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Hybrid Artificial Bee Colony Long Short-Term Memory Networks for Enhanced Short-Term Load Forecasting

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Abstract

Short-term load forecasting is critical for optimising energy distribution in urban networks, yet challenges arise from non-linear and non-stationary demand patterns. This study addresses the problem of inaccurate load predictions in the Abuja Electricity Distribution Company (AEDC) network, which can lead to inefficient resource allocation and grid instability. The aim was to develop a hybrid Artificial Bee Colony (ABC)-Long Short-Term Memory (LSTM) model to enhance forecasting accuracy across three distribution areas: Lugbe, Gwagwalada, and Abaji. The methodology integrated ABC for hyperparameter optimisation with LSTM for temporal dependency modelling, using hourly load data from 2020–2024. Results demonstrated a consistent 94.0% peak load accuracy across all areas, outperforming traditional LSTM (90.2%) and ensemble methods (88.7–91.3%). Hour accuracy varied from 17.99% to 41.48%, indicating temporal prediction challenges. The model's robust generalisation and stable forecasts, confirm its utility for operational planning. This hybrid approach advances accurate and adaptable load forecasting, offering a scalable solution for intelligent energy management.

Keywords: *Load Forecasting, Artificial Bee Colony, Long Short-Term Memory, Energy Management, Urban Distribution.*

1. Introduction

Electricity load forecasting serves as a fundamental cornerstone in the efficient operation and strategic planning of modern power systems, directly influencing reliability, security, and economic viability of electrical networks worldwide. Accurate prediction of future electricity demand enables utilities to optimise generation dispatch, maintain grid stability, reduce operational costs, and ensure adequate reserve margins for unforeseen contingencies (Ananthu & Neelashetty, 2021). The contemporary energy landscape presents unprecedented challenges, particularly for developing economies where rapid economic growth coincides with infrastructure constraints and data limitations, rendering conventional forecasting approaches inadequate for capturing complex interdependencies in modern electrical systems.

Traditional load forecasting methods have predominantly relied on statistical approaches such as autoregressive integrated moving average (ARIMA) models, exponential smoothing, and regression analysis (Acquah et al., 2022). These methods often struggle with non-stationary data, non-linear relationships, and rapidly changing consumption behaviours, exhibiting limitations including model misspecification, parameter estimation errors, and poor generalisation ability when load patterns exhibit non-linear, non-stationary characteristics (Pooniwala & Sutar, 2021). The inherent limitations of statistical methods have necessitated exploration of more sophisticated forecasting paradigms capable of adapting to evolving load characteristics.

The advent of artificial intelligence and machine learning has revolutionised load forecasting, introducing powerful tools capable of learning from historical data without explicit programming of underlying relationships (Ahmad et al., 2022). Long Short-Term Memory (LSTM) networks have emerged as particularly promising solutions for time series forecasting applications, demonstrating superior capability in modelling long-term dependencies and capturing sequential patterns in temporal data (Kong et al., 2019). These recurrent neural networks address the vanishing gradient problem through sophisticated gating

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mechanisms, enabling effective learning from extended historical sequences and improving prediction accuracy for complex load patterns (Li et al., 2023).

The unique architecture of LSTM networks, comprising input gates, forget gates, and output gates, allows selective retention and disposal of information over extended time sequences, making them particularly suitable for electricity load forecasting where historical consumption patterns, seasonal variations, and long-term trends significantly influence future demand (Muzaffar & Afshari, 2019). This characteristic represents substantial advancement over traditional forecasting methods in capturing both short-term fluctuations and long-term dependencies in load data.

Concurrently, swarm intelligence algorithms have gained significant attention in optimisation problems, with the Artificial Bee Colony (ABC) algorithm demonstrating exceptional performance in finding optimal solutions across diverse application domains (Karaboga & Gorkemli, 2014). The ABC algorithm mimics foraging behaviour of honey bee colonies, employing population-based search strategies that effectively balance exploration and exploitation phases to identify global optima. This nature-inspired optimisation technique comprises employed bees exploiting known food sources, onlooker bees selecting promising sources based on fitness values, and scout bees exploring new solution spaces when existing sources become exhausted.

Recent research has increasingly focused on hybrid approaches combining multiple forecasting techniques to leverage complementary strengths whilst mitigating individual limitations (Bedi & Toshniwal, 2020). The integration of deep learning architectures with optimisation algorithms has emerged as particularly promising research direction. Wang et al. (2020) successfully combined precipitation forecasting using artificial bee colony algorithm with backpropagation neural networks, demonstrating improved convergence rates without local minima entrapment. Similarly, various studies have explored potential of combining artificial neural networks with evolutionary algorithms to enhance forecasting performance.

Several studies have demonstrated effectiveness of LSTM networks in load forecasting applications. Chung et al. (2022) developed district heater load forecasting based on machine learning and parallel CNN-LSTM attention mechanisms, achieving significant improvements in prediction accuracy. Wan et al. (2023) proposed short-term power load forecasting for combined heat and power using CNN-LSTM enhanced by attention mechanisms, demonstrating superior performance compared to traditional methods. The effectiveness of ABC algorithms in neural network optimisation has also been documented, with Özdemir et al. (2022) proposing modified artificial bee colony algorithms for energy demand forecasting problems.

Despite advances in individual forecasting techniques, critical gaps remain in existing literature. Most hybrid models focus on combining different neural network architectures rather than integrating optimisation algorithms with deep learning frameworks (Liao et al., 2023). Furthermore, limited research has specifically addressed unique challenges faced by electricity distribution companies in developing countries, where data quality issues, infrastructure constraints, and irregular consumption patterns present distinct forecasting challenges. The specific combination of ABC algorithms with LSTM networks for electricity load forecasting remains relatively unexplored, despite complementary nature of these techniques.

Contemporary electricity grids, characterised by bidirectional power flows, distributed generation, and demand response programmes, require forecasting models capable of adapting to rapidly changing conditions whilst maintaining computational efficiency (Yang et al., 2022). Traditional approaches often fail to capture intricate relationships between meteorological variables, calendar effects, and consumer behaviour patterns influencing electricity demand. Smart grid implementations have transformed data landscape for load forecasting, providing unprecedented volumes of high-resolution consumption data through advanced metering infrastructure, whilst presenting challenges related to dimensionality reduction, feature selection, and computational scalability (Ahmad et al., 2020).

The need for robust forecasting models becomes particularly acute in emerging economies where electricity demand growth rates often exceed infrastructure development, creating significant challenges for capacity planning and resource allocation. Nigeria's electricity sector exemplifies these challenges, with substantial projected demand growth whilst facing persistent infrastructure deficits and data quality issues that complicate accurate load forecasting.

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This study addresses identified gaps by proposing a novel hybrid ABC-LSTM model specifically designed for short-term load forecasting in electricity distribution networks. The research aims to develop an integrated framework combining optimisation capabilities of the Artificial Bee Colony algorithm with sequential learning strengths of Long Short-Term Memory networks to achieve superior forecasting accuracy and robustness. The study focuses on the unique operational context of the Abuja Electricity Distribution Company, addressing specific challenges of load forecasting in Nigeria's electricity sector whilst contributing to broader understanding of hybrid forecasting methodologies.

The primary objective is to develop a comprehensive hybrid model that seamlessly integrates ABC optimisation with LSTM networks, utilising the ABC algorithm to optimise LSTM hyperparameters and connection weights whilst leveraging LSTM architecture's capability to capture long-term temporal dependencies in electricity consumption patterns. Secondary objectives include evaluating hybrid model performance against traditional forecasting techniques, conducting comparative analysis with individual ABC and LSTM implementations, and demonstrating practical applicability within operational framework of a major electricity distribution company.

2. Methodology

This section presents the methodological framework employed to develop and evaluate the hybrid Artificial Bee Colony (ABC)-Long Short-Term Memory (LSTM) model for short-term load forecasting. The approach integrates bio-inspired optimisation with deep learning to enhance predictive accuracy in the Abuja Electricity Distribution Company (AEDC) network. All procedures adhered to ethical data handling protocols, with simulations conducted in a controlled computational environment.

