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Development of Risk-Integrated Load Demand Estimation and Prediction Models for Sustainable Rural Microgrid Planning

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Abstract. Despite increased microgrid adoption in Nigeria's rural electrification, projects often fail due to power imbalances from inaccurate load demand prediction. Current models use Urban or Industrial data, ignoring rural consumption patterns, and lack risk assessment frameworks. This study developed load demand models with risk management for Gwam's rural microgrid in Niger State, Nigeria. Exploratory factor analysis narrowed 14 input variables to 8 significant factors, ranked by fuzzy analytical hierarchy process, where the top five: previous hour load, temperature, humidity, hours of day, and holidays were selected and used in developing the prediction models. Four models were developed: ANFIS, ANFIS-PSO, ANFIS-GA, and ensemble ANFIS. The ensemble model outperformed others (MAPE: 14.69%, approximately 6% superior to conventional ANFIS). A risk management model categorized predictions as low (<10%), medium (10 – 20%), and high (>20%) risk. The ensemble model had 58.02% low-risk and 20.24% high-risk predictions, vs. 44.19% and 31.71% for ANFIS. This risk-aware framework supports operators in predicting failures, optimizing resources, and decision-making under uncertainty for sustainable rural electrification.

1 Introduction

Reliable electricity supply remains a major challenge in many developing regions, particularly rural communities where grid extension is often economically and technically infeasible [1]. Consequently, renewable-energy-based microgrids have emerged as a promising solution for decentralized electrification. However, the long-term sustainability of rural microgrids depends not only on generation technologies but also on the effectiveness of Load Demand Estimation and Prediction Models (LDEPMs). Inaccurate demand forecasts can result in power imbalance, outages, increased operating cost and reduced system reliability. These challenges are amplified in rural microgrids due to renewable energy intermittency, limited historical data, changing socio-economic conditions, and uncertain consumer behaviour [2].

Although artificial intelligence and data-driven forecasting methods have improved prediction accuracy, most existing LDEPMs give limited attention to risks associated with variable selection, data uncertainty, overfitting, changing operating conditions, and post-deployment monitoring. Furthermore, most studies were based on urban or industrial datasets and do not adequately address the unique uncertainties of rural microgrids. This highlights the need for a structured, lifecycle-based risk management framework for rural load forecasting.

To address this gap, this study proposed a risk-sensitive load demand estimation and prediction framework for rural microgrids. The framework integrates risk assesment into input selection, model development, validation, and operational evaluation to improve prediction reliability and decision-making under uncertainty. The study contributes a systematic and generalizable approach that combines advanced predictive modelling with structured risk management, thereby reducing operational impacts such as under-generation, reserve over-allocation, unnecessary energy dispatch and load imbalance.

The rest of the article is structured in the following way: Section 2 reviews related literature with a particular focus on the modeling of risks; Section 3 outlines the proposed risk-based methodology; Section 4 discusses the outcomes of the research and risk evaluation; and finally, Section 5 provides conclusion with future research recommendations.

2 Literature review

2.1 Theoretical Review

The study follows the conventional LDEPM framework involving data acquisition, feature selection, model development, validation, and risk assessment [3].

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2.2 Review of Related Works

Energy consumption, energy infrastructure and consumption patterns have been relatively stable in most of the previous forecasting studies, which have been conducted for urban or semi-urban energy systems. Using structured smart grid data, deep learning has been used for energy management and forecasting in urban microgrids as presented by Abimbola [4], Zhang, et al. [5] and Jahani, et al. [6]. Only a few studies have tried to solve the problem of predictive risk management and uncertainty-aware forecasting for rural microgrids in the context of sustainability, such as Derks and Romijn [7] but they have not been related to the forecasting frameworks used in urban microgrids.

Likewise, Moradzadeh, et al. [8] recognized the intricacies of rural microgrid forecasting and concentrated on the performance of the models instead of integrating operational risks. The above findings suggest that there is limited research work that addresses uncertainty, risk management and predictive robustness in a holistic manner in rural microgrid load demand estimation.

