Enhancing Short-Term Load Forecasting Precision with Hybridized RNN and LSTM Model

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ABSTRACT

This study evaluates the efficiency of various machine learning models for short-term load forecasting (STLF) at the 132KV/33KV Bida Transmission Station. Using load outage data from the Kutigi and Lemu feeder stations and meteorological data from NIMET, the research compares models such as RNN, GRU, LSTM, and a hybrid RNN-LSTM model. The hybrid RNN-LSTM model demonstrated superior performance, achieving low error metrics (MAE: 0.101, RMSE: 0.138) and a near-perfect coefficient of determination (R^2: 0.999). Pearson's correlation analysis was pivotal in feature selection, enhancing the model's predictive accuracy. These findings highlight the hybrid RNN-LSTM model's ability to effectively capture complex temporal patterns, making it a valuable tool for precise STLF. The outcomes have significant implications for improving grid reliability and operational efficiency in the energy sector.

Keywords: Machine learning; K-Nearest Neighbors; Gaussian Regression; Recurrent Neural Network-Long Short-Term Memory; Gradient Boosting Machine.

INTRODUCTION

Electricity is an essential component of modern life, powering homes, industries, communication, and transportation systems. With increasing urbanization, industrial growth, climate change, and population expansion, global electricity demand continues to rise (Saeed et al., 2022). However, many countries face challenges in meeting this growing demand due to the

inability to accurately forecast electricity usage, resulting in inefficiencies in power transmission scheduling (Fallah et al., 2019). Addressing this issue is critical, as accurate electricity demand forecasts enable governments and power companies to plan effectively and promote energy efficiency among consumers (Hong et al., 2016).

Load forecasting, a vital aspect of power system planning, ensures the smooth delivery of electricity. It plays a pivotal role in economic optimization, secure grid operation, and informed decision-making by power system operators (Bashir et al., 2022). Depending on the forecast horizon, load forecasting is categorized into short-term, medium-term, and long-term predictions. Short-term load forecasting (STLF) is particularly crucial for real-time scheduling, energy conservation, resource allocation, generation planning, and infrastructure development (Solyali et al., 2020). However, achieving accurate short-term predictions remains challenging due to complex influences such as weather conditions, seasonal variations, economic trends, and unforeseen events (Jiang et al., 2020).

Traditional statistical methods, such as ARIMA, SARIMAX, and VAR, have been widely used for time series analysis in power load forecasting (Jinxing et al., 2023). While these methods are effective in capturing historical trends, they often struggle with the non-linear, dynamic patterns inherent in electricity demand data. To address these limitations, machine learning (ML) techniques, including Support Vector Regression (SVR), Random Forest (RF), and Gradient Boosting Machines (GBM), have been explored. These methods demonstrate improved capabilities in handling non-linear and complex patterns but often lack the precision required for highly accurate predictions (Atef et al., 2022).

The growing need for more accurate forecasts has led to the adoption of deep learning methods, which excel in capturing complex relationships within data. Deep learning models, such as Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, offer significant advantages over traditional methods by adapting to diverse and non-linear trends in power load data (Szcześniak et al., 2021). Advanced hybrid models, combining RNNs and LSTMs, further enhance predictive performance by extracting intricate temporal patterns and dependencies, making them particularly well-suited for load forecasting tasks (Hua et al., 2023).

In Nigeria, accurate load forecasting is essential for efficient grid management. Generation firms (GENCOs) rely on forecasts to schedule resources, while the Transmission Company of Nigeria (TCN) optimizes grid load flow and mitigates overload risks. Distribution Companies (DISCOs) also depend on load forecasting for effective operations (Edomah et al., 2016).

The 132kV/33kV Bida Transmission Station in Niger State is a critical hub in Nigeria's electricity distribution network, serving residential, commercial, and industrial sectors. Ensuring reliable operation of this station is vital for uninterrupted power supply. However, short-term load forecasting at this station faces challenges due to the interplay of weather conditions, economic activities, holidays, and special events (Zhang et al., 2021).

This study seeks to address these challenges by employing a hybrid deep learning approach, specifically an RNN-LSTM model, to improve the accuracy of short-term load forecasting at the Bida Transmission Station. The proposed model aims to enhance grid management, reduce operational costs, and ensure a consistent

and high-quality electricity supply to consumers.

Load forecasting has long been a focal point in energy management and grid operations, with extensive research yielding diverse forecasting techniques. These studies underscore the strengths and limitations of existing methods while highlighting ongoing challenges in achieving higher accuracy and interpretability. Despite these advancements, critical gaps remain, particularly in the integration of hybrid machine learning models tailored for specific contexts, such as transmission stations like the 132kV/33kV Bida Transmission Station. Additionally, the interpretability of machine learning and hybrid models is a pressing concern, as grid operators require transparency in forecasts to inform their decision-making processes. This study aims to address these gaps by implementing and evaluating a hybrid RNN-LSTM model, providing actionable insights to advance the field.