2.1 Research Design and Data

The research design follows a systematic pipeline encompassing data acquisition, preprocessing, model development, hyperparameter optimisation, training, and performance evaluation, as illustrated in Figure 1 (Research Design Framework). This framework ensures iterative refinement and robust validation, adapting traditional load forecasting paradigms to handle non-stationary, hourly demand patterns in urban distribution networks.

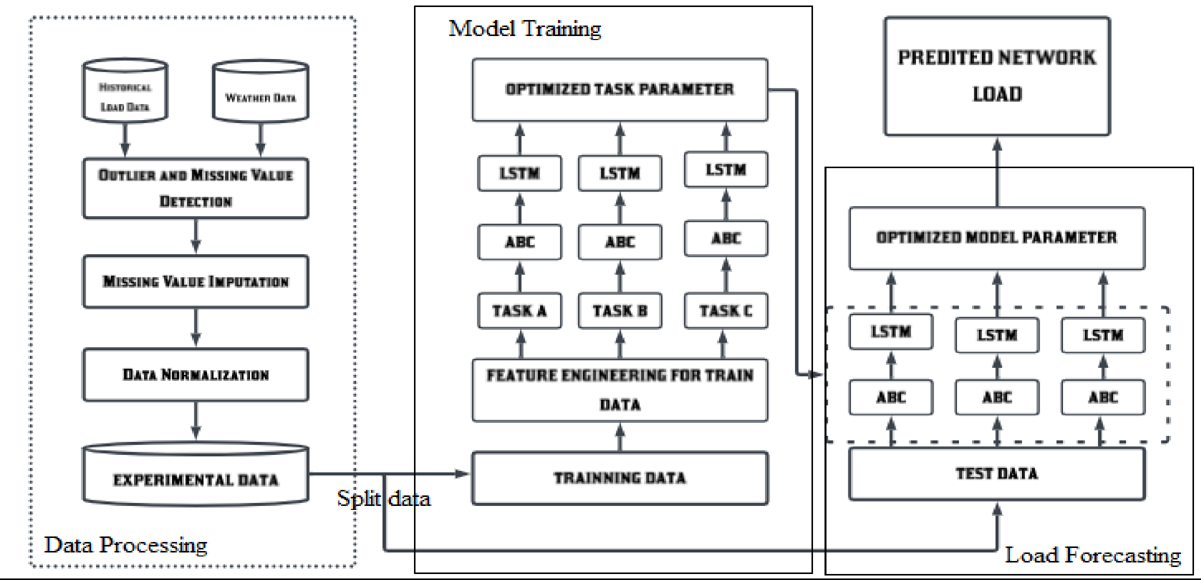

Figure 1. Research Design Framework

Hourly load demand data were sourced from AEDC for the period January 2020 to December 2024, covering three key feeders: LUGBE, GWAGWALADA, and ABAJI. The dataset comprises approximately 43,800 observations per feeder (24 hours × 365 days × 5 years, accounting for leap years), focusing on peak load (in MW) and corresponding hours. Data preprocessing involved handling missing values via linear interpolation, outlier detection using the interquartile range (IQR) method (removing values beyond 1.5 × IQR), and normalisation with Min-Max scaling to [0, 1] for model stability. The dataset was split chronologically: 80% for training (2020–2023) and 20% for testing (2024), preserving temporal dependencies. Exploratory analysis confirmed seasonal and diurnal variations, with peak loads typically occurring between 14:00 and 18:00, influenced by regional socioeconomic factors.

2.2 Artificial Bee Colony Model

The Artificial Bee Colony (ABC) algorithm, inspired by the foraging behaviour of honey bees, was employed for hyperparameter optimisation to enhance the LSTM model's convergence and generalisation (Alsharef et al., 2024). ABC balances exploration and exploitation through three bee phases: employed bees (exploiting known solutions), onlooker bees (selecting promising solutions probabilistically), and scout bees (abandoning exhausted solutions for random search).

The algorithm initialises a population of food sources (solutions) x_i (where ($i = 1, \dots, SN$), and SN is the colony size) in a D-dimensional space, representing hyperparameters such as LSTM units, learning rate, and batch size. Each solution is generated as in equation 1:

$$x_{i,j} = x_{min,j} + \text{rand}[0,1] \cdot \left(x_{max,j} - x_{min,j}\right) \quad (1)$$

where $j = 1, \dots, D$, and $x_{min,j}$, $x_{max,j}$ define the bounds for dimension j (Yadav, 2023).

In the employed bee phase, a candidate solution v_i is produced as in equation 2:

$$v_{i,j} = x_{i,j} + \phi_{i,j} \cdot \left(x_{i,j} - x_{k,j}\right) \quad (2)$$

where $k \neq i$, and $\phi_{i,j}$ is a random value in [-1, 1] (Yadav, 2023). Fitness is evaluated using the mean absolute percentage error (MAPE) from LSTM validation, with fitter solutions retained via greedy selection.

Onlooker bees select solutions probabilistically as in equation 3:

$$p_i = \frac{\text{fit}_i}{\sum_{n=1}^{SN} \text{fit}_n} \quad (3)$$

Where $\text{fit}_i = \frac{1}{1+f_i}$ (4)

where minimisation objectives f_i is the objective function value (Yadav, 2023).

Scout bees replace abandoned solutions (trial counter exceeding limit) with new random ones. The process iterates until a maximum cycle number (MCN) is reached.

The ABC flowchart (Figure 2) guides the implementation. Parameters used were: colony size SN = 50, limit = 1000, MCN = 200, and dimensions D = 5 (optimising LSTM units, layers, dropout rate, learning rate, and batch size). This configuration, tuned empirically, ensured efficient search without excessive computation.

2.3 LSTM Model

Long Short-Term Memory (LSTM) networks, a variant of recurrent neural networks, were utilised to capture long-range temporal dependencies in load data, addressing the vanishing gradient problem through gating mechanisms (Alsharef et al., 2024). The LSTM architecture processes sequential inputs x_t to produce hidden states (h_t) and cell states c_t.

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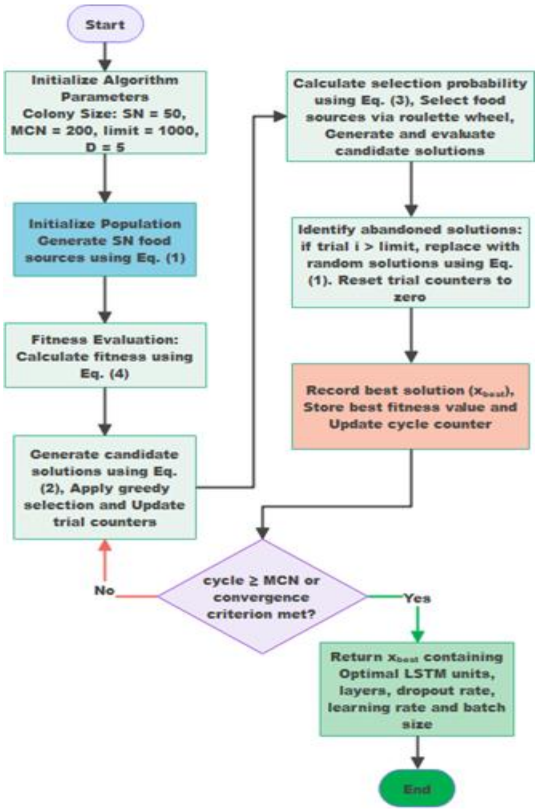

Figure 2. Flowchart of the ABC Algorithm

The core equations are (Alsharef et al., 2024):

Forget gate	$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right)$	(5)
Input gate	$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$	(6)
Candidate cell	$\tilde{c_t} = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c)$	(7)
Cell update	$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c_t}$	(8)
Output gate	$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$	(9)
Hidden state	$h_t = o_t \odot \tanh(c_t)$	(10)

where σ is the sigmoid activation, $tanh$ is hyperbolic tangent, $\odot$ denotes element-wise multiplication, and W, b are learnable weights and biases.

