3:91–101. [CrossRef]

[16] Yoo S, Eom J, Han I. Factors driving consumer involvement in energy consumption and energy-efficient purchasing behavior: evidence from Korean residential buildings. Sustainability 2020;12:1–20. [CrossRef]
[17] Wang Y, Zhang N, Chen X. A short-term residential load forecasting model based on LSTM recurrent neural network considering weather features. Energies 2021;14:1–13. [CrossRef]
[18] Gomes HB, et al. Effect of Meteorological Variables on Energy Demand in the Northeast and Southeast Regions of Brazil. Energies 2024;17:4776–4886. [CrossRef]
[19] Kim IM, Lee YJ, Lee S, Kim D. Temperature Effects on the Industrial Electricity Usage. Environ Resour Econ Rev 2016;25:141–178. [CrossRef]
[20] Mbasso WF, et al. Hybrid modeling approach for precise estimation of energy production and consumption based on temperature variations. Sci Rep 2024;14:24422–24434. [CrossRef]
[21] Na C, Haoshuo F. Short-Term Load Forecasting for Microgrid Considering Weather Characteristics and Source-Load Correlation. In: 2024 IEEE 2nd International Conference on Power Science and Technology (ICPST); 2024. p. 1160–1169. [CrossRef]
[22] Hernández L, et al. Experimental analysis of the input variables' relevance to forecast next day's aggregated electric demand using neural networks. Energies 2013;6:2927–2948. [CrossRef]
[23] Moradzadeh A, Zakeri S, Shoaran M, Mohammadi-Ivatloo B, Mohammadi F. Short-term load forecasting of microgrid via hybrid support vector regression and long short-term memory algorithms. Sustainability 2020;12:1–17. [CrossRef]
[24] Derks M, Romijn H. Sustainable performance challenges of rural microgrids: Analysis of incentives and policy framework in Indonesia. Energy Sustain Dev 2019;53:57–70. [CrossRef]
[25] Yang H, Long J, He P, Zheng Y. Short-term load forecasting of microgrid based on grey correlation analysis and neural network optimized by mind evolutionary algorithm. In: 2019 IEEE Innovative Smart Grid Technologies-Asia (ISGT Asia); 2019. p. 2738–2742. [CrossRef]
[26] Li B, Lu M, Zhang Y, Huang J. A weekend load forecasting model based on semi-parametric regression analysis considering weather and load interaction. Energies 2019;12:3820–3830. [CrossRef]
[27] Muzumdar AA, Modi CN, Vyjayanthi C. Designing a robust and accurate model for consumer-centric short-term load forecasting in microgrid environment. IEEE Syst J 2021;16:2448–2459. [CrossRef]
[28] Zhang A, Zhang P, Feng Y. Short-term load forecasting for microgrids based on DA-SVM. COMPEL 2019;38:68–80. [CrossRef]
[29] Zhang X, Wang J, Zhang K. Short-term electric load forecasting based on singular spectrum analysis and support vector machine optimized by Cuckoo search algorithm. Electr Power Syst Res 2017;146:270–285. [CrossRef]
[30] Alipour M, Aghaei J, Norouzi M, Niknam T, Hashemi S, Lehtonen M. A novel electrical net-load forecasting model based on deep neural networks and wavelet transform integration. Energy 2020;205:1–15. [CrossRef]
[31] Zheng D, Semero YK, Zhang J, Wei D. Short-term wind power prediction in microgrids using a hybrid approach integrating genetic algorithm, particle swarm optimization, and adaptive neuro-fuzzy inference systems. IEEJ Trans Electr Electron Eng 2018;13:1561–1567. [CrossRef]
[32] de Andrade LCM, da Silva IN. Very short-term load forecasting based on ARIMA model and intelligent systems. In: 2009 15th International Conference on Intelligent System Applications to Power Systems; 2009. p. 1–6. [CrossRef]
[33] Huang CM, Huang CJ, Wang ML. A particle swarm optimization to identifying the ARMAX model for short-term load forecasting. IEEE Trans Power Syst 2005;20:1126–1133. [CrossRef]
[34] Wang B, Tai NL, Zhai HQ, Ye J, Zhu JD, Qi LB. A new ARMAX model based on evolutionary algorithm and particle swarm optimization for short-term load forecasting. Electr Power Syst Res 2008;78:1679–1685. [CrossRef]
[35] Taylor JW. Short-term load forecasting with exponentially weighted methods. IEEE Trans Power Syst 2011;27:458–464. [CrossRef]
[36] Chawrasia SK, Hembram D, Bose D, Chanda CK. Design of solar battery swapping station for EV using LSTM-assisted solar power forecasting. Microsyst Technol 2024;30:1087–1098. [CrossRef]
[37] Chawrasia SK, Hembram D, Bose D, Chanda CK. Deep learning assisted solar forecasting for battery swapping stations. Energy Sources Part A Recover Util Environ Eff 2024;46:3381–3402. [CrossRef]
[38] Güneş Ü, Başhan V, Karakurt AS. Predicting tanker main engine power using regression analysis and artificial neural networks. Sigma J Eng Nat Sci 2023;41:216–225. [CrossRef]
[39] Tambunan HB, Priambodo NW, Hartono J, Aditya IA, Triani M. Research trends on microgrid systems: a bibliometric network analysis. Int J Electr Comput Eng 2023;13. [CrossRef]
[40] Shahzad S, Abbasi MA, Ali H, Iqbal M, Munir R, Kilic H. Possibilities, Challenges, and Future Opportunities of Microgrids: A Review. Sustainability 2023;15:1–28. [CrossRef]
[41] Lara-Cerecedo LO, Hinojosa JF, Pitalúa-Díaz N, Matsumoto Y, González-Angeles A. Prediction of the electricity generation of a 60-kW photovoltaic system with intelligent models ANFIS and optimized ANFIS-PSO. Energies 2023;16:1–26. [CrossRef]
[42] Uddin M, Mo H, Dong D, Elsawah S, Zhu J, Guerrero JM. Microgrids: A review, outstanding issues and future trends. Energy Strateg Rev 2023;49:1–16. [CrossRef]