A number of authors suggested advanced AI and hybrid models to improve prediction accuracy. Arkhangelski, et al. [4] used deep learning (Bi-LSTM) to predict load in urban microgrids, and the model resulted in better energy flow optimisation; though it did not evaluate the application in rural areas or included the analysis of risks. Derks and Romijn [7] attributed the early failure of microgrids in rural electrification projects to a lack of attention to service quality yet failed to combine predictive risk mitigation models. eZhang, et al. [5] developed a hybrid model of DA-SVM with lower RMSE and less computational time, but they did not specify the input selection criteria. [8, 9] reported high correlation performance with the SVR-LSTM and Bi-LSTM in rural settings, but emphasized the complexity of the model and no mention of operational or uncertainty risks. The work in [10] included optimization methods (HHO, chaotic PSO, fuzzy-PSO), enhancing performance but not saying anything about the structured risk evaluation, sequence of systematically chosen inputs, and overall preprocessing infrastructure.

Jahani, et al. [6] presented SPM-LSTM that had better short-term performance but did not provide clear variable selection criteria and uncertainty analysis. In the literature, the majority concentrated on accuracy improvement and did not consider predictive risk.

2.3 Research Gaps

Despite recent methodological advances, current LDEPM research lacks formal risk and uncertainty analysis, systematic input variable screening, and rural-specific robustness. This gaps calls for a risk-sensitive LDEPM tailored to rural microgrids to reduce forecast uncertainty, prevent system imbalance, and improve long-term operational reliability.

3 Research Methodology

3.1 Research design

The proposed study uses a mixed-method, 5-stage design : input variable identification via exploratory factor analysis, ranking reduced factors with fuzzy AHP, data pre-processing and analysis, development of ANFIS, ANFIS-PSO, ANFIS-GA and ensemble models, and a risk management framework to assess prediction reliability and mitigate uncertainty.

3.2 Study Area

The Gwam community in Niger State, Nigeria (9°20 N -9°33 N, 6°40 E -6°55 E) was used as a case study to test the models. It is a solar-rich residential area with standard appliances, while grinding and milling use alternative energy sources.

3.3 Data Sources and Collection Method

The research adopted mixed-methodology. A sample of 111 participants in Gwam community measured 14 input variables on load demand (on 5-point Likert scale). 10 microgrid professionals made pairwise comparisons based on FAHP. The climatological information (2021-2023) was sourced at NASA and the hourly load demand at Solemenz Engineering Nigeria Limited.

3.4 Modelling and Analytical Techniques

All analyses were implemented in MATLAB.The modelling process was conducted in a structured manner as follows : (i) Data pre-processing and normalization ; (ii) Selection of the input variables from the data based using EFA and fuzzy-AHP ; (iii) Baseline ANFIS model development with Gaussian membership functions and the hybrid learning approach ; (iv) Model parameter optimization using the PSO and GA with fixed parameters ; (v) Construction of ensemble model with the Random Forest approach ; (vi) Model Validation using k-fold cross-validation ; and lastly evaluation using the MSE, RMSE, and MAPE. A detailed workflow is shown in Fig 1 to 3.

3.4.1 Exploratory Factor Analysis

Exploratory factor analysis (EFA) was performed using reliability testing, KMO, Bartlett's test, PCA extraction and Varimax rotation. Variables with factor loading > 0.7 were retained.

3.4.2 Fuzzy Analytical Hierarchy Process

Fuzzy Analytical Hierarchy Process was used to rank the retained variables using expert pairwise comparisons, fuzzy geometric mean aggregation and consistency ratio verification (CR < 0.1)

3.4.3 Data Pre-processing Framework

Missing data were interpolated, variables normalized using min-max scaling, duplicates removed, and outliers assessed using Z-score analysis. Identified extreme values were manually verified to preserve legitimate peak-load events.