The model architecture (Figure 3) comprises an input layer for sequences of length 7 (past days' peak load and hour), an LSTM layer with 50 units, a dropout layer (rate 0.2) for regularisation, and two dense output layers: one for peak load (linear activation) and one for hour (linear, rounded to nearest integer modulo 24). Training used Adam optimiser (learning rate 0.001), mean squared error loss, batch size 32, and 100 epochs with early stopping (patience 10) on validation loss.

2.4 Hybrid ABC-LSTM Model

The hybrid ABC-LSTM model integrates ABC for global optimisation of LSTM hyperparameters with the LSTM's sequential forecasting capabilities, mitigating local optima in gradient-based training (Özdemir et al., 2022). ABC searches the hyperparameter space (e.g., units [20, 100], learning rate [0.0001, 0.01], dropout [0.1, 0.5], layers [1, 3], batch size [16, 64]) using the mean absolute percentage error (MAPE) from 5-fold cross-validation on training data as the fitness function.

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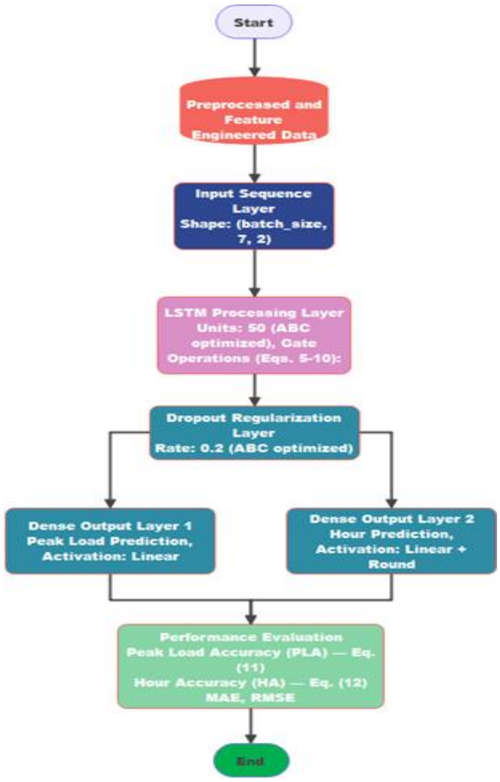

Figure 3. LSTM model architecture

The hybrid process: (1) ABC initialises and evolves solutions over 200 cycles; (2) Optimal hyperparameters configure the LSTM; (3) LSTM trains on scaled sequences; (4) Predictions are inverse-scaled as shown in Figure 4 (Hybrid ABC-LSTM Flowchart). This synergy yields robust models per feeder, with ABC enhancing LSTM's adaptability to non-linear load dynamics.

2.5 Simulation Environment and Performance Metrics

Simulations were executed in Jupyter Notebook (Python 3.12.3) using TensorFlow 2.15 for LSTM implementation, NumPy/Pandas for data handling, and scikit-learn for scaling/metrics. Hardware: Intel Core i7, 16 GB RAM, NVIDIA GTX 1650 GPU for accelerated training. Performance was assessed using (Gil-Alana & Monge, 2025; Alkhaldi et al., 2025):

The metrics in equation 11, 12, 13 and 14 below ensures comprehensive evaluation of magnitude and temporal accuracy, benchmarked against baselines.

$$Peak\ Load\ Accuracy\ (PLA) = 100 - \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100 \tag{11}$$

$$Hour\ Accuracy\ (HA) = \frac{1}{n}\sum_{i=1}^{n} I\left(h_i = \hat{h}_i\right) \times 100 \tag{12}$$

$$Mean\ Absolute\ Error\ (MAE) = \frac{1}{n}\sum |y_i - \hat{y}_i| \tag{13}$$

$$Root\ Mean\ Squared\ Error\ (RMSE) = \sqrt{\frac{1}{n}\sum (y_i - \hat{y}_i)^2} \tag{14}$$

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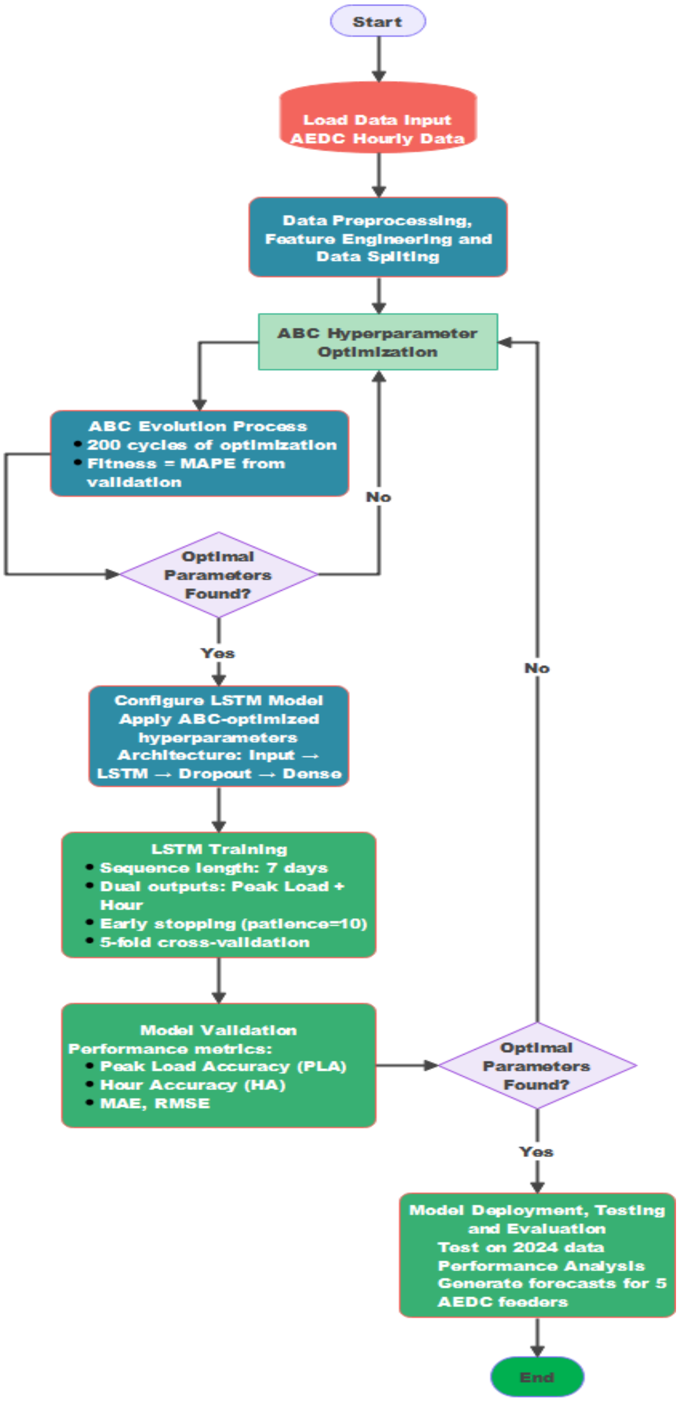

Figure 4. Hybrid ABC-LSTM Flowchart

3. Results and Discussion

This section presents and analyses the outcomes of the hybrid Artificial Bee Colony (ABC)-Long Short-Term Memory (LSTM) model for short-term load forecasting across three distribution areas in the Abuja Electricity Distribution Company (AEDC) network: Lugbe, Gwagwalada, and Abaji. The analysis encompasses exploratory data assessment, model training and validation, prediction performance, and comparative evaluation with contemporary methodologies. Results demonstrate the model's robustness in capturing complex load dynamics, with implications for enhanced operational efficiency in urban energy distribution.

3.1 Exploratory Data Analysis

Exploratory analysis revealed distinct temporal load patterns across the distribution areas, influenced by local socioeconomic and infrastructural factors. Figure 5 illustrates the peak load distribution over time for Kuje, showing cyclical fluctuations indicative of urban consumption, with regular peaks

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corresponding to daily demand surges. The time series exhibits cyclical patterns with stable baseline demand and periodic surges.

