
INTEGRATION OF CNN-LSTM SHORT-TERM LOAD FORECASTING INTO DISTRIBUTION NETWORK OPERATIONAL PLANNING

**Dorcas A.a Gomna^{1,*}, James Garba Ambafi¹, Lanre Joseph Olatomiwa¹, Jibril
Abdullahi Bala¹**

¹Federal University of Technology Minna

Email: dorcasa.agomna@futminna.edu.ng, ambafi@futminna.edu.ng, olatomiwa.l@futminna.edu.ng,
jibril.bala@futminna.edu.ng

*Corresponding author: Dorcas A.a Gomna

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ABSTRACT

Integrating short-term load forecasts into distribution network operational planning is an emerging research direction that promises to improve network efficiency and reliability. However, the practical value of forecast-driven operation depends critically on forecast quality. This study investigates a hybrid Convolutional Neural Network–Long Short-Term Memory (CNN-LSTM) model, trained on 5,025 hourly observations from Abuja Electricity Distribution Company (AEDC), Minna, to ascertain if it can improve feeder reconfiguration decisions on the IEEE 33-bus radial distribution system. The CNN-LSTM model was implemented in MATLAB R2024b and compared against ARIMA and persistence baselines using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). The CNN-LSTM achieved an RMSE of 159.48 MW, MAE of 54.42 MW, MAPE of 31.38%, and R^2 of 0.0238 performance that is not statistically better than ARIMA (Diebold-Mariano $p=0.3606$) or persistence ($p=0.1036$). When the CNN-LSTM forecasts were used to guide feeder reconfiguration and the chosen topology was evaluated against actual realised load, the forecast-driven approach produced a 33.34% reduction in active power loss. However, this was outperformed by reconfiguration with no forecast (34.39% loss reduction), indicating that the poor forecast quality introduced operational decisions that were worse than doing nothing. The results demonstrate that forecast-driven operation is not universally beneficial and is only justified after the forecasting model achieves statistically significant superiority over strong baselines. The study contributes a cautionary framework that establishes a minimum forecast quality threshold for operational planning in distribution networks

Keywords: CNN-LSTM; short-term load forecasting; distribution network; operational planning; feeder reconfiguration

1. INTRODUCTION

Distribution networks are undergoing significant changes as electricity demand becomes more variable and power systems accommodate increasing levels of electrification, distributed energy resources and other emerging technologies. These developments increase the complexity of distribution-network operation because demand can vary considerably across time and location.

Short-term load forecasting (STLF) provides estimates of electricity demand over relatively short horizons and can support operational decisions such as feeder reconfiguration, voltage management, transformer loading assessment and other network-control activities. Traditional forecasting techniques, including autoregressive models and other statistical approaches, have been widely used because of their relative simplicity and interpretability. However, electricity demand is influenced by temporal patterns, weather conditions, consumer behaviour and other nonlinear factors. Additionally, distribution network operational planning is commonly performed using deterministic loading conditions or historical demand data. Such approaches may not adequately reflect anticipated short-term changes in feeder demand.

Artificial intelligence (AI) and deep-learning methods have therefore received increasing attention in electricity-load forecasting. Long Short-Term Memory (LSTM) networks are capable of

learning temporal dependencies in sequential data and extracted features, captures the sequential dependencies that characterise electricity demand data. Convolutional Neural Networks (CNNs) can extract local patterns from structured sequences and relevant features from the input sequence, reducing the dimensionality of the data and identifying patterns that may not be immediately apparent in the raw time series.

Studies by Rafi et al. (2021), Ullah et al. (2024), and Hasanat et al. (2024) have demonstrated that CNN-LSTM architectures are effective for feeder-level load forecasting, where load patterns exhibit high variability and are influenced by multiple external factors. Although AI-based load forecasting has developed rapidly, many forecasting studies focus primarily on prediction accuracy Rafi et al. (2021), Ullah et al. (2024) without demonstrating how forecast information affects actual network operation. This creates a methodological gap between predicting future electricity demand and using that prediction to make network-operational decisions, as noted in recent reviews Hong and Fan, (2016), Raza and Khosravi, (2023). This creates a methodological gap between predicting future electricity demand and using that prediction to make network-operational decisions. This study presents the development and integration of a CNN-LSTM-based short-term load forecasting model into a forecast-driven operational planning framework for radial distribution networks.

