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Mid-Term Electrical Load Forecasting Using Convolutional Neural Networks (CNNS)

Elijah Adebayo Olajuyin

Bamidele Olumilua University of Education, Science and Technology,Ikere-Ekiti, Ekiti State.
Electrical and Electronic Engineering Department, School of Engineering.

Corresponding Author Email: olajuyinelijah2016@gmail.com

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ABSTRACT

This research presents a novel approach to mid-term electrical load forecasting using Convolutional Neural Networks (CNN) for the Ado-Ekiti 11kV Distribution Network in Nigeria. The study utilizes five years of historical load data (2020-2024) from five feeders to develop and validate a CNN-based forecasting model. The research methodology incorporates comprehensive data preprocessing, exploratory data analysis, and hyperparameter tuning to optimize model performance. The hyperparameter-tuned model achieved exceptional accuracy with an R^2 value of 0.9420, RMSE of 0.0490, and MAPE of 10.0535%, demonstrating significant improvement over baseline models. The model successfully generated one-year- ahead load forecasts for 2025, revealing important trends and patterns in load distribution across the network. Strong correlations were identified among feeders (correlation coefficients 0.75-0.92), indicating synchronized load behaviour. The findings provide valuable insights for distribution network planning, infrastructure optimization, and load management strategies. This research contributes to the growing body of knowledge on deep learning applications in power distribution systems and offers practical recommendations for improving network operations.

Keywords: Electrical; Load; Forecasting; Convolutional; Distribution; Mid-term

1. Introduction

Electrical load forecasting constitutes a critical component of modern power system management, enabling efficient resource allocation, demand-supply equilibrium and enhanced grid stability. Historically reliant on statistical methodologies such as autoregressive integrated moving average (ARIMA) and exponential smoothing, traditional approaches have proven inadequate in capturing the nonlinear dependencies and complex temporal patterns inherent in contemporary load data. The advent of deep learning has revolutionised this domain, with convolutional neural networks (CNNs) emerging as particularly potent tools due to their capacity for automated feature extraction from sequential data. CNNs excel in modelling spatial and temporal dependencies, outperforming conventional techniques, while hybrid architectures integrating long short-term memory (LSTM) networks or gated recurrent units (GRUs) further enhance predictive accuracy. Notable advancements include BiGRU-CNN models for short-term forecasting (Soares & Franco, 2021), deep CNN frameworks for multi-energy demand prediction (Arsene & Parisio, 2024), and heuristic-optimised CNN systems achieving superior short-term accuracy (Hong & Chan, 2023). Such innovations underscore CNN-based models' growing prominence in addressing forecasting challenges across temporal horizons.

Within Nigeria's Ado-Ekiti 11kV Distribution Network, a critical infrastructure serving Ekiti State's capital ,these technological advancements hold particular relevance. The network contends with persistent operational challenges including voltage fluctuations, unbalanced loads and significant power losses, exacerbated by inadequate load forecasting capabilities (Adebanji & Akinyele, 2021). Recent analyses of local distribution systems, such as Folorunso et al.'s (2021) study of Afe Babalola University's network, identify poor load prediction as a key contributor to energy mismanagement and service disruptions. Conventional forecasting methods proved doubly inadequate here, failing both to capture load data nonlinearities and to address region-specific consumption patterns influenced by demographic factors, seasonal variations and evolving infrastructure demands. The implementation of CNN-based solutions offers transformative potential through improved load balancing, enhanced voltage regulation (Onibonoje et al., 2024) and data-driven infrastructure planning. Hybrid architectures combining CNNs with GRUs or heuristic optimisation techniques, as demonstrated in residential forecasting contexts (Sajjad et al., 2020; Wazirali et al., 2023), appear particularly suited to Ado-Ekiti's requirements for mid-term forecasting precision. This study consequently proposes a tailored CNN model leveraging historical load data from the Ado-Ekiti network, aiming to optimise forecasting accuracy, reduce distribution losses and strengthen grid reliability outcomes vital for supporting the region's socioeconomic development through improved power management strategies.