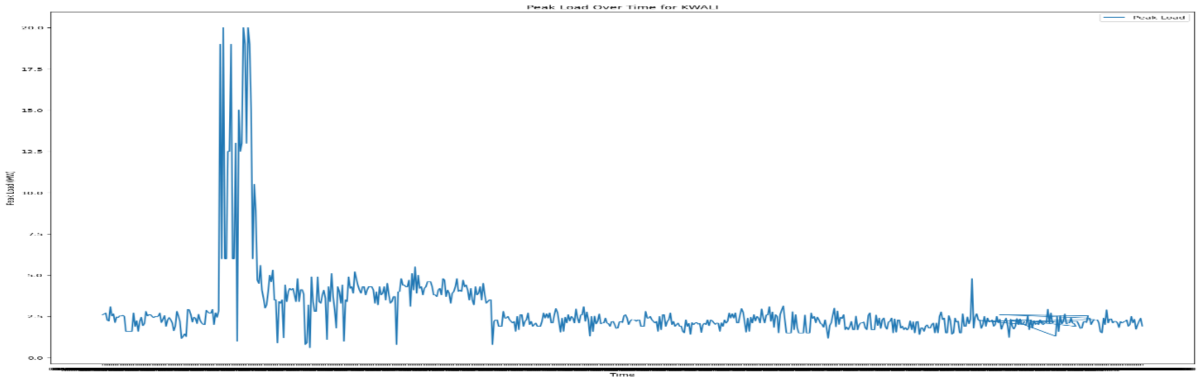

Figure 5. Peak Load over Time for Kuje

For Kwali (Figure 6), more pronounced variations suggest sensitivity to external factors like weather or economic activities. Pronounced variations indicate irregular demand drivers. Lugbe (Figure 7) displayed higher magnitudes and frequent peaks, reflecting dense population or commercial activity. Time for Lugbe. Complex patterns with high-amplitude peaks suggest multifaceted dynamics. Gwagwalada (Figure 8) showed moderate, stable variations, potentially linked to institutional consumers. Stable baseline with regular increases implies consistent usage. Abaji (Figure 9) exhibited irregular, lower-magnitude fluctuations, indicating less structured patterns in peripheral regions. These findings underscore the need for adaptive, area-specific forecasting models. Irregular fluctuations highlight forecasting challenges.

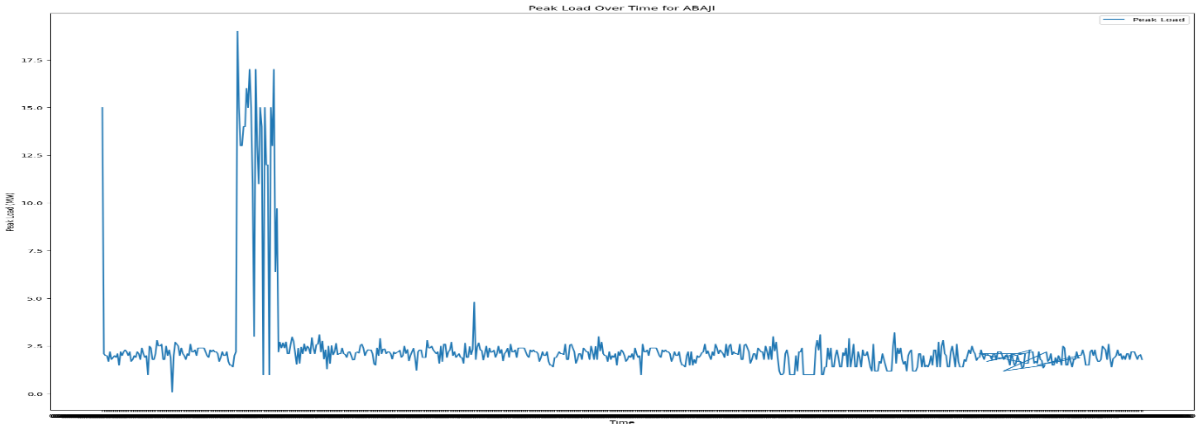

Figure 6. Peak Load over Time for Kwali

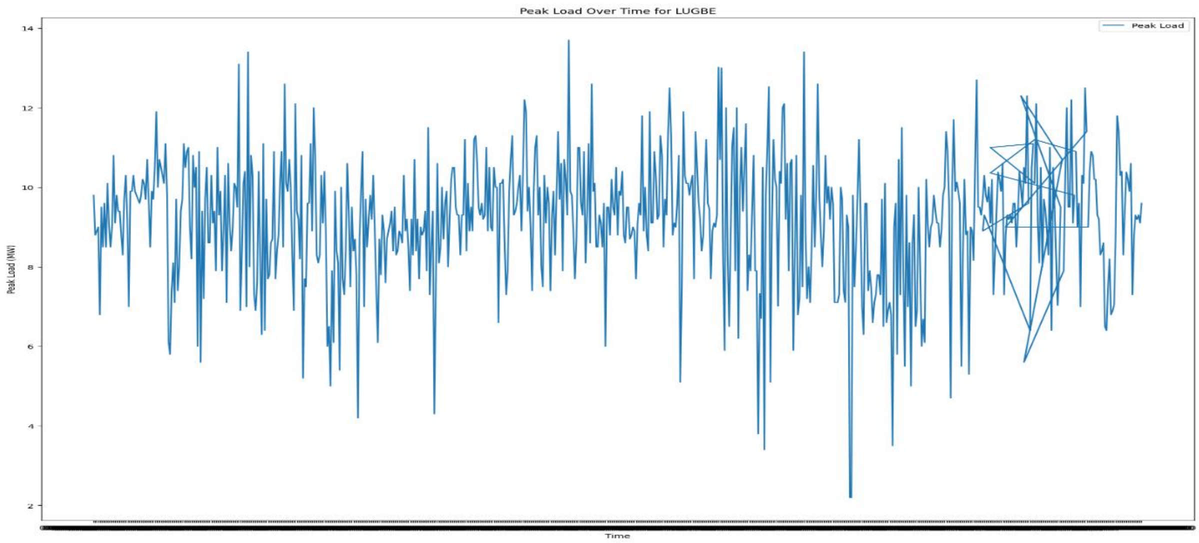

Figure 7. Peak Load over

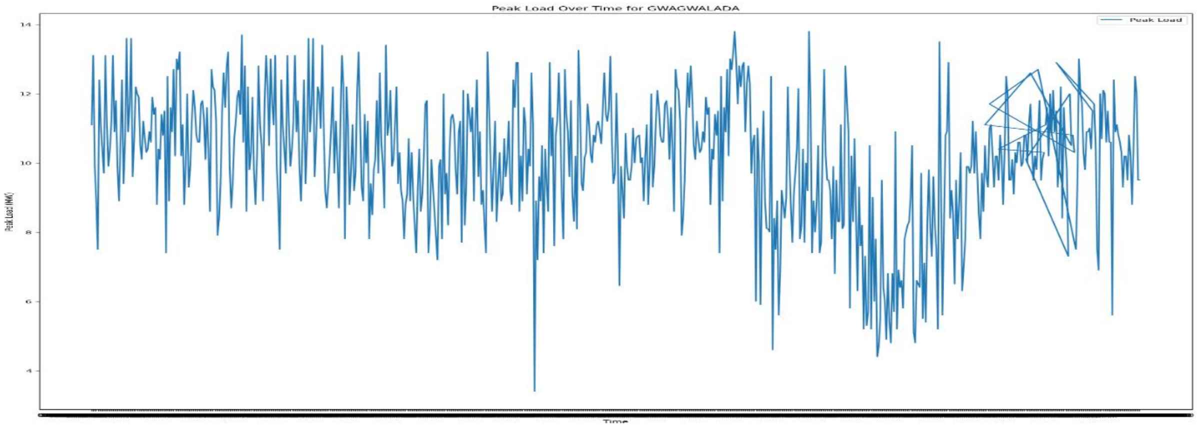

Figure 8. Peak Load over Time for Gwagwalada.