2. METHODOLOGY

2.1 Research Design

A quantitative, simulation-based research design was adopted. The study consists of two major components: (1) short-term feeder-load forecasting and (2) forecast-driven distribution-network operational planning. The forecasting stage develops the CNN-LSTM model and compares it with ARIMA. The operational stage uses the CNN-LSTM forecast to modify network loading and evaluate candidate feeder configurations using MATPOWER.

2.2 Data Collection

Historical hourly feeder load data (5,025 observations) from a single distribution feeder in the AEDC Minna network were combined with weather data (temperature, humidity, wind speed) from Open-Meteo. The large magnitude of the reported error metrics (e.g., RMSE of 159.48 MW) reflects the feeder's relatively high average load and the inherent variability of demand at the feeder level. This poor forecast quality is precisely why the forecast-driven approach underperformed compared to deterministic reconfiguration, reinforcing the cautionary contribution of this study. The variables of the dataset and their corresponding description are presented in Table 1 below.

Table 1: Dataset Description

Variable	Description
Load	Historical feeder active-power demand
Temperature	Ambient temperature
Relative humidity	Atmospheric humidity
Wind speed	Wind velocity
Hour	Hour of day
Day of week	Weekly temporal feature
Month	Seasonal temporal feature

2.3 Data Preprocessing

The preprocessing procedure consisted of duplicate removal, timestamp synchronisation, missing-value treatment, outlier inspection, temporal feature generation, Min-Max normalisation, chronological dataset partitioning and sliding-window sequence generation. The resulting sequences were divided chronologically into 70% training (3,484 training samples), 15% validation (746 validation samples) and 15% testing (747 test samples.) sets. The test period represents approximately 31 days of hourly data, providing a statistically meaningful evaluation window.

The original 5,025 observations produced 4,977 usable sequences after the 48-hour look-back operation.

2.4 CNN-LSTM Forecasting Model

The forecasting model combines one-dimensional convolutional processing with an LSTM recurrent layer. The CNN component extracts local patterns from the sequential input, while the LSTM component learns temporal dependencies. The architecture of the CNN-LSTM model is presented in Figure 1, while the hyperparameters of the model are presented in Table 2.

