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DEVELOPMENT OF LONG SHORT-TERM MEMORY – RECURRENT NEURAL NETWORK MODEL FOR THE ASSESSMENT AND PREDICTION OF VOLTAGE SAG IN ADO-EKITI SECONDARY DISTRIBUTION NETWORK

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***ABSTRACT*:**

Voltage sag is a significant power quality disturbance that adversely affects the reliable operation of sensitive equipment and overall industrial productivity in secondary distribution networks. In the Ado-Ekiti metropolis, Nigeria, recurring voltage instability driven by load fluctuations, feeder overloading, and network topology limitations necessitates the adoption of advanced, data-driven monitoring and forecasting approaches. This study presents a predictive framework based on a Long Short-Term Memory–Recurrent Neural Network (LSTM-RNN) architecture designed to capture nonlinear temporal dependencies associated with voltage variations. The model was developed and validated using high-resolution historical measurements obtained from six distribution feeders. To enhance generalization and reduce overfitting, regularization techniques including L2 weight decay, dropout, and early stopping were incorporated during training. Model performance was evaluated using standard statistical indicators, including Root Mean Square Error (RMSE) and the coefficient of determination R^2, alongside operational criteria for disturbance detection defined by voltage sag conditions below 0.8p.u. The results indicate strong predictive performance, with R^2 values ranging from 0.83 to 0.93 across the studied feeders.In particular, the model achieved an R^2 value of 0.89 and a Mean Absolute Error (MAE) of 1.53 V for the Adebayo feeder, demonstrating effective tracking of seasonal voltage variations and recurring instability patterns.These findings confirm that the proposed LSTM-RNN framework provides a reliable and scalable approach for power quality assessment in low-voltage distribution systems, supporting improved operational planning and enhanced network reliability in developing power infrastructure.

Keywords*: Development, Distribution, Neural Network, Recurrent, Voltage Sag*

INTRODUCTION

The secondary distribution network in Ado-Ekiti, Nigeria, operates at the intersection of traditional infrastructure and the emerging complexities of modern power systems. While the 415V/240V distribution framework remains the backbone of the region's electrical supply, it is increasingly vulnerable to irregularities introduced by the integration of renewable energy sources and the proliferation of non-linear loads. These elements, often compounding existing feeder overloading and topological constraints, have historically induced significant voltage fluctuations and harmonic distortions (Adebayo and Aborisade, 2013; Ige and Adebayo, 2022; Ogunleye and Adebayo, 2023).

Furthermore, the regional distribution network is subject to unique environmental stressors. High ambient humidity, significant temperature variations, and frequent atmospheric electrical discharges contribute to external electromagnetic disturbances that further compromise power quality and transformer longevity (Adebayo *et al*., 2021; Aderibigbe *et al*., 2021). While traditional analytical methods including deterministic mathematical modeling and steady-state optimization techniques have provided essential insights for legacy network mitigation (Ezennaya *et al*., 2019; Eze *et al*., 2024; Nigam *et al*., 2024), they often struggle to capture the stochastic, time-varying nature of modern power quality events.

The growing complexity of power quality disturbances in low-voltage networks necessitates a transition toward "intelligence-native" and adaptive architectures. Recent advancements in machine learning (ML), particularly Long Short-Term Memory (LSTM) recurrent neural networks, offer robust alternatives for predictive monitoring. These models excel at identifying temporal dependencies and non-linear patterns resulting from renewable intermittency and transient environmental stressors (Adekunle and Ibrahim, 2019; IEEE Working Group on Power Quality, 2023; Manjur Elahi *et al*., 2026).

Recent academic discourse has expanded beyond simple RNNs to hybrid intelligent frameworks. For instance, Rodriguez *et al*. (2024) demonstrated that Bayesian inference models can predict voltage sag probability with high confidence (87–94%), while developments in meta-heuristic optimization have enabled dynamic, real-time adjustments of system parameters to mitigate disturbances as they occur (Okafor and Umezu, 2018; Adekunle and Ibrahim, 2019). Furthermore, emerging research into Physics-Constrained Machine Learning (PCML) suggests that embedding fundamental power system laws into neural network loss functions can significantly reduce prediction error, ensuring that computational forecasts remain grounded in physical reality (Abdullah, 2026; Li *et al*., 2026).