[43] Alghamdi TA, Javaid N. A survey of preprocessing methods used for analysis of big data originated from smart grids. IEEE Access 2022;10:29149–29171. [CrossRef]

[44] Trivedi R, Patra S, Khadem S. A data-driven short-term PV generation and load forecasting approach for microgrid applications. IEEE J Emerg Sel Top Ind Electron 2022;3:911–919. [CrossRef]

[45] Semero YK, Zhang J, Zheng D, Wei D. An accurate very short-term electric load forecasting model with binary genetic algorithm based feature selection for microgrid applications. Electr Power Compon Syst 2018;46:1570–1579. [CrossRef]

[46] Hu Z, Zhu Y. Cross-project defect prediction method based on genetic algorithm feature selection. Eng Rep 2023:1–15. [CrossRef]

[47] Tsalikidis N, Mystakidis A, Tjortjis C, Koukaras P, Ioannidis D. Energy load forecasting: one-step ahead hybrid model utilizing ensembling. Computing 2023:1–33. [CrossRef]

[48] Yang J, Su C. Robust optimization of microgrid based on renewable distributed power generation and load demand uncertainty. Energy 2021;223:1–13. [CrossRef]

[49] Nammouchi A, Aupke P, Kassler A, Theocharis A, Raffa V, Di Felice M. Integration of ai, iot and edge-computing for smart microgrid energy management. In: 2021 IEEE International Conference on Environment and Electrical Engineering and 2021 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe); 2021. p. 1–6. [CrossRef]

[50] Solaun K, Cerdá E. Climate change impacts on renewable energy generation. A review of quantitative projections. Renew Sustain Energy Rev 2019;116:1–16. [CrossRef]