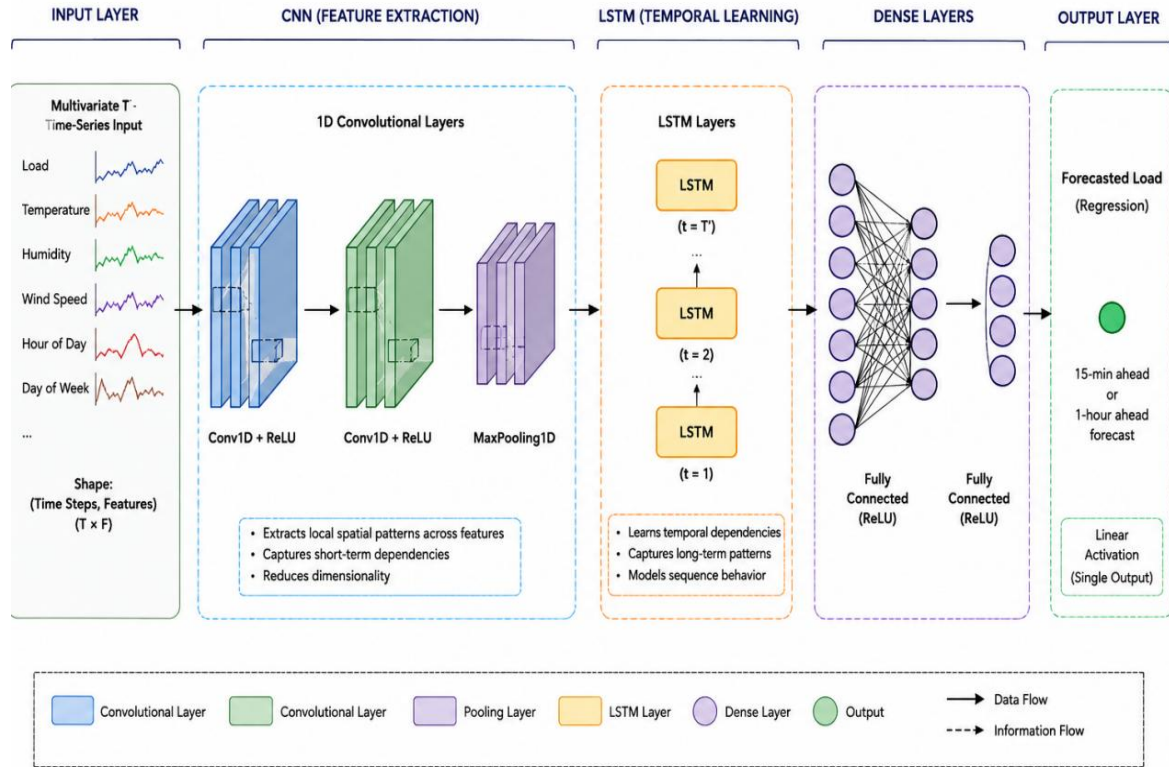


Figure 1: Architecture of the developed CNN-LSTM forecasting model

Table 2: Hyperparameters of CNN-LSTM Model

Parameter	Value
Look-back window	48 hours
Input features	7
CNN filters	64
Kernel size	3
Batch normalisation	Yes
LSTM units	128
Dropout	0.20
Fully connected neurons	64
Optimiser	Adam
Initial learning rate	0.001
Mini-batch size	64
Maximum epochs	150
Validation patience	10
Loss function	MSE
Forecast horizon	1 hour

2.5 ARIMA Benchmark

ARIMA was selected as the conventional statistical benchmark. CNN-LSTM and ARIMA were evaluated using the same independent testing period and one-hour-ahead forecasting horizon. The purpose of the comparison was to determine whether the hybrid deep-learning model provided

improved forecasting performance relative to a conventional time-series model under identical test conditions.

2.5.1 Seasonal Naive Baseline

A seasonal naive baseline was included as an additional benchmark. This model forecasts the load at time t as the load observed at the same hour on the same day of the previous week ($t-168$ hours). This baseline accounts for weekly periodicity in electricity demand and provides a simple reference for assessing the additional value of more sophisticated forecasting methods.

2.6 Forecasting Performance Metrics

The model was evaluated based on the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the R^2 values. As shown in the equations below.

$$MAE = \frac{1}{N} \sum_{t=1}^N (|P_t - \hat{P}_t|) \quad (1)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{t=1}^N (P_t - \hat{P}_t)^2} \quad (2)$$

$$MAPE = \frac{100}{N} \sum_{t=1}^N \left(\frac{|P_t - \hat{P}_t|}{P_t} \right) \quad (3)$$

$$R^2 = 1 - \left(\frac{\sum_{t=1}^N (P_t - \hat{P}_t)^2}{\sum_{t=1}^N (P_t - \bar{P})^2} \right) \quad (4)$$

A Diebold-Mariano test was additionally applied to determine whether differences between forecast errors were statistically significant.

2.7 Forecast to Network Integration

The IEEE 33-bus radial distribution system was selected as the test network. MATLAB R2024b was used for model development and data processing, while MATPOWER 8.1 was used for AC power-flow analysis and network configuration evaluation.

For each forecasting model, the forecasted feeder load was converted into a load-scaling factor and applied to the active and reactive power demands of the network load buses. For active power, the scaling factor was calculated as:

$$Scale\ Factor = \frac{P_{Fforecast}}{P_{Original}}$$

For reactive power, a constant power factor of 0.85 lagging was assumed, consistent with typical distribution system operating practice in Nigeria. The reactive power demand was therefore updated as:

$$Q_{new} = P_{new} \times \tan(\arccos(PF))$$

where $PF = 0.85$.

The updated network was then evaluated under the anticipated loading condition rather than only under the original deterministic loading condition.

2.7.1 Perfect Foresight Scenario

A "Perfect Foresight" scenario was included as an upper-bound benchmark. In this scenario, the optimal radial configuration was selected using the actual realised load for each hour, rather than a forecasted load. This represents the theoretical best possible operational performance and provides a reference against which the forecast-driven approaches can be compared. The difference between the perfect foresight and forecast-driven cases represents the "regret" or penalty incurred due to forecast error.