Forecasting methodologies generally fall into five categories: physical models, statistical methods, machine learning (ML), deep learning (DL), and hybrid methods. Physical models rely on the fundamental principles of physics and are commonly applied in specific scenarios. For instance, Dolara et al. (2015) evaluated three physical models to forecast photovoltaic (PV) power generation at Politecnico di Milano. While these models demonstrated reliability under stable weather conditions, their performance declined in fluctuating environments, revealing a need for more adaptable approaches.

Statistical models, including regression-based techniques, have been widely employed for short-term and long-term load forecasting. Müller and Trutnevyte (2020) used statistical methods to project PV system installations in Switzerland, achieving accurate forecasts. However, these models often struggle to account for complex, non-linear relationships in power demand data.Machine learning methods, including Support Vector Machines (SVM), Random Forest (RF), and Artificial Neural Networks (ANN), have been explored to overcome the limitations of statistical models. Li et al. (2021) and Rao et al. (2022) evaluated several ML algorithms for short-term load forecasting in clustered microgrids. Their findings highlighted the ANN model's superior performance in capturing complex data patterns, outperforming traditional methods.

Deep learning techniques, particularly Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, have further advanced load forecasting. These methods excel in handling non-linear and dynamic patterns by leveraging their multilayered architectures and memory blocks (Du et al., 2023). For instance, Han et al. (2019) demonstrated the effectiveness of an Extreme Learning Machine (ELM)-based hybrid model using meteorological data, outperforming ARIMA and KNN methods. Similarly, Zhang et al. (2018) utilized a CNN-LSTM approach to improve PV power interval forecasting, achieving an average MAE of 2.13%.

Hybrid methods, which combine ML and metaheuristic techniques, have gained traction for their enhanced accuracy. Das et al. (2018) emphasized the utility of Genetic Algorithms (GA) in optimizing hybrid models, while Jaidee and Pora (2019) demonstrated the effectiveness of a GA-LSTM model for short-term load forecasting. Zheng et al. (2021) proposed a PSO-LSTM model for 30-minute power output forecasting, achieving notable accuracy improvements.

In the context of STLF, models must address the challenges posed by global population growth, industrialization, economic activities, and environmental concerns (Somu et al., 2020). Traditional

mathematical models, such as multiple linear regression and exponential smoothing, often fall short in this regard (Zheng et al., 2024). By contrast, hybrid models like the RNN-LSTM employed in this study provide a robust framework for capturing complex temporal dependencies and improving forecast precision. The proposed study builds on this foundation, aiming to enhance the accuracy and interpretability of STLF for the 132kV/33kV Bida Transmission Station through a novel hybrid RNN-LSTM model.

MATERIALS AND METHODS

This study employed a systematic approach, comprising a series of distinct steps: data acquisition, feature extraction, model training, and load output prediction. The methodology is outlined below and illustrated in Figure 1, which provides a visual representation of the research framework.

The process commenced with the collection of experimental datasets from diverse sources. Subsequently, various machine learning (ML) and deep learning (DL) models were developed and evaluated to assess their performance in load forecasting. The models underwent rigorous training and evaluation to determine their efficacy. The following subsections provide a detailed explanation of each step, offering a comprehensive overview of the methodological framework employed in this study.