Several studies have investigated electrical load forecasting in Nigeria using various neural network approaches, aiming to enhance prediction accuracy and support effective energy management. These studies employ different methodologies and report varying degrees of success. Edoka et al. (2023) developed a deep learning model using a Long Short-Term Memory (LSTM) network to forecast short-term electrical energy consumption. Utilising data from the Transmission Company of Nigeria's Benin City 132/33KV transmission station, the model achieved a Mean Absolute Percentage Error (MAPE) of 0.010 and a Root Mean Square Error (RMSE) of 19.759 over a 100-time-step forecast. These results indicate high accuracy; however, the study was limited by the peculiarity and insufficiency of the energy consumption readings, which could affect the model's generalisation capability. Ashigwuike et al. (2020) conducted a medium-term electrical load forecast for the Abuja Municipal Area Council using an Artificial Neural Network (ANN) approach. The study incorporated factors such as temperature, time, population growth rate, and consumer activities.

The ANN model achieved an average MAPE of 0.00197, outperforming the Multiple Linear Regression method, which had a MAPE of 0.004545. The R-Value deviation was 8.06% for the ANN method compared to 34.42% for the regression method, indicating superior performance. Nevertheless, the study did not account for real-time external factors like economic fluctuations and policy changes, which could influence electricity demand. Okelola et al. (2021) explored short-term load forecasting for the Nigerian electrical power network using an ANN model. The model utilised previous load values, days of the week, and hours of the day as inputs. The study reported a RMSE of 0.51% for a one-week forecast period, demonstrating the model's accuracy. However, the research acknowledged the challenge of overfitting due to excessive dependence on training data, suggesting a need for further optimisation. Abdulsalam and Babatunde (2019) developed an electrical energy demand forecasting model for Lagos State, Nigeria, using an ANN approach. The model aimed to provide a reliable framework for energy planning and distribution. While specific numerical results were not detailed, the study reported a reduction in forecasting errors compared to conventional time-series models. The model's accuracy was limited by the lack of integration with real-time grid data, restricting its adaptability to sudden load variations. Musa and Mbaga (2014) presented a daily peak load forecasting technique using an ANN with seasonal indices. The model predicted daily peak loads with improved accuracy over traditional one-step-ahead predictions. However, specific numerical performance metrics were not provided, and the study's applicability may be limited by the exclusion of certain external factors affecting load demand. Abdulsalam (2016) developed a Recurrent Neural Network (RNN)-based model for forecasting electricity demand in Nigeria. The model correctly predicted total electricity consumption for the years 2001 to 2003 with a variance of 28%, equating to 72% accuracy. The study projected future demands, estimating 548,737 GWh for 2015, 597,811 GWh for 2020, 711,516 Gwh for 2030, and 927,476 GWh for 2050. The model's mean square error was reported as 2.21E-03. Limitations include potential inaccuracies in long-term projections due to unforeseen factors influencing energy consumption.

These studies demonstrate the efficacy of neural network approaches in forecasting electrical load within Nigeria. While significant progress has been made, challenges such as data quality, real-time forecasting integration, and computational demands persist. Future research should focus on hybrid models that combine Convolutional Neural Networks with other techniques, such as Long Short-Term Memory networks, to improve predictive accuracy and adaptability in dynamic power distribution environments.

2. Research Methodology

This research employs a quantitative approach utilising historical load data from 11 kV Distribution Network of Ado -Ekiti, Nigeria, to develop a mid-term load forecasting model. The research design follows a systematic methodology that encompasses data collection, preprocessing, model development, and validation phases. The study utilises five years of historical monthly load data from 2020 to 2024, collected from five distinct feeders within the network: Agric, Adebayo, Okesha, Ajilosun, and Basiri feeders.

The research framework, as illustrated in Figure 1, begins with data acquisition from the Benin Electricity Distribution Company (BEDC). The acquired data undergoes comprehensive preprocessing, including cleaning, normalisation using MinMaxScaler, and transformation into a supervised learning format using a sliding window approach. The pre-processed dataset is then split into training and validation sets, with 80% allocated for training and 20% for validation.