3.4.4 Predictive Model Development

Four predictive models were developed for load demand prediction : ANFIS, ANFIS-PSO, ANFIS-GA and Ensemble ANFIS. The ANFIS model employed a Sugeno-type fuzzy inference system with five inputs (previous hour load, temperature, humidity, hour of the day, and holidays), Guassian membership functions, hybrid learning, 243 fuzzy rules, 1,488 parameters, 50 training epochs, and an error tolerance of 0.05. ANFIS-PSO optimized ANFIS parameters using 50 particles, 50 iterations, an inertia weight of 0.5, and cognitive and social coefficients of 1.5. ANFIS-GA employed a population size of 50, crossover rate of 0.8, mutation rate of 0.17, elite count of 2, and tournament selection. The Ensemble model combined ANFIS, ANFIS-PSO and ANFIS-GA predictions using a Random Forest (TreeBagger) meta-model with 50 trees.

Model selection and optimization were based on prediction accuracy (MAPE, RMSE, and MSE) and operational reliability through the reduction of high-risk predictions (>20% deviation). The framework also supported opportunity-cost optimization by improving resource allocation, reserve scheduling, and operational efficiency through reduced forecasting errors.

To ensure statistical robustness and generalization, k-fold cross-validation was applied during training, while the dataset was divided into 70% training, 15% validation, and 15% testing subsets. Hyperparameters were tuned using the validation set, and the independent test set was used to assess predictive performance on unseen data. In addition, statistical relationships between selected predictors and load demand were verified during pre-processing and model development to ensure both contextual relevance and prediction effectiveness.