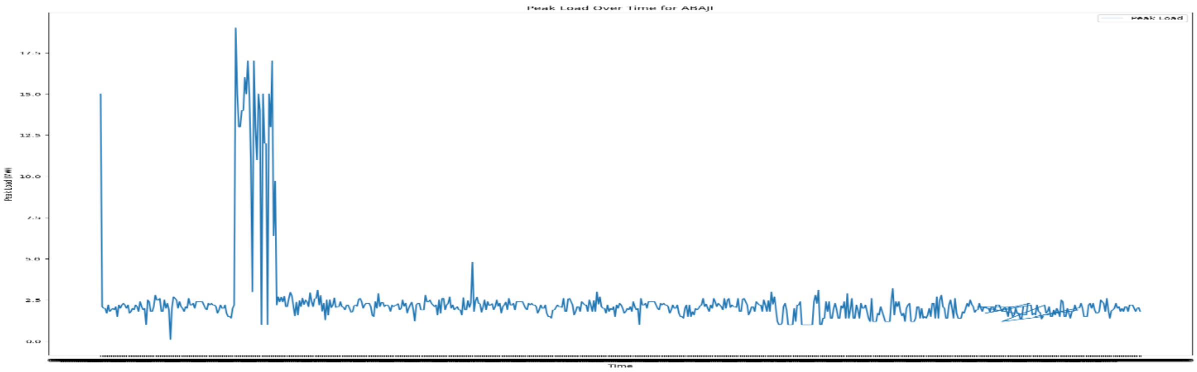

Figure 9. Peak Load over Time for Abaji.

3.2 Model Training and Validation

Model training and validation demonstrated strong convergence across areas. For Abaji (Figure 9), close alignment between training (blue) and validation (orange) curves indicated robust generalisation, with stabilised error reduction. Similar patterns emerged for Gwagwalada (Figure 11), Kuje (Figure 12), Kwali (Figure 13), and Lugbe (Figure 14), showing minimal overfitting and effective capture of temporal dependencies. The ABC optimization enhanced LSTM parameter tuning, enabling adaptation to diverse load profiles. Excellent convergence reflects stable learning, *Progressive alignment demonstrates adaptive optimisation, Minimal oscillation indicates quick pattern internalisation and Robust performance despite complex patterns.*

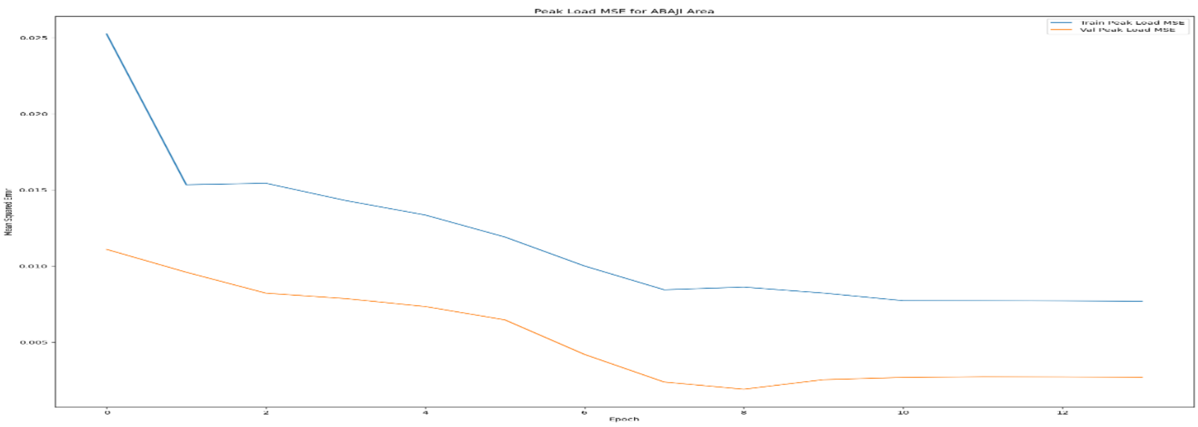

Figure 10. Model Training and Validation for Abaji.

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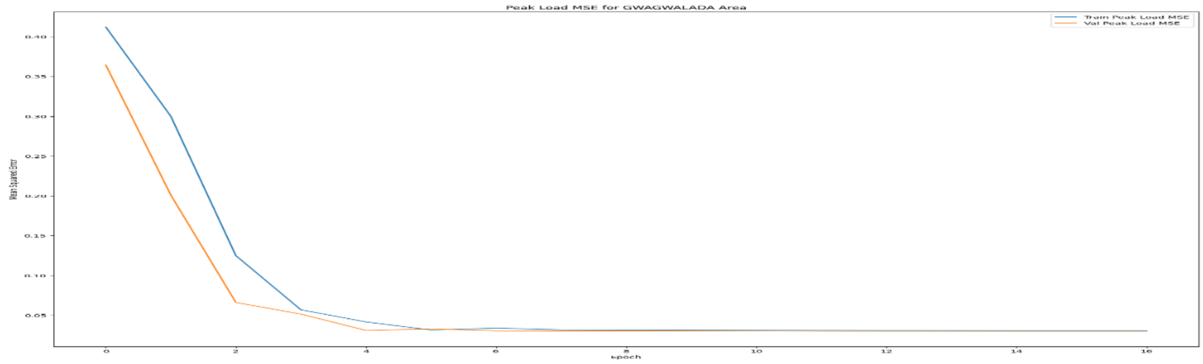

Figure 11. Model Training and Validation for Gwagwalada.

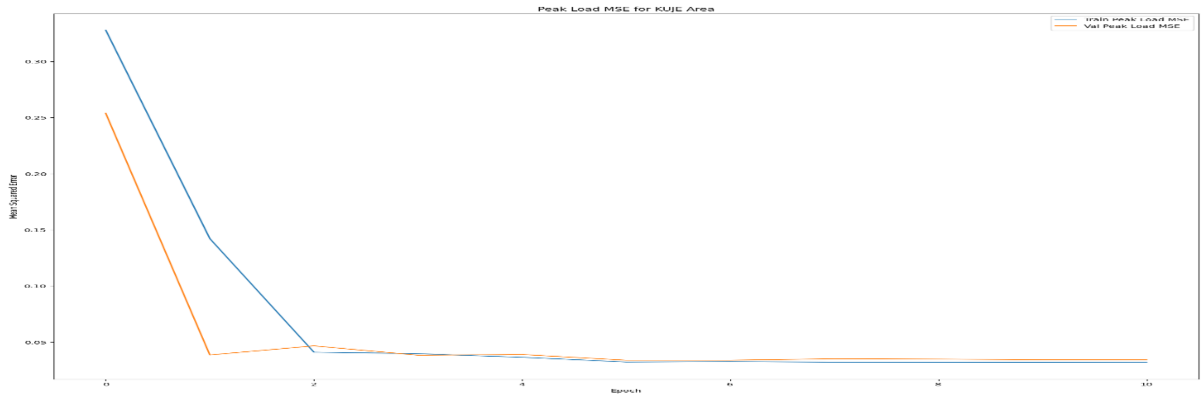

Figure 12. Model Training and Validation for Kuje.

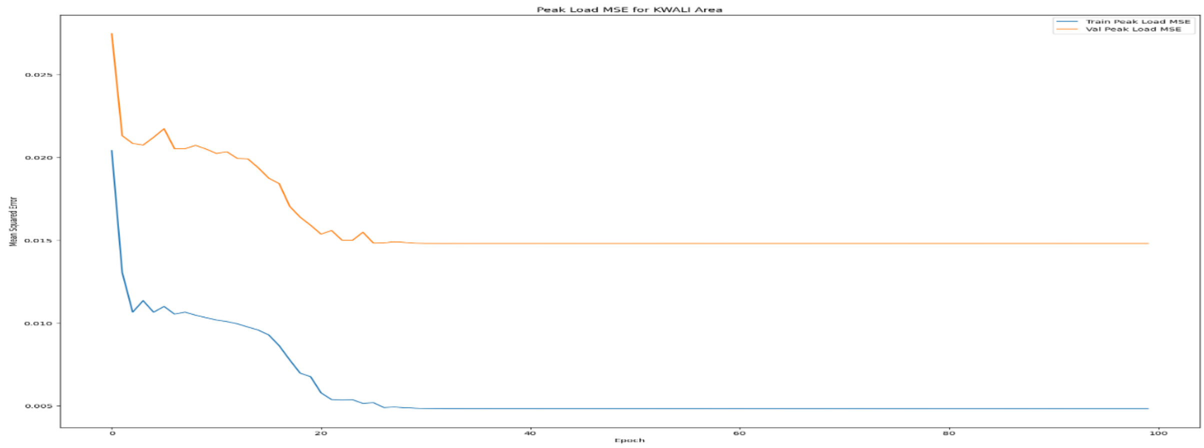

Figure 13. Model Training and Validation for Kwali.