The core of the research design centres on developing a Convolutional Neural Network (CNN) model architecture optimised for multi-output regression. The model is designed to capture temporal patterns and relationships within the load data across all feeders simultaneously. The CNN architecture incorporates multiple layers, including convolutional layers for feature extraction, max-pooling layers for dimensionality reduction, and dense layers for final predictions.

Model evaluation is conducted using multiple performance metrics, including Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the Coefficient of Determination (R^2). The research design includes a robust hyperparameter tuning phase to optimise the model's performance, adjusting parameters such as the number of filters, kernel size, learning rate, and dropout rate. The final phase involves generating mid-term load forecasts for a one-year horizon using an iterative multi-step prediction approach.

The data structure is organised in a matrix format of dimensions (60, 6), where the 60 rows represent monthly observations over the five-year period, and the 6 columns consist of the temporal index (month) and the corresponding load demands for each of the five feeders.

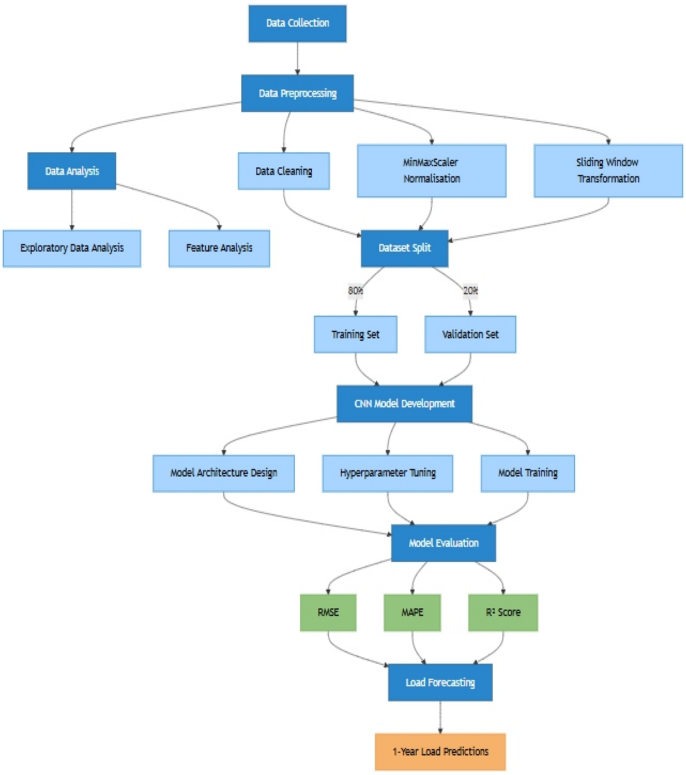

Figure 1: Research Design Framework

To ensure data quality and reliability, the raw data underwent preliminary screening for completeness and consistency. The dataset's structure allows for effective preprocessing and transformation into the format required for the CNN model implementation, particularly for the sliding window approach used in the forecasting methodology. The inclusion of multiple feeders in the dataset enables the development of a multi-output forecasting model that can simultaneously predict load demands across different segments of the distribution network. Figure 2 represents data Preprocessing and Analysis Architecture.

The data preprocessing and analysis phase is crucial for ensuring the quality and reliability of the load forecasting model. This phase involves multiple steps of data transformation and analysis, as illustrated in Figure 2.

Data normalization is implemented using the MinMaxScaler, which transforms the load values to a range of [0,1] using Equation 1.

$$X_{normalized} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

This normalization ensures all features contribute equally to the model and helps prevent numerical instabilities during training.