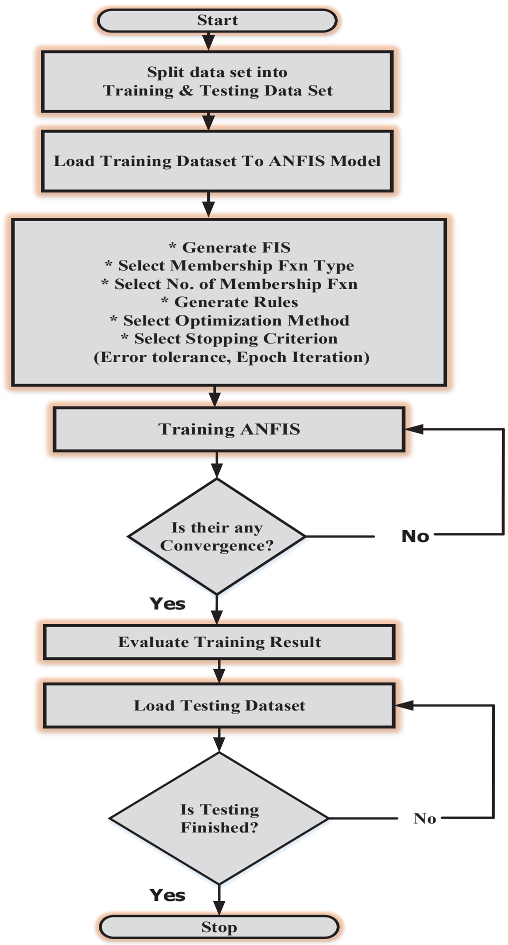

Fig 1. ANFIS Model

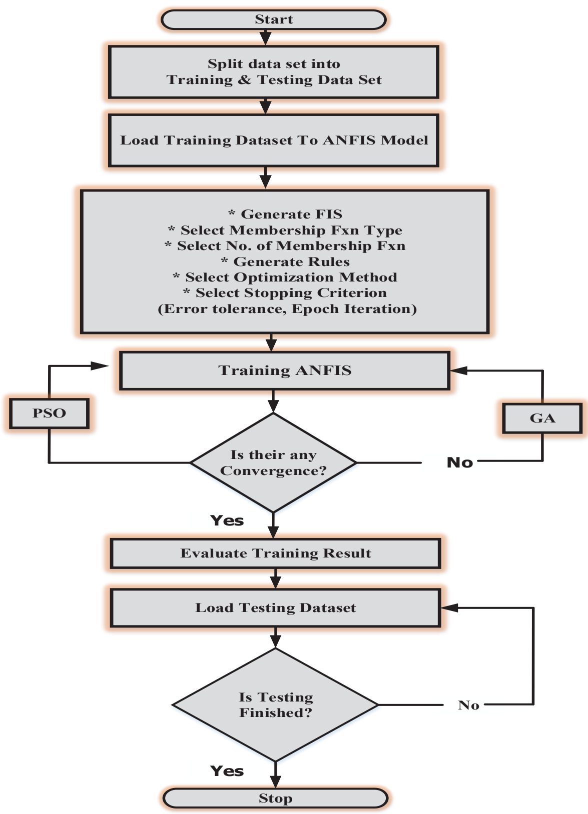

Fig 2. ANFIS-PSO and ANFIS-GA

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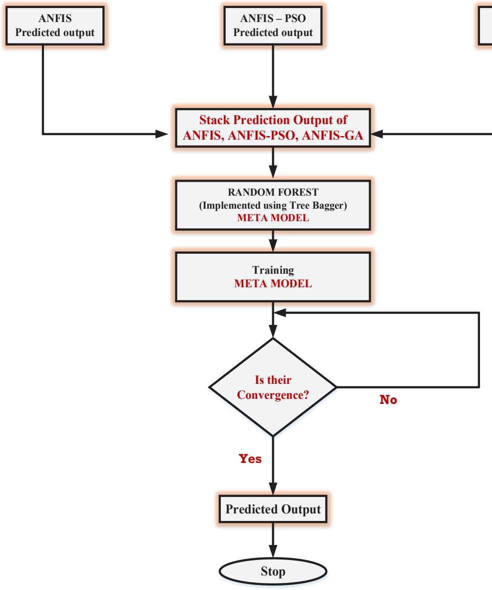

Fig 3. Ensemble ANFIS Model

Mathematical formulations of ANFIS, PSO, GA and ensemble learning follow standard implementations reported in the literature [11].

3.4.5 Risk Management Framework

The risk management framework was divided into three (3) processes as depicted in Fig 4 risk identification, risk assessment and mitigation.

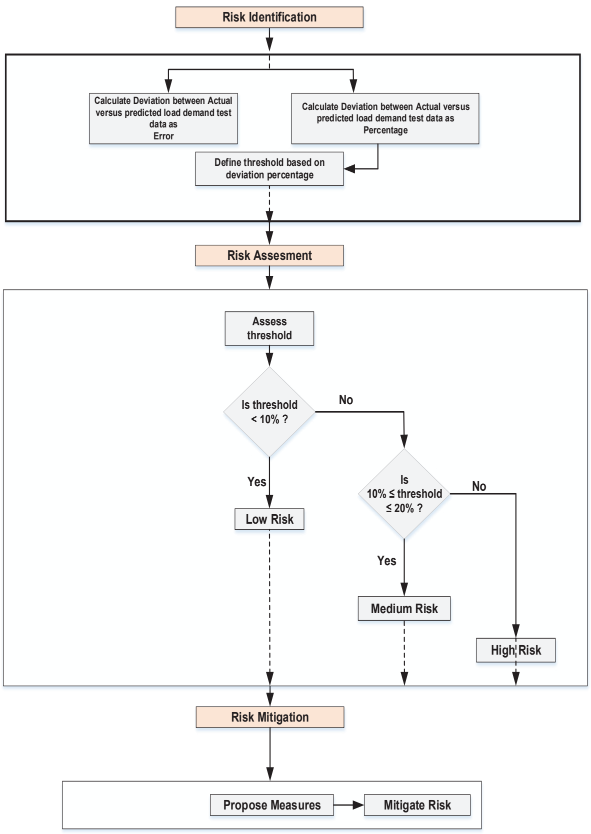

Fig 4. Risk Management for LDEPMs

Risk identification

The risk identification is given by Equation 1.

$$\text{Deviation Percentage} = \left|\frac{\text{Actual} - \text{Predicted}}{\text{Actual}}\right| \text{x}100 \quad (1)$$

To avoid numerical problems, when computing percentage deviations, extremely low or zero actual loads were treated with a small regularization constant (ε) inserted in the denominator as required. This kept the percentage away from being undefined and avoided artificially high operational risk levels for off-peak rural microgrids.