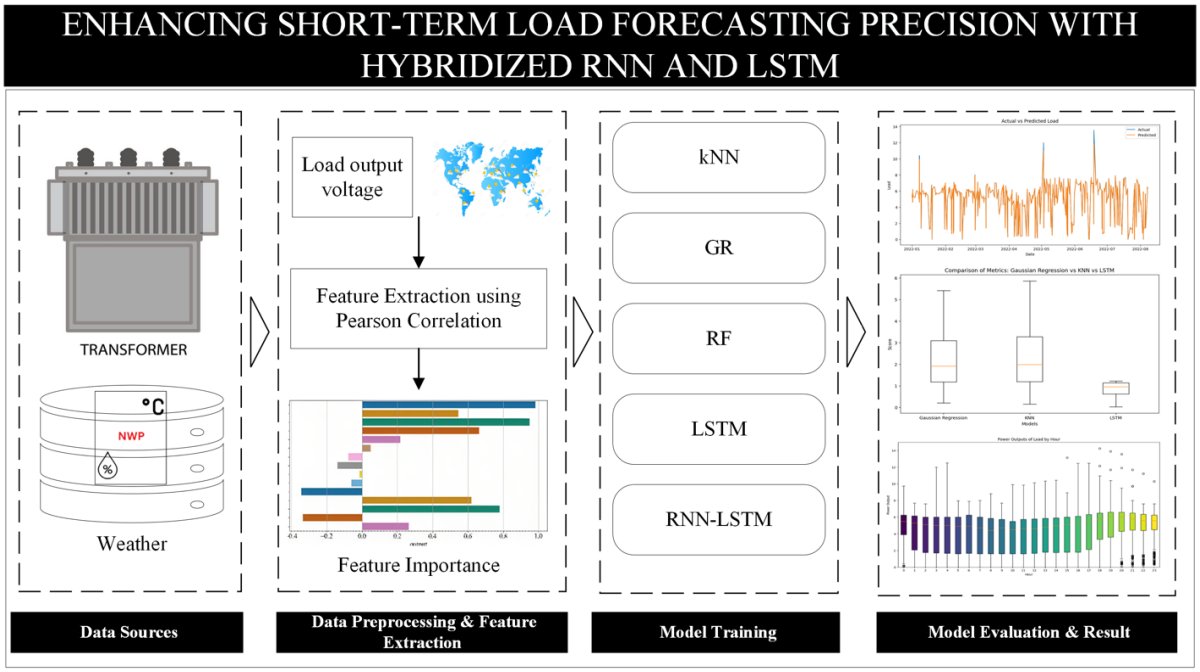


Figure 1. Methodological framework of the research design and dataflow

Data Collection and Study Area

The experimental datasets for this study were sourced from two main data providers. Hourly load output data for two transformers were acquired from the Bida transmission station in Niger State, Nigeria. Figure 2 depicts the study area which has a latitude of 9.083333° N and a longitude of 6.016667° E showing the Spatial context and boundaries of the region under investigation. These load

outputs originated from the Kutigi feeder and the Lemu feeder, offering valuable insights into the electricity consumption patterns within the region. Figure 3 shows the diagram of the single-line transmission of the Bida station. To compensate for model training additional meteorological data were obtained from the Nigerian Meteorological Agency (NIMET) encompassing variables such as temperature, humidity, wind speed and precipitation.

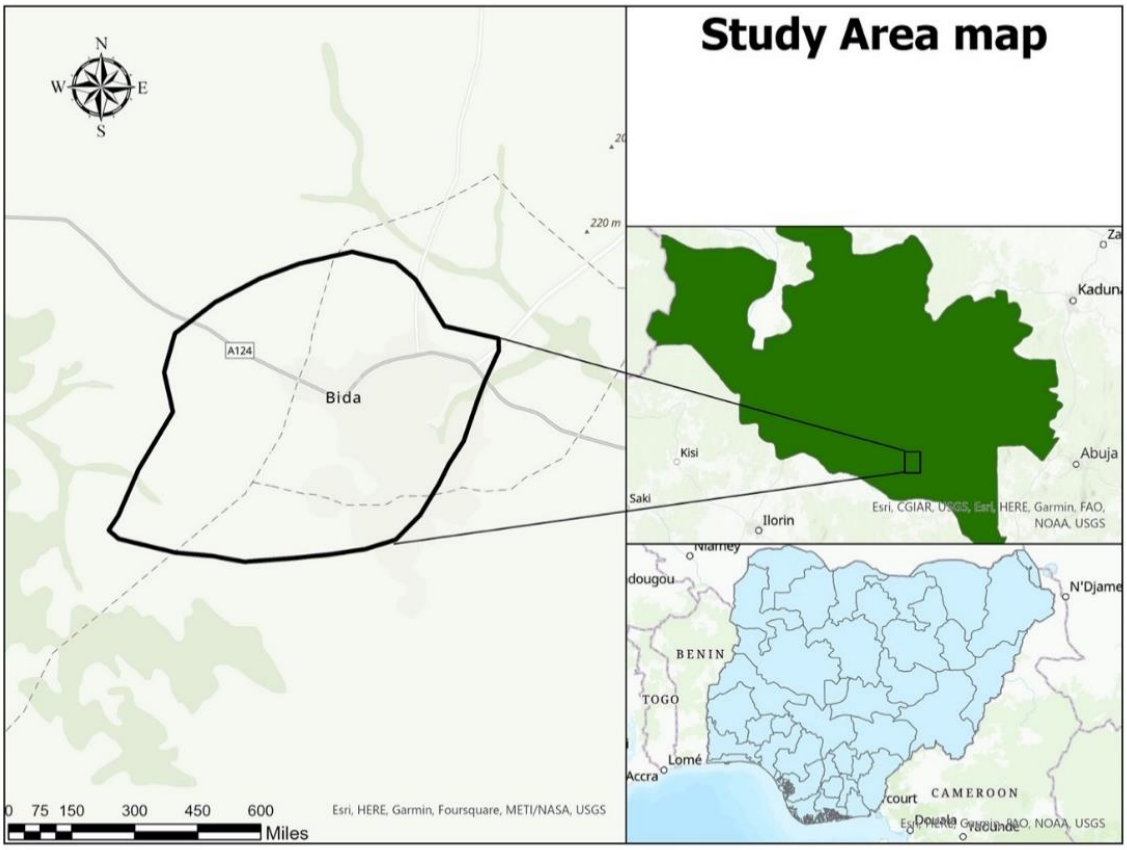


Figure 2. Geographical location of the study area: Bida, Niger State, Nigeria.