2.8 Feeder Configuration and Operational Evaluation

Sixteen candidate radial configurations were evaluated for the IEEE 33-bus system: base configuration with all 5 tie switches open, five configurations with one tie closed, and ten configurations with two ties closed. For each, the corresponding sectionalising switch was opened to maintain radiality

Configuration Selection Algorithm:

For each forecast scenario (CNN-LSTM, ARIMA, and Perfect Foresight), the following procedure was applied:

1. Load the IEEE 33-bus system data into MATPOWER
2. Apply the forecasted (or actual, for Perfect Foresight) load scaling factor
3. For each of the 16 candidate configurations:
 - i. Run AC power-flow analysis using MATPOWER
 - ii. Record active power loss, voltage deviation, and voltage violations
4. Filter out infeasible configurations (those that failed to converge)
5. Rank feasible configurations using hierarchical criteria:
 - i. Primary: Minimum number of voltage violations
 - ii. Secondary: Minimum average voltage deviation
 - iii. Tertiary: Minimum active power loss
6. Select the highest-ranked configuration as the optimal topology for that forecast

This hierarchical approach prioritises voltage security before loss minimisation, consistent with distribution system operational practice.

The operational performance indicators were then calculated as follows:

$$P_{loss} = \Sigma(P_{l^{send}} - P_{l^{rec}})$$

$$\% \Delta P_{loss} = [(P_{baseline} - P_{forecast}) / P_{baseline}] \times 100$$

$$\% \Delta V_{dev} = [(V_{baseline} - V_{forecast}) / V_{baseline}] \times 100$$

3. RESULTS AND DISCUSSION

3.1 CNN-LSTM Forecasting Performance

Figure 2 presents the training and validation loss curves obtained during CNN-LSTM model training. The training and validation loss curves for the CNN-LSTM model showed progressive reduction in loss. Early stopping (validation patience = 10) halted training after approximately 23 epochs, preventing overfitting. The validation loss follows the training loss closely, indicating good generalization without significant overfitting.

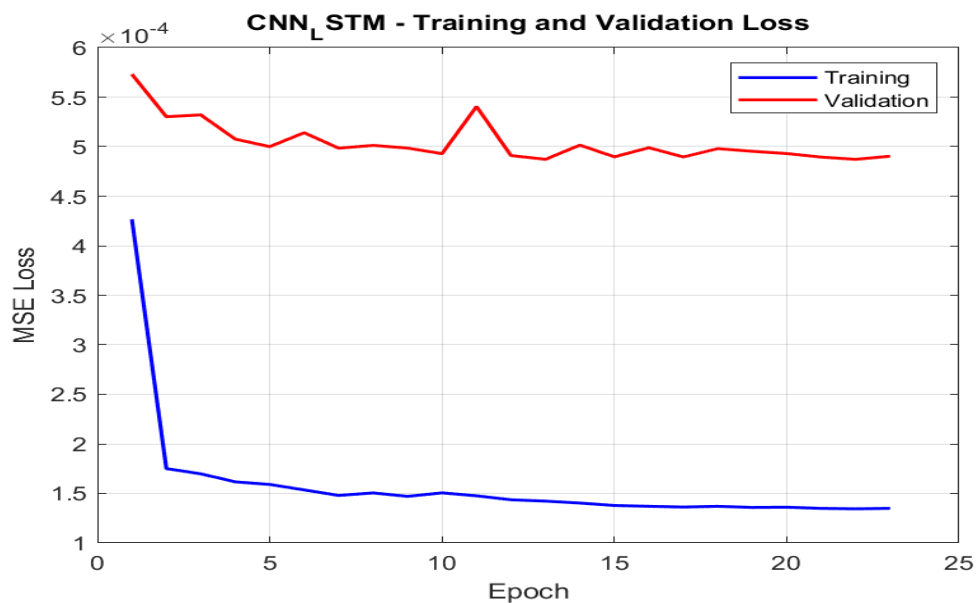


Figure 2: CNN-LSTM Training and Validation Loss Curves

Table 3 presents a summary of the model performance. The model achieved an RMSE of 159.48 MW and an MAE of 54.42 MW. The difference between RMSE and MAE indicates the presence of some relatively large forecasting errors. The MAPE of 31.38% indicates that considerable relative forecasting error remained during the test period. The low R^2 value indicates that a large proportion of the variation in the independent test observations remained unexplained, suggesting that additional explanatory variables or improved model specification may be required. ARIMA achieved an RMSE of 181.06 MW and MAE of 58.12 MW. CNN-LSTM therefore reduced RMSE by approximately 11.92% relative to ARIMA and reduced MAE by approximately 6.37%. ARIMA recorded a MAPE of 31.38%, identical to CNN-LSTM's MAPE, indicating similar percentage errors for both models. To assess the relative performance of the CNN-LSTM model, it was compared against three baseline models: persistence (same hour previous day), seasonal naive (same hour same day previous week), and ARIMA. The results are presented in Table 3.