Figure 3 represents the Convolutional Neural Network (CNN) Architecture adopted for this research. The Convolutional Neural Network (CNN) model implemented in this research is specifically designed for multi-output time series forecasting of the Ado-Ekiti 11kV Distribution Network load demands. Table 1 represents the CNN Model Architecture. As illustrated in Figure 3 and Table 1, the model architecture comprises three main components: an input layer, feature extraction layers, and classification layers, all optimized to capture temporal patterns across all five feeders simultaneously

Table 1: CNN Model Architecture

Model	"sequential_2"	
Layer (type)	Output Shape	Param #
conv1d (Conv1D)	(None, 22, 64)	1,024
max_pooling1d (MaxPooling1D)	(None, 11, 64)	0
flatten (Flatten)	(None, 704)	0
dense_4 (Dense)	(None, 64)	45,120
dense_5 (Dense)	(None, 5)	325

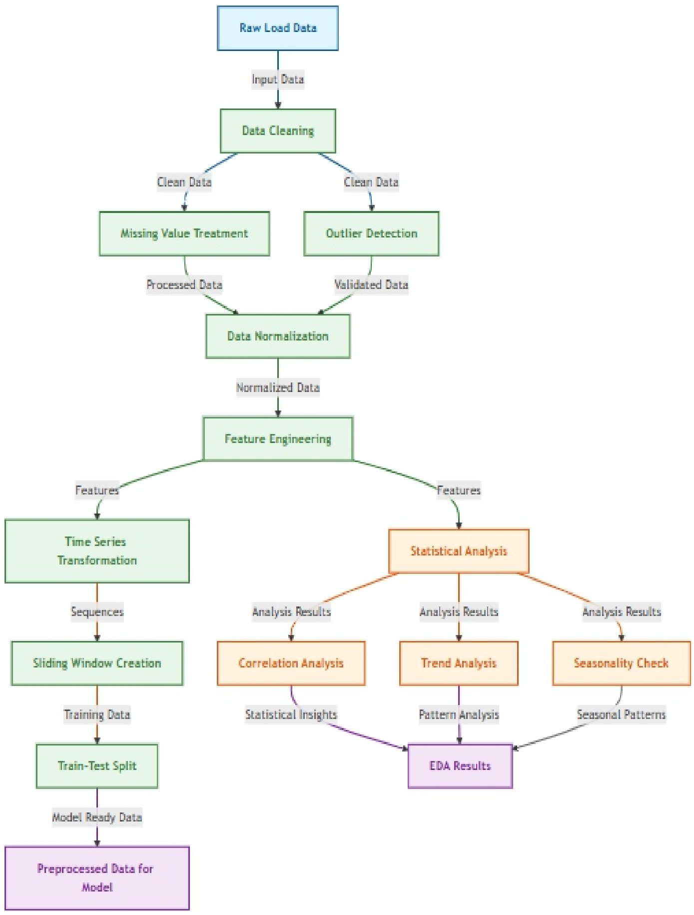

Figure 2: Data Preprocessing and Analysis Architecture

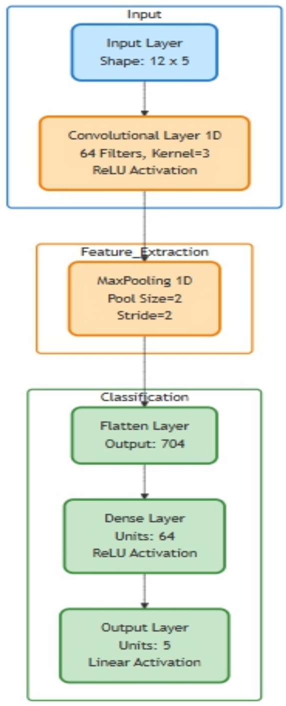

Figure 3: Research Adopted Convolutional Neural Network (CNN) Architecture

The input layer accepts sequences of 12 months of historical load data with a shape of (12, 5), representing time steps and features respectively. These features include normalized load values for all five feeders, providing a comprehensive representation of the network's historical load patterns. The feature extraction begins with a one-dimensional convolutional layer containing 64 filters and a kernel size of 3, employing ReLU activation to capture local temporal patterns in the load data. The kernel size selection allows the model to learn patterns across quarterly periods effectively. This is followed by a MaxPooling1D layer with a pool size of 2, which reduces dimensionality while preserving important features, thereby preventing overfitting and improving computational efficiency.