Risk assesment

The percentage deviation was compared with predefined thresholds to classify risk levels based on established predictive error-based risk categorization practices and previous studies [12]. Although risk can only be fully determined after actual load realization, the framework supports operational planning through continuous model validation, periodic retraining, ensemble learning, and reduction of high-risk predictions, thereby improving model reliability and robustness.

Risk levels were defined as: low risk (<10%), medium risk (10-20%), and high risk (>20%). Low-risk predictions indicate minimal operational concern, medium risk predictions require monitoring and corrective measures, while high-risk predictions demand immediate attention due to their potential impact on system performance.

These thresholds were incorporated as operational performance targets for rural microgrids. Forecast deviations above 20% were considered unacceptable because they may result in undersupply, overloading, and inefficient resource scheduling. Consequently, the framework aimed to maximize low-risk predictions and minimize high-risk predictions.

The risk-sensitive approach also supports opportunity-cost optimization by reducing operational inefficiencies associated with inaccurate load forecasts.

The selected thresholds are particularly suitable for rural microgrids due to their low inertia, limited reserve margins, and high sensitivity to supply-demand imbalance, where large prediction errors can significantly affect system reliability and resource utilization.

Risk mitigation

Appropriate mitigation measures were recommended based on the identified risk level to reduce the likelihood and impact of forecasting errors. The proposed framework does not explicitly estimate predictive uncertainty bounds or confidence intervals during prediction. Therefore, it functions as a retrospective operational risk assesment tool based on prediction deviations. Future studies should incorporate probabilistic forecasting, confidence interval estimation, and ensemble variance analysis to enable real-time uncertainty quantification and proactive risk-informed decision-making.

The framework focuses on uncertainties associated with load demand estimation and prediction. While it captures demand-side risks that may contribute to power imbalance, generation variability, storage limitations, and network-level disturbances are beyond its current scope and should be considered in future integrated microgrid risk management frameworks.

3.5 Model Evaluation Metrics

The assessment of the model was done using mean absolute percentage error (MAPE), root mean square error (RMSE) and mean squared error as given in Equation 2 to 4.

For very low-load or zero-load periods, to avoid distortion of Mean Absolute Percentage Error (MAPE) during such periods, the calculation of MAPE was limited to actual loads above a threshold value or not equal to zero. When the actual load was close to zero, a small regularization term (ε) was placed in the denominator to prevent undefined or over-inflated percentage errors. The effect on the overall evaluation was minor because the three-year continuous dataset on hourly residential load was not typically homogeneous with zero load conditions. In addition, the RMSE and MSE metrics were kept as complementary to ensure strong and scale-independent prediction assessment.

$$\mathrm{MAPE} = \frac{1}{N}\sum_{m=1}^{N} \mathrm{abs}\left(\frac{\mathrm{Load}_{forecast}(m) - \mathrm{Load}_{actual}(m)}{\mathrm{Load}_{actual}(m) + \varepsilon}\right) \times 100 \tag{2}$$

where abs; stands for absolute value

N *;* is the total number of hours in the data set. In the case of this work $N = 26{,}280$ (3years) as this was the available data set as at the time of collecting these datasets.

m; stands for the m^{th} hour in the data set

$\mathrm{Load}_{forecast}(m)$; is the predicted load for the m^{th} hour;

$\mathrm{Load}_{actual}(m)$; is the actual load for the m^{th} hour (this is the load obtained from the microgrid).

ε ; Small regularisation constant introduced to avoid division by zero during near-zero load conditions.