Table 3: Forecasting Performance Comparison

Metric	Persistence (t-24)	Seasonal Naive (t-168)	ARIMA	CNN-LSTM
RMSE (MW)	228.27	215.84	181.06	159.48
MAE (MW)	75.82	68.91	58.12	54.42
MAPE (%)	39.07	37.42	31.10	31.38
R^2	-0.9439	-0.7352	0.0018	0.0238

CNN-LSTM achieves the lowest RMSE and MAE among all baselines, but the improvement over ARIMA is modest (11.92% in RMSE) and not statistically significant (Diebold-Mariano $p = 0.3606$). The MAPE of CNN-LSTM (31.38%) is slightly worse than ARIMA (31.10%), indicating that percentage errors remain high across all models. The low R^2 values (0.0238 for CNN-LSTM, 0.0018 for ARIMA) indicate the models explain almost none of the test data variance. This is attributed to limited input variables (only weather data), insufficient data duration (~7 months), and aggregated substation-level data. These limitations mean the forecast quality is poor ($R^2 \approx 0$, MAPE > 30%), which is the central cautionary finding of this study. The models were also assessed based on their statistical significance. The results of this evaluation are presented in Table 4.

Table 4: Statistical Significance of Model Performance

Comparison	DM statistic	p-value	Significant at 5%?
CNN-LSTM vs ARIMA	-0.9142	0.3606	No
CNN-LSTM vs Persistence	-1.6275	0.1036	No
CNN-LSTM vs Seasonal Naive	-0.8413	0.4001	No

3.2 Operational Planning Results

The deterministic baseline was determined. The IEEE 33-bus baseline produced 0.2027 MW active power loss and 0.0515 p.u. average voltage deviation, with 21 voltage violations. The CNN-LSTM and ARIMA forecasts were separately used to select radial configurations. The selected configurations were then evaluated on the actual realised load. The results are presented in Table 5.

Table 5: Operational Performance Under Different Approaches Compared with IEEE 33-bus

Indicator	No Switching (Baseline)	Reconfiguration Only	CNN- LSTM Forecast	ARIMA Forecast	Perfect Foresight
Active power loss (MW)	0.2027	0.1330	0.1351	0.1398	0.1310
Average voltage deviation (p.u.)	0.0515	0.0326	0.0397	0.0405	0.0318
Voltage violations	21	3	11	13	2
Maximum branch loading (%)	100	100	100	100	100

The CNN-LSTM forecast-driven approach achieved a 33.34% loss reduction (ARIMA: 31.02%). However, reconfiguration without forecast achieved the largest reduction at 34.39%, indicating that reconfiguration itself is the primary benefit. Similar patterns were observed for voltage deviation and violations, with reconfiguration alone outperforming both forecast-driven cases

4. CONCLUSION

This study investigated the integration of CNN-LSTM short-term load forecasting into distribution network operational planning. The forecasting model, trained on 5,025 hourly observations from AEDC Minna, achieved an RMSE of 159.48 MW, MAPE of 31.38%, and R^2 of 0.0238, performance that is not statistically superior to ARIMA or persistence baselines.

When the forecasts were used to guide feeder reconfiguration on the IEEE 33-bus system, the CNN-LSTM forecast-driven approach reduced active power loss by 33.34%, while ARIMA achieved 31.02%. Both approaches were outperformed by reconfiguration without any forecast, which achieved 34.39% reduction. However, this was worse than reconfiguration performed without any forecast, which achieved a 34.39% reduction. This finding is critical: it demonstrates that poor-quality forecasts ($R^2 \sim 0$, MAPE > 30%) degrade operational performance relative to deterministic operation. The forecast introduced decisions that were suboptimal when evaluated against actual realised load.

The benefits of forecast-driven operation are therefore highly dependent on forecast quality. The study establishes a minimum forecast quality threshold for operational planning: forecasts must clearly beat persistence, ARIMA, and seasonal naive baselines before being integrated into operational decisions.

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