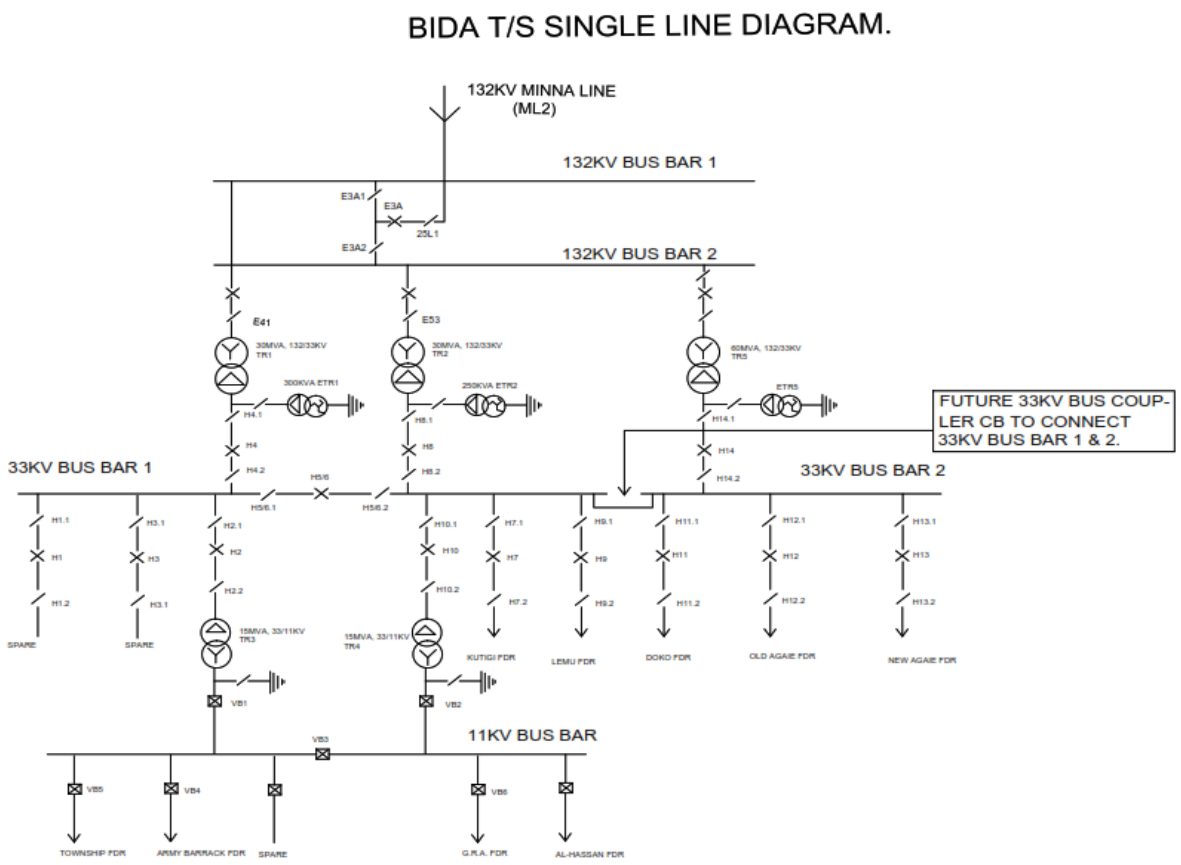


Figure 3. Schematic diagram of the single-line transmission station in Bida, illustrating the key components and infrastructure of the power transmission system

Data Preprocessing

The collected data underwent preprocessing to ensure its suitability for model training and evaluation. This stage involved handling missing values, scaling the data, and removing any outliers that could potentially impact the model's performance. The Lemu feeders were observed to have recorded about 447 instances where the transformer was faulty which could be as a result of overcurrent, earth fault, feeder maintenance or even an electrical emergency. Hence the load output during this instance is considered as missing values which were all removed before model training to avoid model bias. Subsequently, the Kutigi feeder has a missing load output record of 1009.

The features extracted from this data are detailed in Table 1, outlining the load output as the targeted feature and the remaining variables as inputs for each model. The datasets were consolidated based on the date of load readings, resulting in a dataset comprising 8760 observations spanning from January 2022 to December 2022. To facilitate model training and testing, the dataset was divided into 70% for training and 30 % for testing, ensuring a robust assessment of the model's predictive performance. Data normalization was performed, which transforms data values to

improve the quality and consistency of the data. The scaling range utilized was from 0 to 1. The normalization is important because it not only allows data to be compared accurately and interpreted correctly but is also necessary for better model training and improving the overall quality of predictions. The adopted formulas for normalization are described below.

$$\mu = \frac{1}{M}\sum_{m=1}^{M} C \quad (1)$$

$$\sigma = std(c) = \sqrt{\frac{\sum(x_i-\mu)}{M}} \quad (2)$$

$$C_{standardized} = {(C-\mu)}/{\sigma} \quad (3)$$

$$Z_{predicted-actual} = C = \sigma \cdot Z_{predicted-Standardized} + \mu \quad (4)$$

Where μ represents the mean, s represents the standard deviation, and C represents the data used. In the data set, x_i represents each value and M represents the size of the data set. In equation (3), the standardization of data is represented before training, and $Z_{predicted-actual}$ in equation (4) is the actual data to be used to evaluate the performance of the trained network during testing.