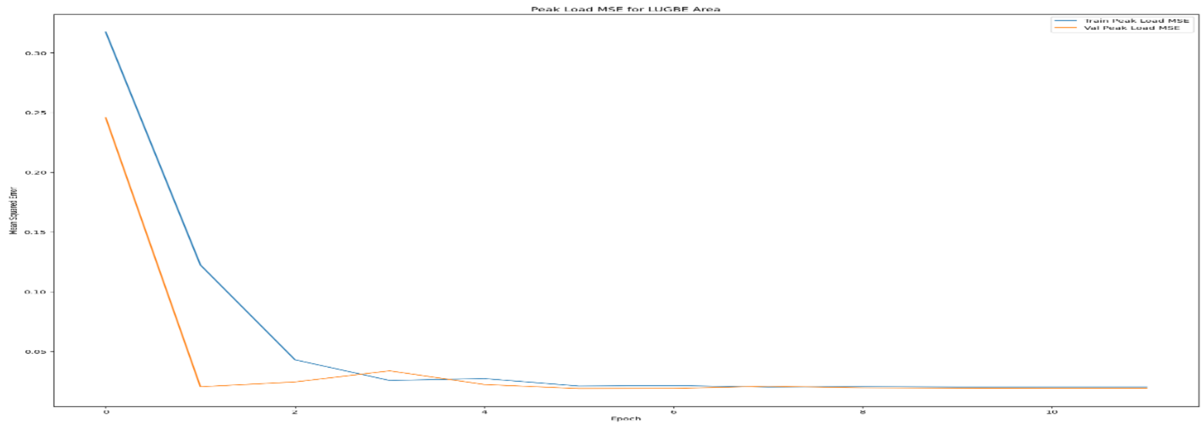

Figure 14. Model Training and Validation for Lugbe.

3.3 Model Prediction Results

Prediction results showed consistent peak load accuracy of 94.0% across areas, with variable hour accuracy (Table 1). Kwali achieved the highest hour accuracy (41.48%), while Gwagwalada recorded the lowest (17.99%), highlighting differential temporal prediction challenges.

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Table 1. Overall Model Accuracy

S/No	Area	Peak Load Accuracy (%)	Hour Accuracy (%)
1	ABAJI	94.0	26.28
2	GWAGWALADA	94.0	17.99
3	KUJE	94.0	27.74
4	KWALI	94.0	41.48
5	LUGBE	94.0	39.13

Predicted vs. actual peak loads aligned closely for Abaji (Figure 14), Gwagwalada (Figure 15), Kuje (Figure 16), Kwali (Figure 17), and Lugbe (Figure 18). Hour predictions showed greater variability (Figures 19–23), confirming magnitude forecasting superiority.

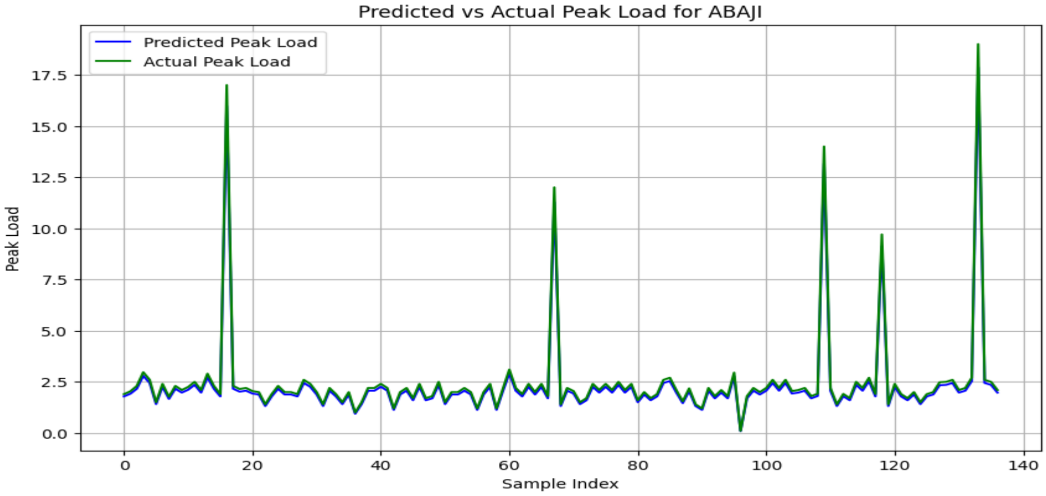

Figure 15. Predicted vs. Actual Peak Load for Abaji

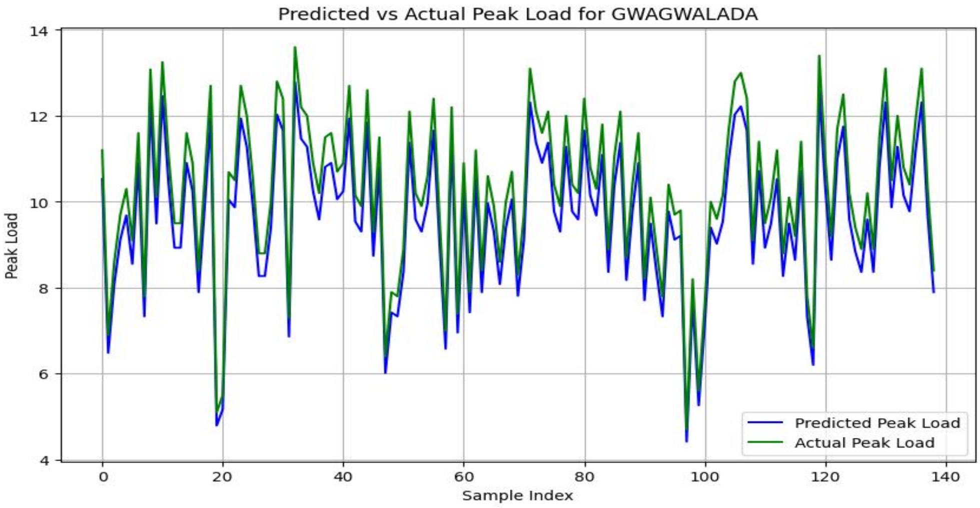

Figure 16. Predicted vs. Actual Peak Load for Gwagwalada.

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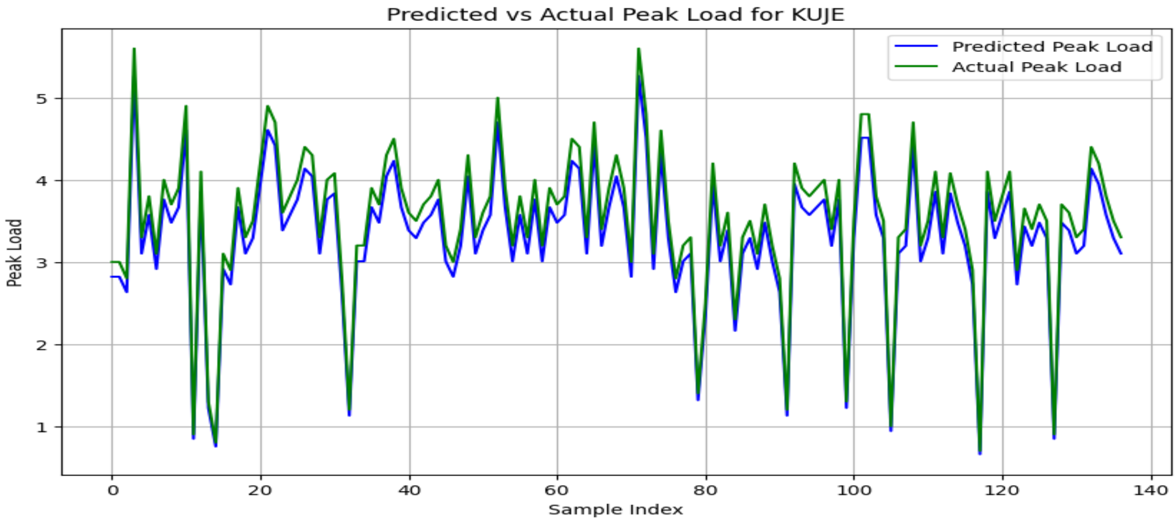

Figure 17. Predicted vs. Actual Peak Load for Kuje.