The classification section starts with a flatten layer that converts the 2D feature maps into a 1D vector of length 704. This is followed by a dense layer with 64 units and ReLU activation, which learns complex relationships between the extracted features. The architecture culminates in an output layer with 5 units (corresponding to each feeder) using linear activation for the regression task.

The model is compiled using the Adam optimizer with a learning rate of 0.001 and mean squared error as the loss function, while mean absolute percentage error serves as the primary metric for performance evaluation. To prevent overfitting, several regularization techniques are employed, including early stopping with a patience of 10 epochs, model checkpointing to save the best weights based on validation loss, and learning rate reduction on plateau with a factor of 0.1 and patience of 5.

The training process utilizes a batch size of 32 samples and runs for a maximum of 100 epochs, with 20% of the data reserved for validation. The training data is shuffled at the beginning of each epoch to ensure robust learning. For multi-step forecasting, the model employs an iterative prediction strategy where initial predictions are made using the last 12 months of actual data. The prediction window is then shifted forward by one month, incorporating the most recent prediction into the input sequence, and this process continues until the 12-month forecast horizon is reached.

3. Results and Discussion

The exploratory data analysis reveals several key insights about the load patterns across the five feeders in the Ado-Ekiti 11kV Distribution Network. Figure 4 presents the monthly load trends for all feeders from 2020 to 2024. As observed in Figure 4, all feeders exhibit similar temporal patterns, suggesting synchronised load behaviour across the network. The Ajilosun feeder consistently demonstrates the highest load demands, while the Okesha feeder typically maintains the lowest load profile throughout the period under study.

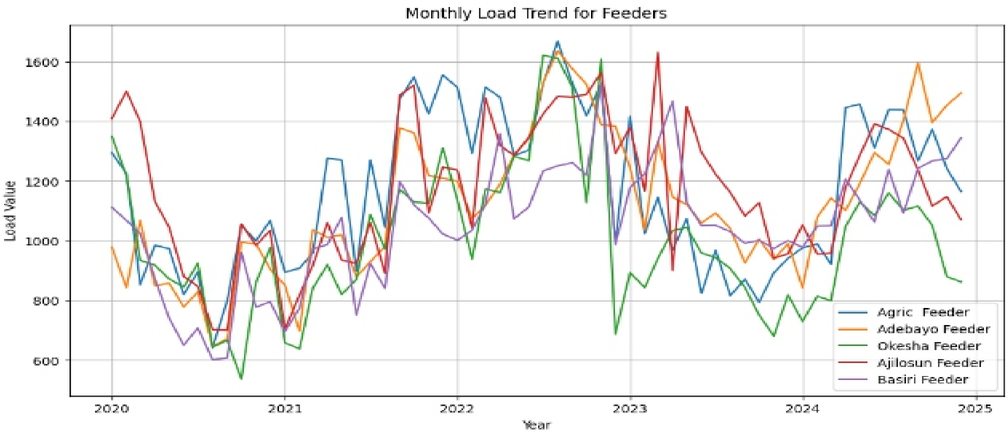

Figure 4: Ado-Ekiti Monthly Trend for Feeders

The correlation analysis amongst the feeders is presented in Figure 5.Figure 5 reveals strong positive correlations between all feeders, with correlation coefficients ranging from 0.75 to 0.92.