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{M=1}^{N} (A_m - F_m)^2} \tag{3}$$

Where A_M ; is the actual load for the m^{th} hour

F_m ; is the predicted load for m^{th} hour;

$$\mathrm{MSE} = \frac{1}{N}\sum_{M=1}^{N} (A_m - F_m)^2 m^{th} \tag{4}$$

4 Results and Discussion

4.1 Variable Identification, Assesment, Reduction and Ranking

Fourteen candidate variables identified from literature were evaluated using Exploratory Factor Analysis (EFA), which retained eight variables with factor loadings above 0.7: humidity (0.900), hour of the day (0.868), holidays (0.845), temperature (0.843), previous hour load (0.810), customer time of electricity use (0.784), educational level (0.747), and weekends (0.727). The prominence of these variables agrees with previous load forecasting studies that identified historical demand and weather-related factors as key predictors [10,11].

The retained variables were subsequently ranked using Fuzzy-AHP based on expert judgements, were all consistency ratios were below 0.10 confirming the reliability of expert's evaluations. The final rankings were ; previous hour load (0.3149), temperature (0.2298), humidity (0.1790), hour of the day (0.0904), holidays (0.0669), customer time of electricity use (0.0572), educational level (0.0331), and weekends (0.0287), where the top five variables were selected and data sets comprising 26,280 hourly records was collected over three years (2021-2023), which were the available datasets as at the time of conducting this research. Prior to modelling, missing values were interpolated, variables were normalized using min-max scaling, outliers were assessed using a z-score threshold of 3, and dataset was partitioned into 70% training, 15% validation, and 15% testing subsets. The processed data were then used to develop and evaluate the prediction models within the proposed risk management framework.

Table 1. Representative sample dataset

Time(t)	1	2	3	4	-	-
L(t-1) kW	15.30	14.62	14.51	18.39	-	-
Temp (^{0}C)	22.5	21.71	21.04	20.43	-	-
Humidity (%)	12.63	12.39	12.02	11.60	-	-
Hour	1	2	3	4	-	-
Holiday	1	1	1	1	-	-
L(t) kW	16.09	15.30	14.63	14.51	-	-

4.2 Comparative Analysis of the Models

The Ensemble ANFIS model achieved the best performance (MAPE = 14.695) as shown in Table 2, outperforming ANFIS, ANFIS-PSO, and ANFIS-GA, while also recording the lowest RMSE and MSE values. Consistent with previous studies [10, 11], the results confirm the effectiveness of ensemble learning for nonlinear load forecasting. The model demonstrated strong generalization through k-fold cross-validation and reduced high-risk prediction errors, thereby supporting reliable, cost-effective, and sustainable rural

Microgrid operation.

Table 2. Comparison Table for the Four (4) Models

T.DS	ANFIS		
	Mape (%)	**Rmse**	**Mse**
O.TD	20.97	3.99	15.93
WD	20.68	3.90	1.24
WKND	21.70	4.20	17.66
ANFIS-PSO			
O.TD	19.93	3.55	12.58
WD	19.71	347	12.03
WKND	20.50	3.73	13.93
ANFIS-GA			
O.TD	19.81	3.30	10.90
WD	19.68	3.24	10.51
WKND	20.14	3.45	11.87
Ensemble-ANFIS			
O.TD	14.69	2.41	5.81
WD	14.64	2.40	5.78
WKND	14.83	2.43	5.90

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

4.3 Risk Management Framework Results

4.3.1 Risk Classification Methodology

Deviations of prediction in each of the four models were determined using Equation 6 and grouped into three levels of risks, based on deviation percentage : low risk (less than ten percent), medium risk (between 10 and 20 percent), and high risk (more than twenty percent). Each model was calculated using frequency distributions and percentages, with regard to the 3,942-hour test data set.

To validate the suitability of these thresholds, a sensitivity analysis was performed by slightly varying the deviation limits (±2-5) and observing the resulting changes in risk classification across the test data.