Table 1. Summary of dataset characteristics: description of features

Type	Source	Feature	Description
Dependent (y)	Feeder Transformer	Date	Registration date from each feeder
		Load Output	Output of transformer feeders (MW)
Independent (x)	Weather	Temperature	Outside temperature
		Relative humidity	Amount of water vapor present in air
		Wind speed	Air movement from one point to another
		Precipitation	Water that falls from the cloud
	Derived Features	Month	Month
		Hour	Hour

Feature Extraction

Upon merging the datasets, the subsequent step involved identifying relevant features to predict the load output from the transformers. To expand the feature sets, derived features such as month and hour were extracted from the load output registration date. Figure 4 visually represents the relationship between load output and the factors of month and hour for the transformers.

From Figure 4(a), a noticeable surge in load output from the kutigi feeder transformer was observed during specific periods, notably in January-February, May-June, and October-December. This pattern was

presumed to align with the beginning of the New Year, Eid celebrations, and the year-end, suggesting an increase in electricity usage during these periods. Additionally, a significant decrease in load output was observed between the hours of 5 to 13, indicating reduced usage during these times, potentially due to people being occupied with work or other activities.

In contrast, Figure 4(b) depicted the load output variation by hour and month for the Lemu feeder, which exhibited a pattern aligned with the monthly distribution across the region supplied with electricity. During hourly observations, it was noted that the voltage supplied by this feeder tended to be higher from 16 to 23 hours. This observation suggests that the region served by this feeder tends to use electricity more during off-working hours, possibly indicating increased consumption during leisure or non-work-related activities in the evenings.

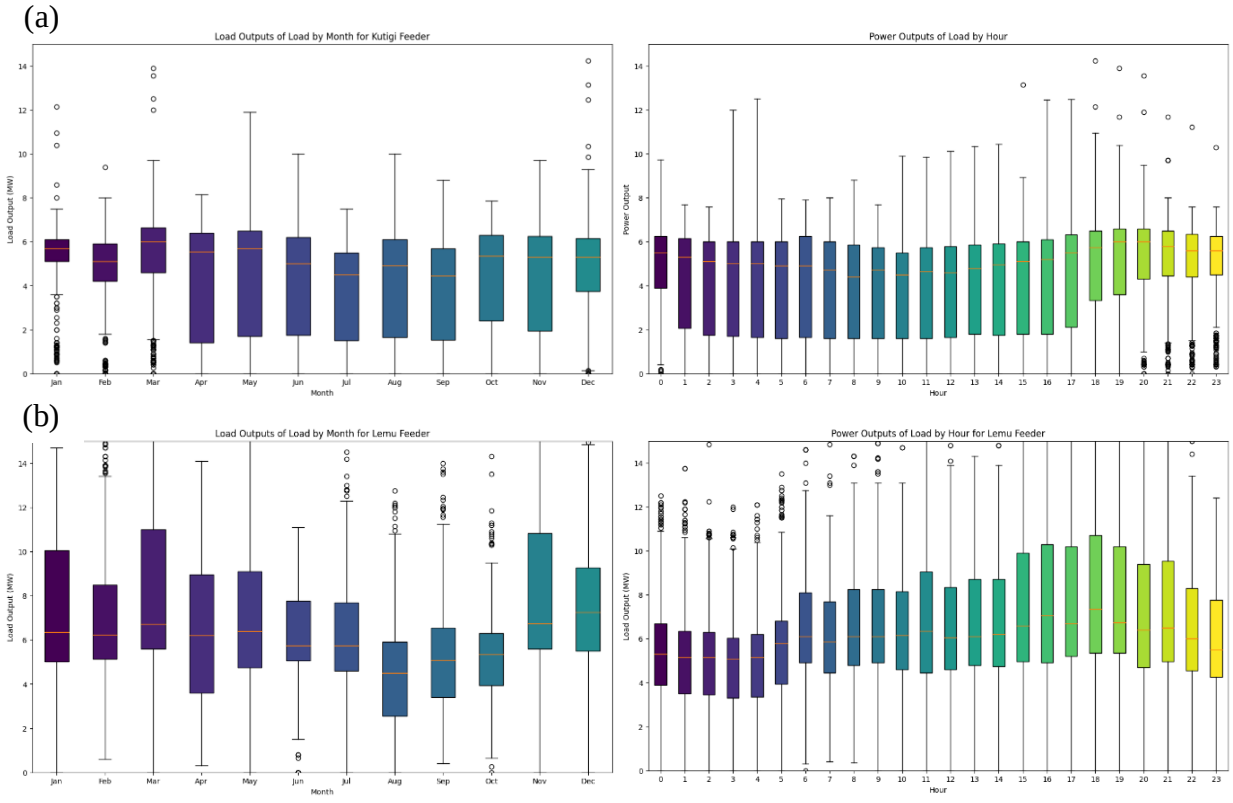


Figure 4. Monthly and hourly load output patterns: comparative analysis of (a) Kutigi feeder and (b) Lemu feeder, showing the variation in load demand across different months and hours of the day

Hybridized Model Development

The ensemble model development process is outlined in Algorithm 1 and Table 2. The approach involves training RNN and LSTM models on pre-processed data, leveraging their strengths in learning time dependencies and handling long-term dependencies. The combination of these models aims to enhance prediction accuracy through a multi-model ensemble technique.The ensemble architecture consists of three stacked recurrent layers, each with 50

hidden units and tanh gate activation. The output is passed through a Time Distributed layer with hidden units corresponding to the sequence length and activated by the Sigmoid function.