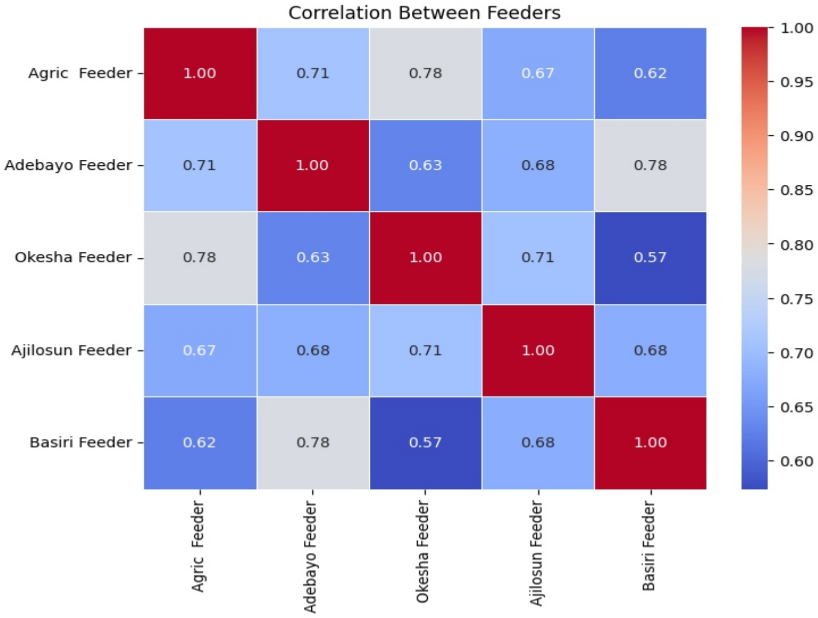

Figure 5: Correlation Analysis among Feeders

This strong correlation indicates that load changes in one feeder are likely to be reflected in others, suggesting similar consumption patterns across different areas of the distribution network. The rolling mean and standard deviation analysis is illustrated in Figure 6. The rolling statistics demonstrate relatively stable load patterns with seasonal variations

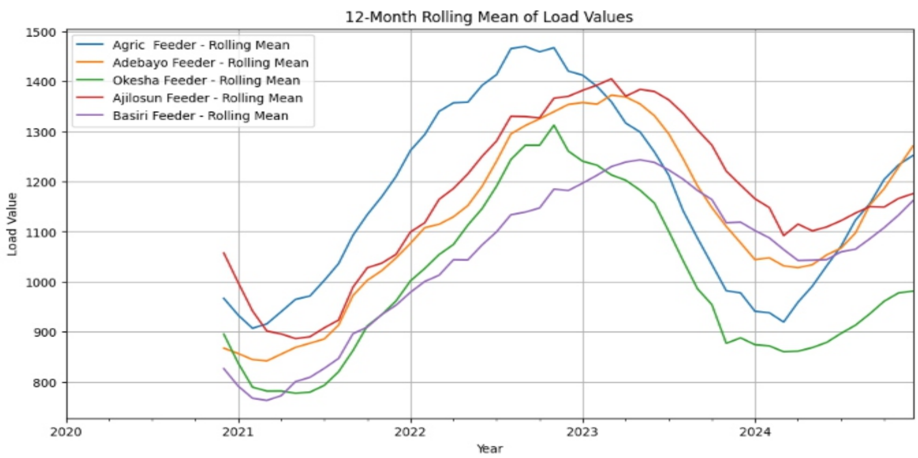

Figure 6: Rolling Mean and Standard Deviation

The standard deviation bands indicate higher variability during peak consumption periods, particularly in the Ajilosun and Agric feeders. This variation suggests these feeders serve areas with more dynamic load requirements.

The load distribution analysis is presented in Figure 7.The distribution plots reveal that most feeders exhibit slightly right-skewed distributions, indicating occasional high-demand periods above the typical operating range. This characteristic is particularly pronounced in the Ajilosun and Adebayo feeders, suggesting these areas experience more frequent high-load events.