[51] Irmak E, Kabalci E, Kabalci Y. Digital Transformation of Microgrids: A Review of Design, Operation, Optimization, and Cybersecurity. Energies 2023;16:1–58. [CrossRef]

[52] Al Mamun A, Sohel M, Mohammad N, Sunny MSH, Dipta DR, Hossain E. A comprehensive review of the load forecasting techniques using single and hybrid predictive models. IEEE Access 2020;8:134911–134939. [CrossRef]

[53] Kondaiah V, Saravanan B, Sanjeevikumar P, Khan B. A review on short-term load forecasting models for micro-grid application. J Eng 2022;2022:665–689. [CrossRef]

[54] Fahad MU, Arbab N. Factor affecting short term load forecasting. J Clean Energy Technol 2014;2:305–309. [CrossRef]

[55] Hammad MA, Jereb B, Rosi B, Dragan D. Methods and models for electric load forecasting: a comprehensive review. Logist Sustain Transp 2020;11:51–76. [CrossRef]

[56] Phuangpornpitak N, Prommee W. A study of load demand forecasting models in electric power system operation and planning. GMSARN Int J 2016;10:19–24.

[57] Bakar NNA, Hassan MY, Sulaima MF, Mohd Nasir MNI, Khamis A. Microgrid and load shedding scheme during islanded mode: A review. Renew Sustain Energy Rev 2017;71:161–169. [CrossRef]

[58] Arkhangelski J, Mahamadou AT, Lefebvre G. Data forecasting for optimized urban microgrid energy management. In: 2019 IEEE International Conference on Environment and Electrical Engineering and 2019 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe); 2019. p. 1–6. [CrossRef]

[59] Izzatillaev J, Yusupov Z. Short-term load forecasting in grid-connected microgrid. In: 2019 7th International Istanbul Smart Grids and Cities Congress and Fair (ICSG); 2019. p. 71–75. [CrossRef]

[60] Yao Q, Meng X, Wang H, An Y. Short-term load forecasting of office building microgrid based on EA-NN. In: 2019 IEEE International Conference on Power, Intelligent Computing and Systems (ICPICS); 2019. p. 408–412. [CrossRef]

[61] Ma H, Tang JM. Short-term load forecasting of microgrid based on chaotic particle swarm optimization. Procedia Comput Sci 2020;166:546–550. [CrossRef]

[62] Moradzadeh A, Moayyed H, Zakeri S, Mohammadi-Ivatloo B, Aguiar AP. Deep learning-assisted short-term load forecasting for sustainable management of energy in microgrid. Inventions 2021;6:1–11. [CrossRef]

[63] Teferra DM, Ngoo LM, Nyakoe GN. Fuzzy-swarm intelligence-based short-term Load forecasting model as a solution to power quality issues existing in microgrid system. J Electr Comput Eng 2022;2022:1–14. [CrossRef]

[64] Kampouropoulos K, Andrade Rengifo F, García Espinosa A, Romeral Martínez JL. A combined methodology of adaptive neuro-fuzzy inference system and genetic algorithm for short-term energy forecasting. Adv Electr Comput Eng 2014;14:9–14. [CrossRef]

[65] Sabeti SMN, Deevband M. Hybrid evolutionary algorithms based on PSO-GA for training ANFIS structure. Int J Comput Sci Issues 2015;12:78.

[66] Guleryuz D. Determination of industrial energy demand in Turkey using MLR, ANFIS and PSO-ANFIS. J Artif Intell Syst 2021;3:16–34. [CrossRef]

[67] Ferdosian M, Abdi H, Karimi S, Kharrati S. Short-term load and spinning reserve prediction based on LSTM and ANFIS with PSO algorithm. J Eng 2024;2024:e12356. [CrossRef]

[68] Oladipo S, Sun Y, Amole AO. Investigating the influence of clustering techniques and parameters on a hybrid PSO-driven ANFIS model for electricity prediction. Discov Appl Sci 2024;6:1–17. [CrossRef]