The analysis indicated that the absolute distribution of the low-, medium-, and high-risk predictions differed marginally ; however, the relative performance ranking of the models was consistent with the Ensemble model having the highest proportion of the low-risk predictions and the lowest proportion of the high-risk predictions. This validates the strength and useful feasibility of the thresholds chosen as guides to rural microgrid operations.

4.3.2 Comparative Risk Analysis of the Developed Models

The Ensemble model was superior in all the evaluation scenarios (overall, weekdays, weekends), and the highest percentages of low-risk (58.02%, 44.19%, 45.89) and the lowest percentages of high-risk (20.24%, 29.81, 31.71) were compared with other models. This finding aligns with established risk-management principles which emphasize that reducing high-deviation prediction events improves operational reliability, minimizes uncertainty, and enhances decision-making effectiveness in complex energy systems [12].

The results were also consistent under the sensitivity analysis, which further supports that the operational decisions taken based on the model output is not affected by the slight difference in the choice of threshold.

4.3.3 Risk Mitigation Strategies

Based on the risk classification framework, mitigation measures were defined for each risk level. For low-risk predictions (<10%), routine monitoring, periodic validation, and model updates were considered sufficient to maintain forecasting reliability. For medium-risk predictions (10-20%), enhanced data validation, more frequent model retraining, and additional performance verification were recommended to prevent performance degradation. For high-risk predictions (>20%), emergency response measures, including backup power coordination, demand-side management, model recalibration, and root-cause investigation, were required. Contingency actions such as reserve generation and emergency load shedding were also incorporated to address worst-case scenarios.

The risk profile of the Ensemble model showed that approximately 58% of predictions required only low-risk mitigation, while about 20% required high-risk intervention, indicating lower operational stress and emergency response requirements compared with the individual models

4.3.4 Validation of Results

The selected input variables and their rankings were consistent with previous studies [10,11], confirming their relevance for load demand prediction. The superior performance of the Ensemble model compared with ANFIS, ANFIS-PSO and ANFIS-GA also agrees with earlier findings that hybrid and ensemble approaches improve forecasting accuracy in complex nonlinear systems [11,12]. The proposed risk management framework complements conventional accuracy metrics by incorporating prediction-risk thresholds based on established industry practices [10,11], with the ensemble model achieving 58.02% low-risk predictions.

Furthermore, the use of k-fold cross-validation, independent testing datasets, and multiple performance indicators (MAPE, RMSE and MSE) verified the statiscal robustness and generalization capability of the proposed framework. The Ensemble model consistently exhibited the lowest prediction errors across training, testing, and cross-validation stages, demonstrating its reliability for rural microgrid load prediction.

5 Conclusion and Recommendations

This study developed risk-sensitive load demand estimation and prediction models for the rural microgrid of Gwam community, Nigeria, addressing limitations of conventional forecasting approaches that inadequately consider rural consumption characteristics and operational risks. Among the developed models, the Ensemble ANFIS model achieved the best performance with a MAPE of 14.69% and RMSE of 2.41, confirming the effectiveness of ensemble learning for complex nonlinear load forecasting problems [11, 12]. Previous hour load, temperature, and humidity were identified as the most influential predictors, while risk assessment classified prediction deviations as low (<10%), medium (10-20%), and high (>20%), with the ensemble model achieving 58.02% low-risk predictions.

The study demonstrates that integrating risk assessment into forecasting model development and evaluation can improve prediction reliability, resource allocation, reserve scheduling, and operational decision-making under uncertainty. Unlike conventional approaches that focus solely on statistical accuracy, the proposed framework incorporates operational risk thresholds to support more reliable and sustainable rural microgrid planning.

Future work should validate the framework across different rural communities, investigate additional data sources and optimization techniques, and explore deep learning and household-level forecasting approaches.

Although the framework effectively addresses demand-side uncertainty, future studies should integrate generation, storage, and network-related risks to enhance overall microgrid resilience. Furthermore, implementation in other locations should include site-specific input-variable assessment and validation to account for differences in climatic, operational, and socio-economic conditions.

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