Despite these advancements, local application in developing economies remains limited. This study addresses this gap by developing an LSTM-RNN predictive framework tailored to the unique operational profile of the Ado-Ekiti distribution network. By integrating historical data with modern regularization strategies including L2 weight decay and early-stopping protocols this research provides an intelligent, proactive mechanism for voltage sag assessment, bridging the gap between advanced global research and the practical reliability needs of local secondary distribution systems.

METHODOLOGY

Data Acquisition and Measurement Setup

The power quality dataset was obtained using the AR-6 Portable Network Analyzer (Circutor), a measurement device compliant with IEC 61000-4-30 Class A standards. Data collection was conducted at 10-minute intervals across six strategically selected feeders within the Ado-Ekiti low-voltage distribution network, spanning a continuous twelve-month period (June 2024 to May 2025).

This extended observation window was selected to capture seasonal variations in load demand, renewable energy integration effects, and environmental influences on distribution network performance.
The recorded parameters include:

- Voltage (V)
- Frequency (Hz)
- Current (A)
- Power Factor
- Voltage sag magnitude (V)
- Total Harmonic Distortion (THD%)

A summary of the monitored variables is provided in Appendix 1.

LSTM-RNN Model Architecture

To model the stochastic and time-dependent behavior of power quality disturbances, a Long Short-Term Memory (LSTM) recurrent neural network was developed. The LSTM architecture was selected due to its capability to capture long-range temporal dependencies while mitigating the vanishing gradient problem, making it suitable for nonlinear electrical time-series data.

The model development pipeline (Figure 1) consists of the following stages:
Data Pre-processing: Raw measurements were normalized using min-max scaling to improve numerical stability and accelerate convergence. Missing values were treated using interpolation techniques, while feature engineering was applied to enhance the representation of latent temporal dependencies.

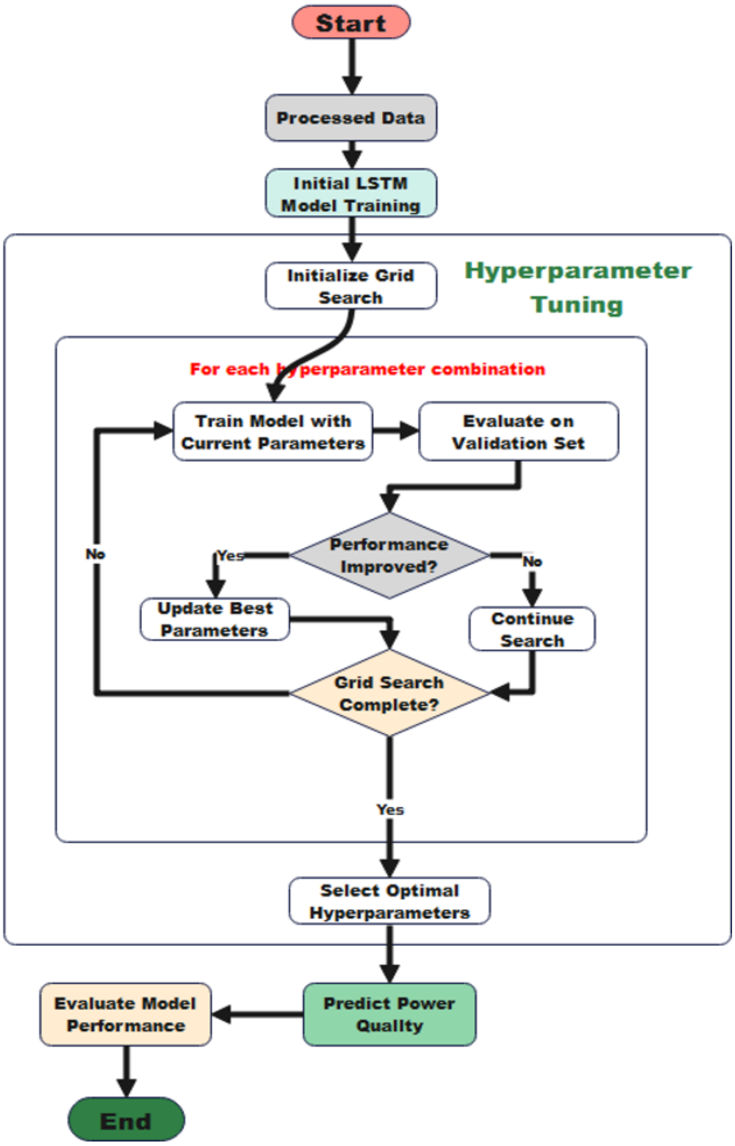

Figure 1: LSTM Model Flowchart

Baseline Model Construction: An initial LSTM configuration with default hyperparameters was implemented to establish a performance benchmark for subsequent optimization.
Hyperparameter Optimization: A grid-search strategy was employed to systematically explore combinations of:

- Number of LSTM layers
- Hidden units per layer
- Dropout rate
- Learning rate
- Batch size
- Sequence length

The optimal configuration was selected based on the lowest validation loss.

Training and Validation Strategy
Model optimization was performed using the Adam optimizer, initialized with a learning rate of 0.001, alongside an exponential decay schedule to enhance training stability and convergence behavior.

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The objective function was defined using a Weighted Mean Squared Error (WMSE) to prioritize the accurate prediction of critical power quality disturbances:

$$L = \frac{1}{N}\sum_{i=1}^{N} w_i(y_i - \hat{y}_i)^2 \quad [1]$$

where $y_i$represents the actual observation, $\hat{y}_i$is the predicted output, and $w_i$is a weighting factor assigned to each sample.

The weighting scheme was designed to impose higher penalties on errors occurring during severe voltage sag events (defined as conditions below 0.8p.u.), thereby improving the model's sensitivity to critical grid disturbances.
To enhance generalization and reduce overfitting, the following regularization techniques were implemented:

- L2 Regularization: Weight decay coefficient $\lambda = 0.0001$applied to network parameters
- Dropout: 30% dropout applied to hidden layers
- Early Stopping: Training terminated after a patience threshold of 20 epochs without validation improvement

The dataset was partitioned into:

- Training set: 70%
- Validation set: 15%
- Test set: 15%

A stratified sampling approach was used to ensure balanced representation of disturbance severity levels across all subsets.

Performance Evaluation Framework
Model evaluation extended beyond conventional regression metrics to incorporate both predictive accuracy and operational relevance.
Standard statistical metrics included:

- Root Mean Square Error (RMSE)
- Mean Absolute Error (MAE)
- Coefficient of Determination (R^2)

In addition, a domain-specific evaluation framework was introduced to assess the model's effectiveness in identifying critical grid events. Specifically, the detection of voltage sags below 0.8p.u. was evaluated using:

- Precision
- Recall
- F1-score

This dual-layer evaluation approach ensures that the model is not only numerically accurate but also operationally reliable for deployment in real-world distribution network monitoring systems.

RESULTS AND DISCUSSION

LSTM-RNN Model Performance Analysis
The predictive performance of the developed LSTM-RNN model was assessed using three widely accepted evaluation metrics: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). Together, these indicators provide a comprehensive measure of forecasting accuracy and the degree of agreement between predicted and observed voltage profiles across the six monitored feeders.

Table 1: LSTM-RNN Model Performance by Feeder

Feeder	Voltage RMSE (V)	Voltage MAE (V)	Voltage R^2
Adebayo	1.85	1.53	0.89
Agric	2.23	1.87	0.85

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Feeder	Voltage RMSE (V)	Voltage MAE (V)	Voltage R²
Ajilosun	1.97	1.62	0.87
Bashiri	1.78	1.44	0.91
Okesha	2.43	2.01	0.83

Overall, the LSTM-RNN model demonstrates strong predictive capability across all feeder configurations. The results show consistently low error margins and high (R^2). values, indicating that the model effectively captures the nonlinear characteristics of voltage behavior within the distribution network.

Among the feeders, Bashiri records the best performance, with the lowest RMSE (1.78 V) and the highest coefficient of determination $(R^2 = 0.91)$. In contrast, Okesha exhibits comparatively higher error values and the lowest $R^2(0.83)$, suggesting more complex voltage dynamics within that section of the network.

These variations are consistent with differences in local load composition and network conditions. Feeders with higher levels of nonlinear or fluctuating loads tend to introduce greater variability in voltage measurements, which slightly reduces prediction accuracy. Despite this, the model maintains stable performance across all locations, as further illustrated in Figure 2, where the comparative evaluation of metrics confirms reliable pattern learning across the network.