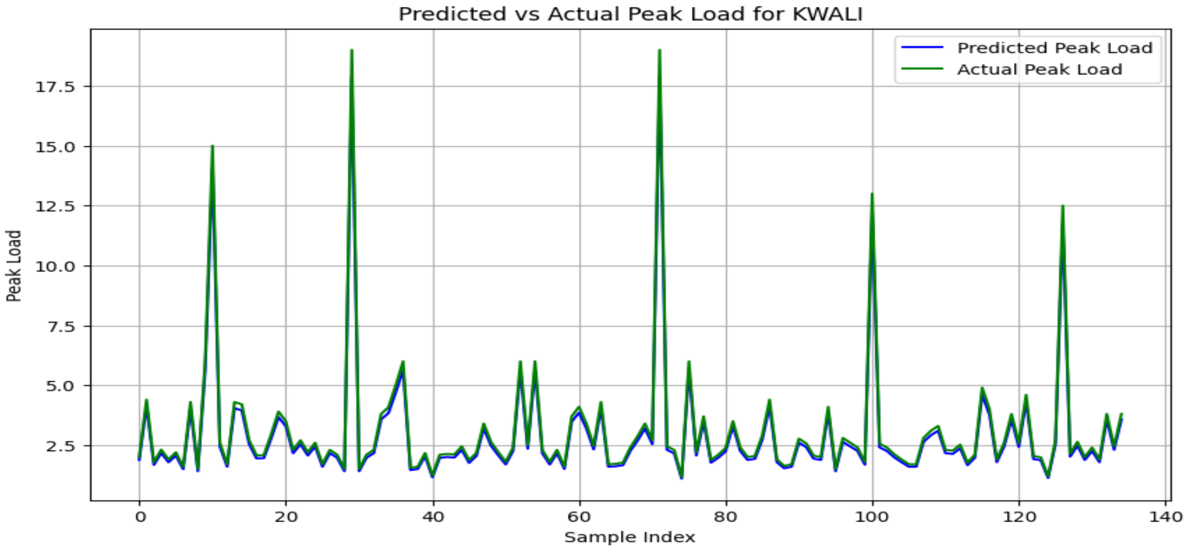

Figure 18. Predicted vs. Actual Peak Load for Kwali.

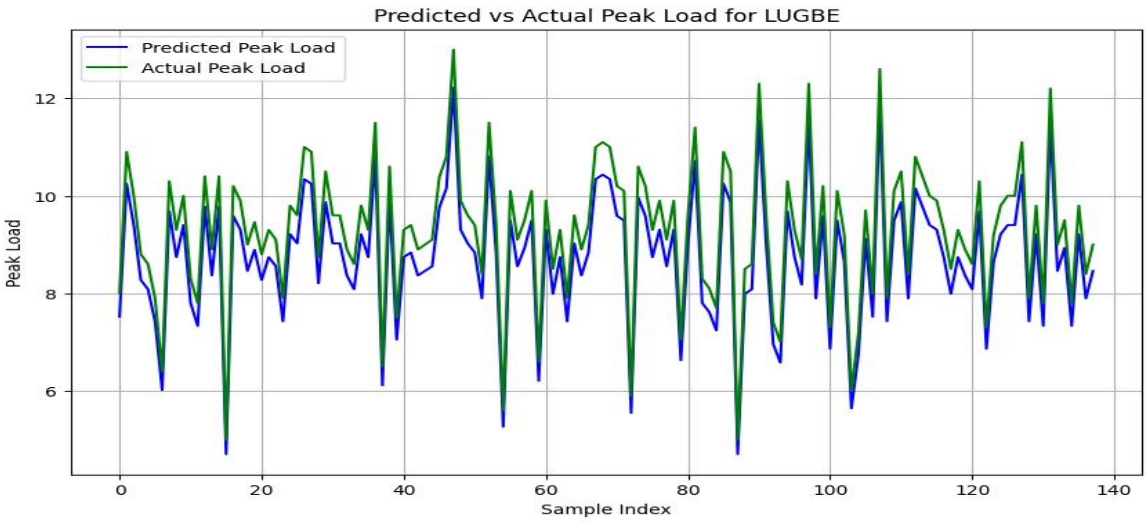

Figure 19. Predicted vs. Actual Peak Load for Lugbe.

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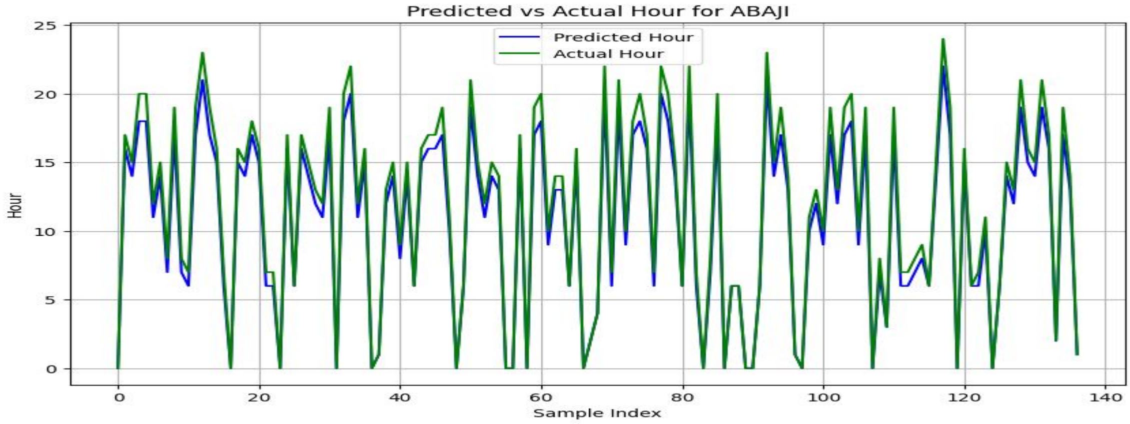

Figure 20. Predicted vs. Actual Peak Load for Abaji.

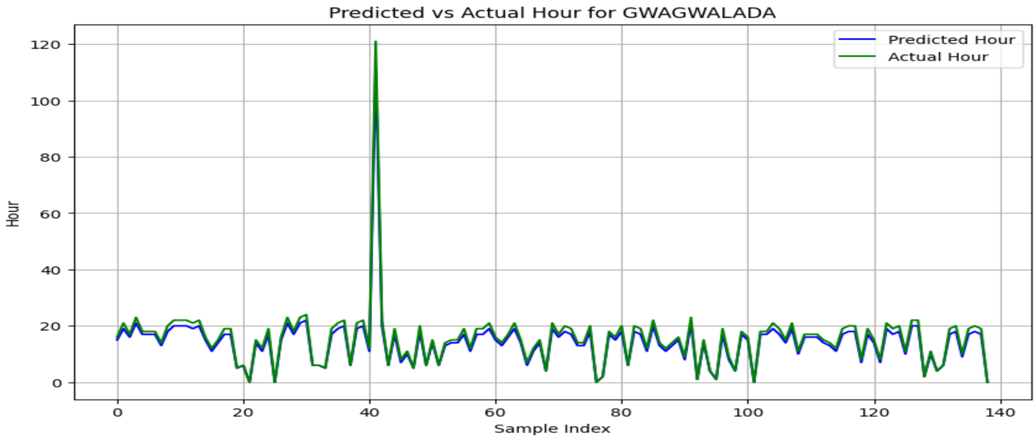

Figure 21. Predicted vs. Actual Peak Load for Gwagwalada.