Each model is trained independently until convergence using MSE as the loss function and Adam as the optimizer.The ensemble layer is trained using a standard neural network with one dense layer, Sigmoid activation, and the Adam optimizer. The final prediction is generated through this ensemble layer. The proposed ensemble model is compared with established models, including GR, RF, and kNN, due to their widespread recognition and effectiveness. These models are implemented using the Scikit-learn library. The kNN model forecasts by averaging observations in the neighborhood, while GR serves as a probabilistic regression model, handling complex relationships and providing uncertainty estimates.

Algorithm 1: Proposed Ensemble RNN-LSTM Architecture for Load Forecasting

Input: Dataset: $(\boldsymbol{D} = \{(\boldsymbol{x_i}, \boldsymbol{y_i})\}_{\{\boldsymbol{i=1}\}}^{\boldsymbol{m})}$
Output: Ensemble Prediction $(\boldsymbol{P_f})$
Initialization:
    For $(\boldsymbol{t})$ from 1 to $(\boldsymbol{T})$:
        learn $(\boldsymbol{R_1})$ based on $(\boldsymbol{D})$. //$(\boldsymbol{R_1})$- RNN
    For $(\boldsymbol{t})$ from 1 to $(\boldsymbol{T})$:
        learn$(\boldsymbol{L_1})$ based on $(\boldsymbol{D})$. //$(\boldsymbol{L_1})$ LSTM
    end
Prediction:
    For $(\boldsymbol{t})$ from 1 to $(\boldsymbol{m})$:
        $(\boldsymbol{P_1} = \boldsymbol{D}(\boldsymbol{R_1})$ // $(\boldsymbol{P_1})$ prediction; data $(\boldsymbol{D})$
        $(\boldsymbol{P_2} = \boldsymbol{D}(\boldsymbol{L_1})$
    end
Weighted Ensemble:
    For $(\boldsymbol{t})$ from 1 to $(\boldsymbol{T})$:
    Learn $(\boldsymbol{wP_1}, \boldsymbol{wP_2})$ based on $(\boldsymbol{D})$ //$(\boldsymbol{w})$ weights
    end
Final Prediction:
    For $(\boldsymbol{t})$ from 1 to $(\boldsymbol{m})$:
    $\boldsymbol{P_f} = \boldsymbol{P_{1(wP_1)}} + \boldsymbol{P_{2(wP_2)}} + \boldsymbol{P_{3(wP_3)}}$
    end

Table 2: Parameter settings for all trained model

Model	Parameter	Value
kNN	K	15
GR	Alpha	0.1
	Kernel	1.0
RNN-LSTM	Neurons	50
	layers	3
	Batch size	32
	Learning rate	0.01
	Epoch	100
	Loss Function	MSE
	Optimizer	Adam

The detailed examination of model prediction results, as presented in Table 3, provides valuable insights into the performance of various models in short-term load forecasting at the 132kV/33kV Bida Transmission Station. The kNN model demonstrates effectiveness in capturing local patterns, with a competitive MAE of 0.877 and RMSE of 1.328 for the Kutigi Feeder. However, its limitations in handling complex nonlinear relationships are evident.In contrast, the GR model exhibits resilience in handling uncertainties, with a competitive performance of MAE 0.476 and RMSE 0.701 for Kutigi. However, it struggles to accurately capture short-term fluctuations. The LSTM model displays commendable accuracy, particularly in Kutigi, with an MAE of 0.564 and RMSE of 0.653.

The hybridized RNN-LSTM architecture excels in capturing sequential dependencies and temporal patterns, emerging as the top performer across all metrics. It achieves an exceptional MAE of 0.101 and RMSE of 0.138 for Kutigi, and a remarkable MAE of 0.022 and RMSE of 0.031 for Lemu. The R2 values affirm the outstanding predictive capabilities of the RNN-LSTM model, reaching 0.999 for Kutigi and 0.980 for Lemu.Figures 5-7 provide additional context to the numerical results. Figure 5 illustrates the load output predictions, where the RNN-LSTM model's predictions closely align with the actual load output. Figure 6 provides scatter plots of the developed models against the actual power output, with the RNN-LSTM model displaying patterns closely aligned with the actual load output. Figure 7 presents the Boxplot of the model performance differences.

Table 3. Result from model prediction

Models	Kutigi Feeder			Lemu Feeder		
	MAE	**RMSE**	**R^2**	**MAE**	**RMSE**	**R^2**
kNN	0.877	1.328	0.859	0.075	0.107	0.738
GR	0.476	0.701	0.956	0.466	0.522	-
LSTM	0.564	0.653	0.966	0.054	0.080	0.822
RNN	0.357	0.434	0.984	0.048	0.070	0.875
RNN-LSTM	**0.101**	**0.138**	**0.999**	**0.022**	**0.031**	**0.980**