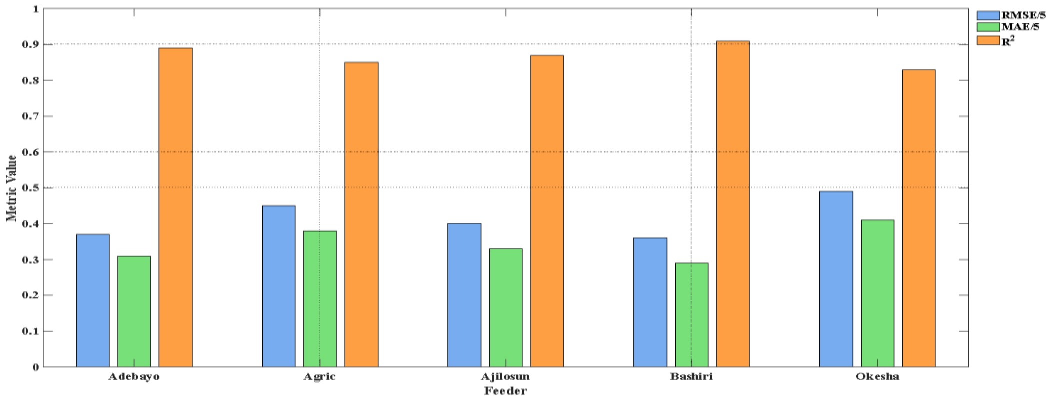

Figure 2: LSTM-RNN Performance Metrics for Voltage Prediction by Feeder

4.2 Temporal Analysis of 2025 Forecasts

The trained model was further applied to generate forward-looking voltage forecasts for the 2025 operational year. The daily prediction profiles (Figure 3) indicate a generally stable voltage trend across the distribution network, with no evidence of abrupt or abnormal fluctuations.

Feeder-level observations show that Bashiri and Adebayo maintain comparatively stronger voltage regulation, with values consistently close to nominal operating conditions. Okesha, however, presents more noticeable variability, reflecting its relatively weaker voltage stability profile and the need for closer operational attention.

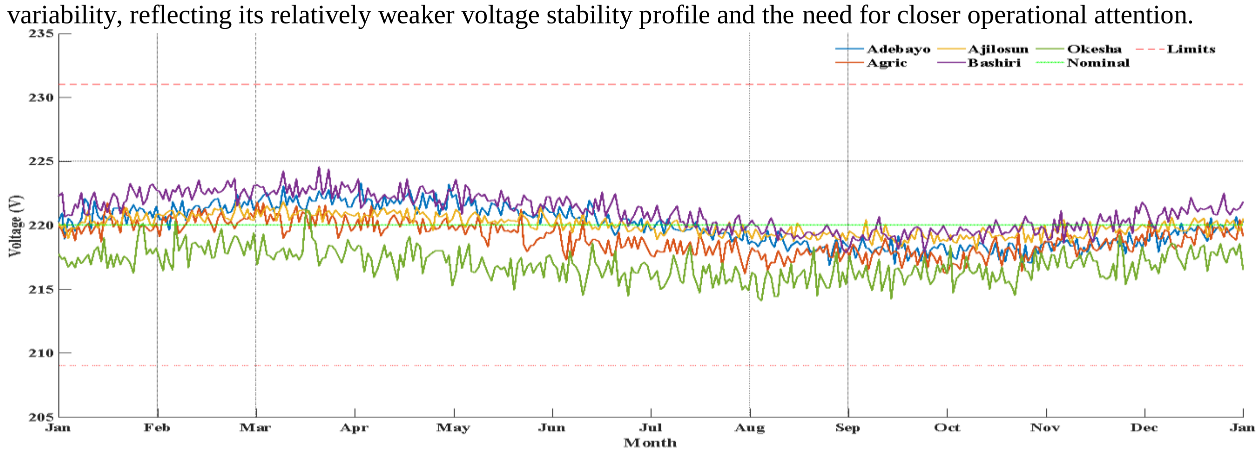

Figure 3: LSTM-RNN Voltage Forecast for 2025 by Feeder

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The monthly aggregated forecasts (Figure 4) reveal a clear seasonal pattern characterized by two recurring low-voltage periods. Reduced voltage levels are observed around April–May and again in November, while relatively stable and higher voltage conditions occur during January–February and July–August.