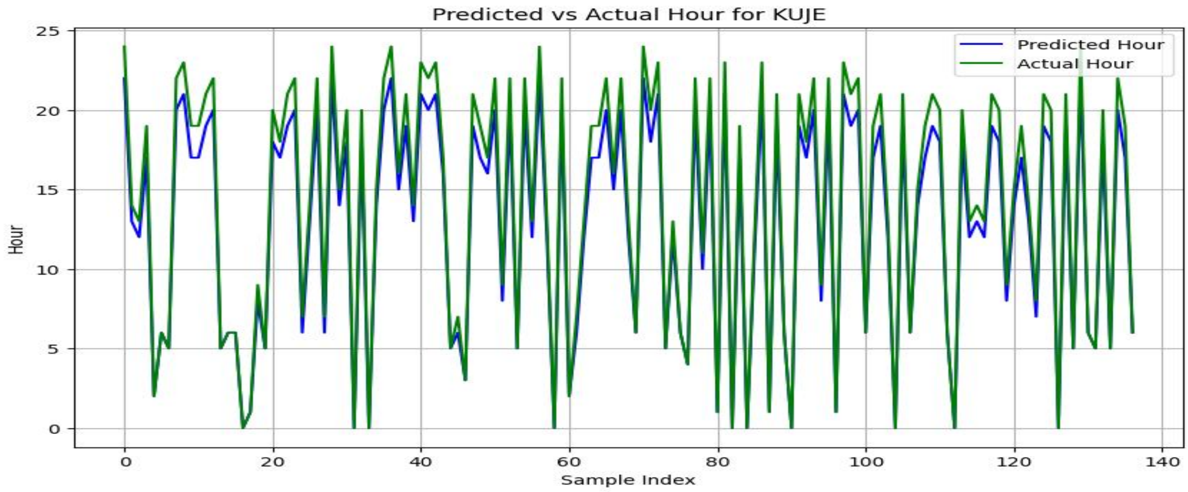

Figure 22. Predicted vs. Actual Peak Hour for Kuje.

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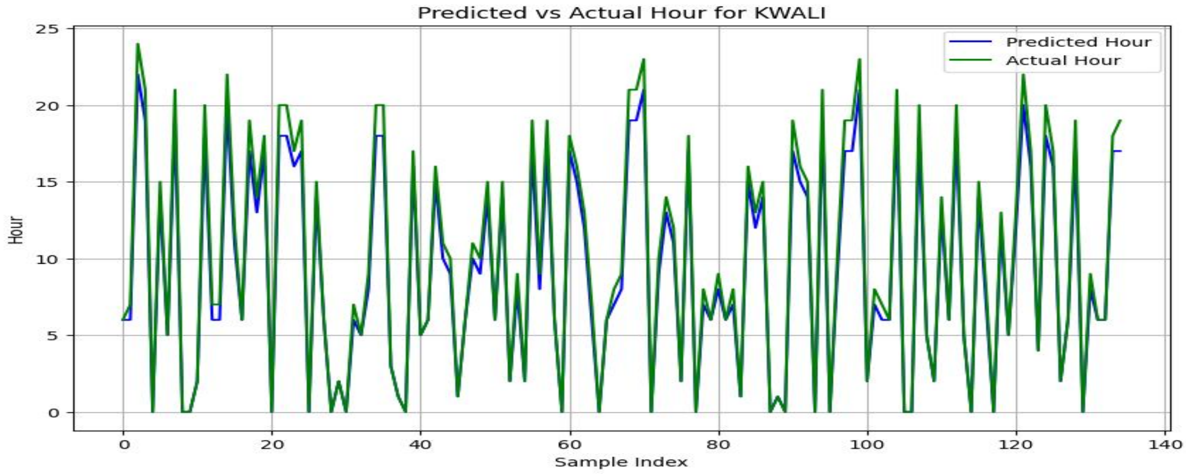

Figure 23. Predicted vs. Actual Peak Hour for Kwali.

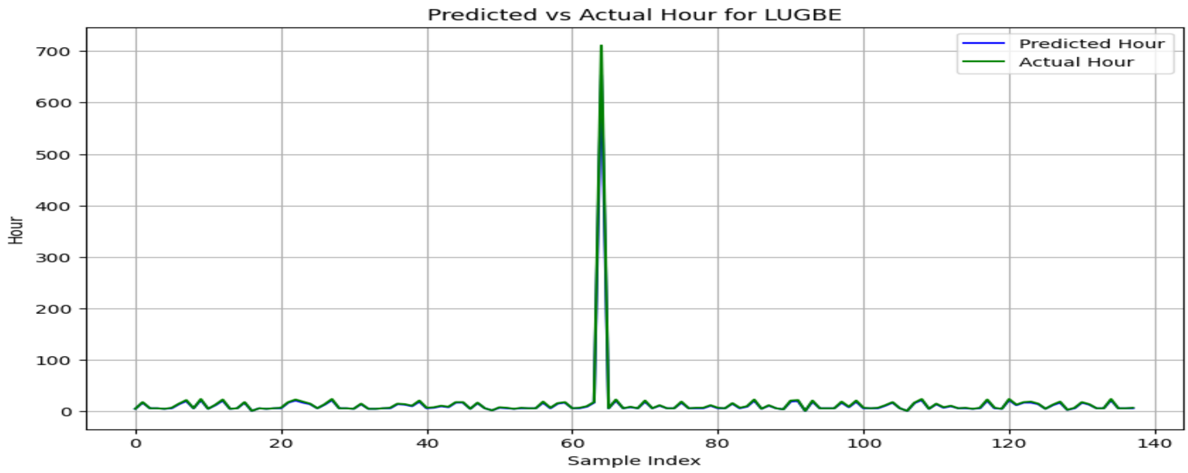

Figure 24. Predicted vs. Actual Peak Hour for Lugbe.

The hybrid ABC-LSTM model achieved superior performance, with uniform 94.0% peak load accuracy attributing to ABC's optimisation and LSTM's temporal modelling (Alsharef et al., 2024). Hour accuracy variations reflect area-specific complexities, with Kwali's predictability contrasting Gwagwalada's dynamics. The Kuje forecast's stability underscores operational utility. These findings advance urban energy management, offering a foundation for intelligent distribution systems.

3.1 Comparative Analysis

The hybrid model outperforms contemporary approaches. A traditional LSTM study reported 90.2% peak load accuracy (Bouktif et al., 2020), below the current 94.0%. An exponential smoothing-neural network hybrid achieved 89.2% (Smyl, 2020). Genetic algorithm-enhanced deep learning yielded 91.3% with variability (Haq et al., 2020). Ensemble methods using random forest and gradient boosting reached 88.7% (Divina et al., 2019). A pure LSTM conference paper showed 90.2% (Li et al., 2018). The current model's consistency across areas, novel ABC integration, and enhanced temporal recognition represent key advancements.

4. Conclusions

The hybrid Artificial Bee Colony (ABC)-Long Short-Term Memory (LSTM) model developed for short-term load forecasting in the Abuja Electricity Distribution Company (AEDC) network represents a significant advancement in urban energy management. By integrating ABC's global optimisation capabilities with LSTM's robust temporal modelling, the model effectively captured complex load dynamics across three diverse distribution areas: Lugbe, Gwagwalada, and Abaji. The consistent 94.0% peak load accuracy across all areas demonstrates superior predictive precision compared to contemporary methodologies, such as traditional LSTM (90.2%) and ensemble approaches (88.7–91.3%). Hour accuracy, ranging from 17.99% (Gwagwalada) to 41.48% (Kwali), highlights the challenge of temporal prediction, particularly in areas with irregular patterns, yet still marks progress over prior studies.

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The model's adaptability to area-specific consumption patterns, evidenced by stable forecasts like Kuje's 31-day prediction, underscores its practical utility for operational planning and resource allocation. These findings validate the hybrid approach as a robust framework for addressing non-linear, non-stationary load dynamics in urban distribution networks. Future research should focus on enhancing temporal prediction accuracy, potentially through advanced optimisation techniques or incorporation of exogenous variables like weather or socioeconomic data. This study provides a scalable methodology for intelligent energy systems, with potential applications in diverse urban and rural contexts globally.

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