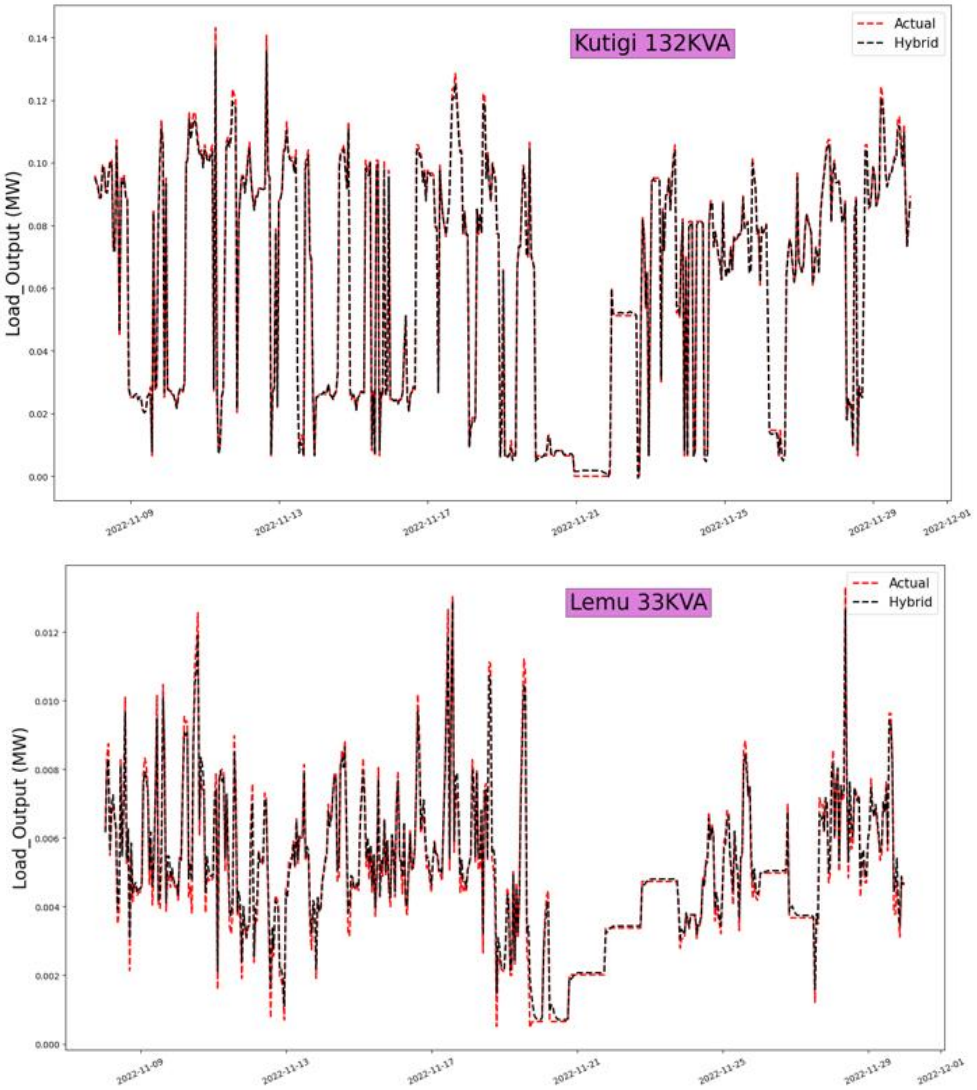


Figure 5. Predicted load output for kutigi and lemu feeders: actual vs. forecasted values

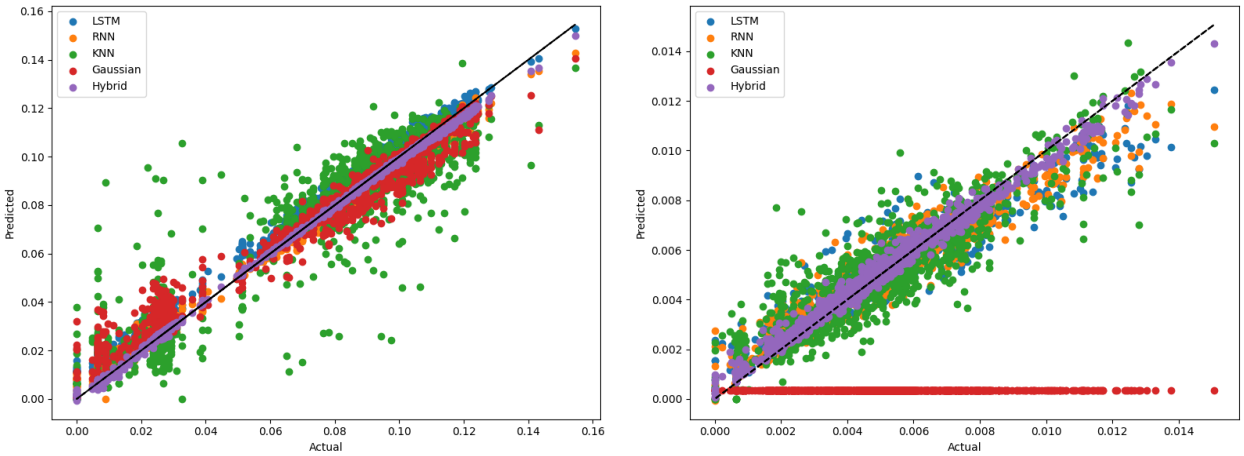


Figure 6: Plot of predicted vs. actual load values for all models, evaluating prediction accuracy and performance