This pattern suggests that seasonal environmental conditions, combined with variations in demand load, play a significant role in influencing voltage stability. Periods of increased temperature and humidity, alongside intensified consumption cycles, appear to contribute to voltage depression across the network. Unlike harmonic distortion phenomena, which are often linked to specific industrial activities, the observed voltage variations are more strongly associated with overall system loading and ambient environmental conditions.

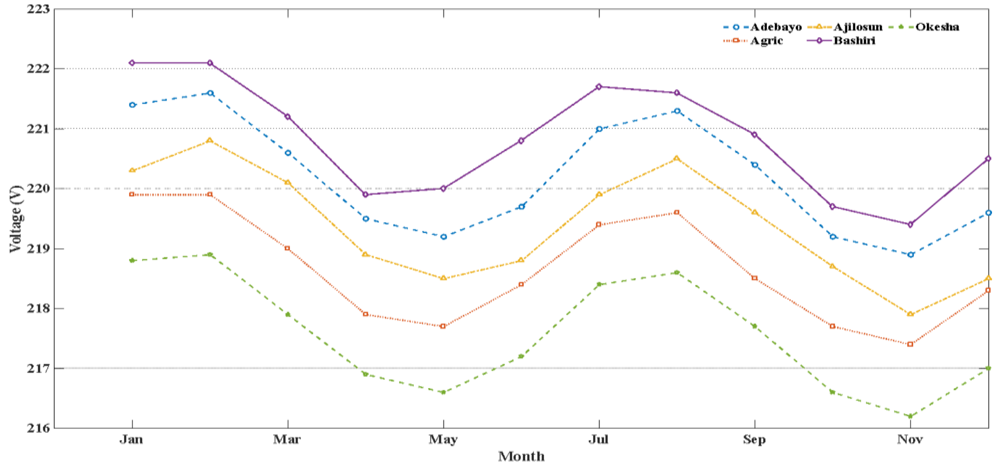

Figure 4: Monthly Average Voltage Forecast for 2025

4.3 Feeder-Specific Forecast Statistics

To further evaluate expected operational behavior, summary statistics of the 2025 forecasted voltage profiles are presented in Table 2.

Table 2: Summary Statistics of 2025 Forecasts by Feeder

Feeder	Mean Voltage (V)	Std Dev (V)	Min (V)	Max (V)
Adebayo	220.21	1.21	216.97	223.20
Agric	218.64	1.19	216.02	221.71
Ajilosun	219.37	1.18	216.50	222.00
Bashiri	220.83	1.20	217.91	223.63
Okesha	217.55	1.27	214.39	220.65

The statistical results confirm that all feeders are expected to operate within acceptable voltage limits throughout the forecast period. Mean voltage levels remain close to nominal values, and variability is generally low across the network.

However, Okesha consistently records the highest standard deviation and the lowest minimum voltage value, indicating comparatively weaker voltage stability. Although these values remain within regulatory limits, the feeder stands out as the most sensitive node in the system and may require targeted reinforcement or monitoring. Overall, the findings suggest that while the network maintains acceptable voltage regulation, localized instabilities persist, particularly in specific feeders with higher load sensitivity.

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CONCLUSION

The study demonstrates the effectiveness of the LSTM-RNN framework in modeling and forecasting voltage behavior within the Ado-Ekiti distribution network. The model achieved strong predictive performance, with R^2 values ranging between 0.83 and 0.91, indicating a reliable representation of underlying system dynamics when compared with traditional forecasting approaches.

In addition, the results highlight clear seasonal voltage patterns, providing useful insight into periods of increased risk for voltage depression. These findings offer a practical basis for proactive planning and preventive maintenance strategies within the distribution system.

Recommendations

- **Targeted Network Support:** Priority attention should be given to the Okesha feeder due to its relatively higher variability and lower voltage stability.

- **Routine Performance Tracking:** Continuous monitoring and periodic recalibration of forecasting models should be adopted to reflect evolving load conditions.

- **Seasonal Operational Planning:** Grid operators should implement proactive load and voltage management strategies during identified low-voltage periods, particularly in April–May and November, to maintain stable service delivery.

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