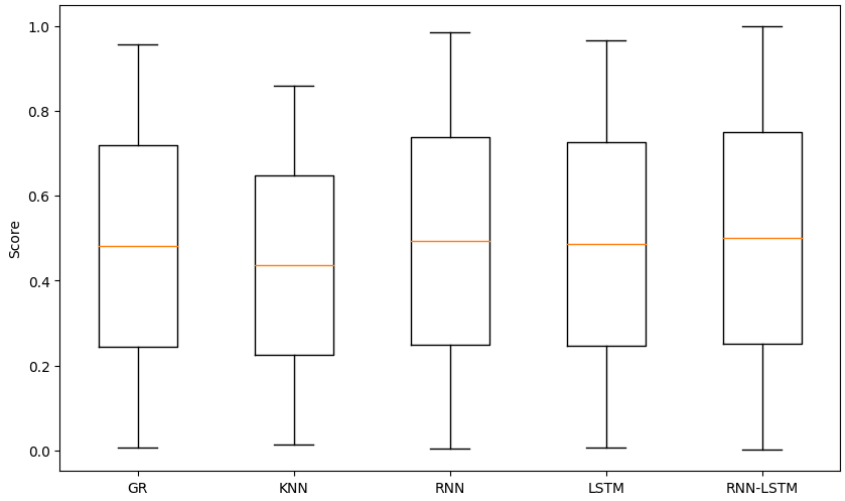


Figure 7: Boxplot of prediction errors: comparative analysis of model performance and variability

RESULT AND DISCUSSION

This section presents a comparative analysis of the study's results with those of previous studies, using RMSE and MAE as evaluation metrics. Table 4 summarizes the accuracy of the proposed hybrid method in comparison to other deep learning approaches for energy output forecasting.The results indicate that the proposed RNN-LSTM model outperforms existing DL models, achieving lower RMSE and MAE values for both Kutigi and Lemufeeder transformers, despite diverse climate conditions. Notably, the RNN-LSTM model exhibits significant

improvements over the ANN-LSTM model (Wentz et al., 2022), with reductions in RMSE (10.00% to 1.38%) and MAE (4.885% to 1.01%). Similar reductions are observed when compared to the CNN-LSTM model (Wan et al., 2023), with RMSE decreasing from 0.343% to 0.031% and MAE from 0.022% to 0.0220%.

Furthermore, the RNN-LSTM model demonstrates superior performance compared to the DE-LSTM model (Akhter et al., 2022), with RMSE decreasing from 64.67% to 0.138% and MAE from 9.47% to 0.101%. The model also outperforms the Hybrid GA-SVM model (Wang et al., 2017) and the GA-CNN model (Jaidee and Pora, 2019), consistently achieving lower RMSE and MAE values for both feeder transformers.These findings highlight the effectiveness of the proposed hybrid RNN-LSTM model, showcasing its remarkable performance and positioning it as a highly promising solution for short-term load forecasting at the 132kV/33kV Bida Transmission Station. The results demonstrate the model's competitiveness with existing DL approaches in the literature, emphasizing its potential for accurate and reliable load forecasting.

Table 4: Model comparison with others from literature

Models	Reference	RMSE (%)	MAE (%)
ANN – LSTM	Wentz *et. al* (2022)	10.00	4.885
CNN - LSTM	Wan *et.,al* (2023)	0.343	0.022
DE-LSTM	Wang *et. al* (2017)	64.67	9.47
Hybrid GA-SVM	Jaidee *et. al* (2019)	52.8	7.42
RNN-LSTM (Kutigi)	Present study	0.138	0.101
RNN-LSTM (Lemu)	Present study	0.031	0.0220

CONCLUSION

Developing accurate power prediction models is essential for building a more sustainable energy future. This paper presents an approach that leverages the benefit of the combined RNN-LSTM model. This method significantly enhances the Precision of load output forecasts. The results demonstrate the RNN-LSTM model's exceptional performance, marked by significantly lower RMSE and MAE values. The findings from this paper enhance the understanding of short-term load forecasting at the 132kV/33kV Bida Transmission Station. Various machine learning models, including KNN, GR, LSTM and RNN, were compared. The RNN-LSTM model excelled, offering precise short-term load predictions. The study's findings reveal that the integration of the RNN-LSTM model in short-term load forecasting at the 132kV/33kV Bida Transmission Station yielded exceptional results, outperforming conventional machine learning models. This model demonstrated superior predictive capabilities in capturing complex temporal patterns, offering a more accurate representation of the electricity demand dynamics within the station's operational context. This project significantly

contributes to the field of load forecasting by showcasing the efficiency of neural network models, particularly the RNN-LSTM architecture, in the domain of short-term load prediction. The study's findings expand the current understanding of load forecasting methodologies by demonstrating the superiority of RNN-LSTM models in capturing temporal Dependencies, an aspect crucial for short –term load productions.

CONFLICT OF INTEREST

No conflict of interest

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