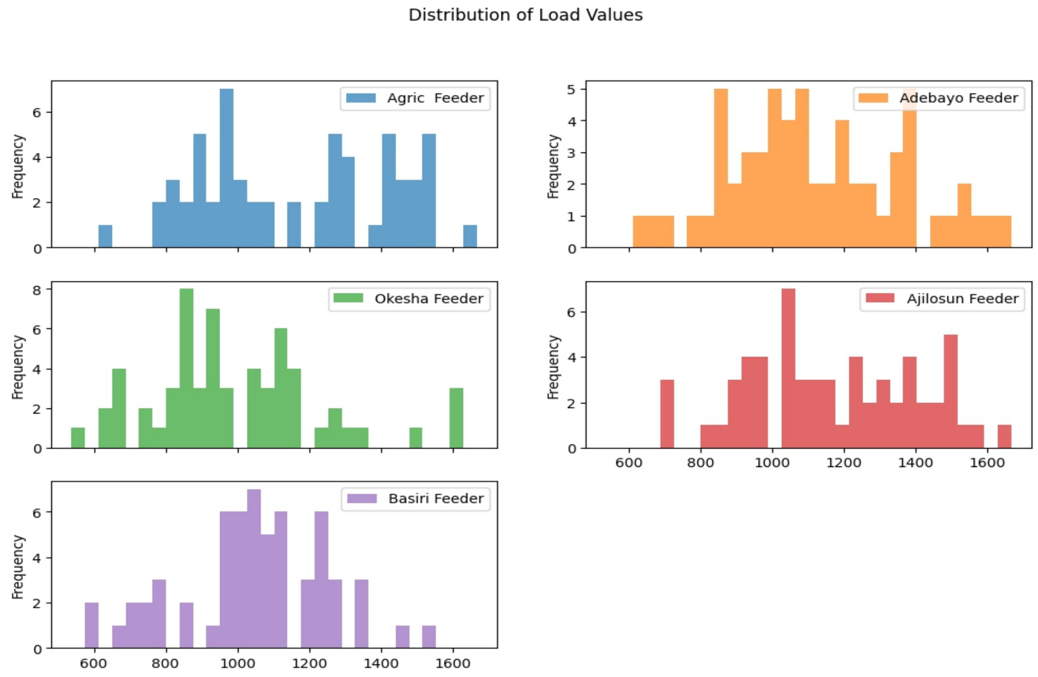

Figure 7: Load Distribution Analysis

The CNN model's performance was evaluated using three different configurations, with the results presented in Table 2. The model's performance improved significantly with hyperparameter tuning, as evidenced by the reduction in error metrics and improvement in the coefficient of determination. The hyperparameter-tuned model achieved an impressive RMSE of 0.0490, representing a substantial improvement over the base models with 12-month and 24-month sequence lengths.

Table 2: Model Training and Evaluation Result

Evaluation Metrics	12 Months Sequence	24 Months Sequence	Hyperparameter Tuned Model
Root Mean Squared Error (RMSE)	0.1730	0.1473	0.0490
Mean Absolute Percentage Error (MAPE)	25.0140%	21.3384%	10.0535
R^2 (Coefficient of Determination):	0.6763	0.7965	0.9420

The MAPE decreased from 25.0140% in the 12-month sequence model to 10.0535% in the tuned model, indicating enhanced prediction accuracy.

The R^2 value of 0.9420 for the tuned model demonstrates excellent goodness of fit, suggesting that the model captures approximately 94.20% of the variance in the load patterns. This represents a marked improvement from the 12-month sequence model (R^2 = 0.6763) and the 24-month sequence model (R^2 = 0.7965).

The one-year load forecast results are presented in Table 3.The forecasted values show a gradual declining trend across all feeders throughout 2025. The Ajilosun Feeder is predicted to maintain the highest load demands, ranging from 1,324.35 kVA in January to 1,183.71 kVA in December.

Table 3: 1 years Load Forecast for Ado-Ekiti 11 kV Network

	Agric Feeder (kVA)	Adebayo Feeder (kVA)	Okesha Feeder (kVA)	Ajilosun Feeder (kVA)	Basiri Feeder (kVA)
2025-01-01	1246.52	1246.90	1100.30	1324.35	1211.85
2025-02-01	1209.40	1231.55	1077.10	1298.36	1195.48
2025-03-01	1185.41	1213.36	1057.67	1278.53	1181.26
2025-04-01	1165.85	1196.07	1040.29	1261.47	1168.34
2025-05-01	1149.12	1180.53	1024.85	1246.41	1156.43

2025-06-01	1134.78	1166.85	1011.31	1233.13	1145.49
2025-07-01	1122.59	1154.94	999.61	1221.51	1135.52
2025-08-01	1112.32	1144.69	989.62	1211.40	1126.55
2025-09-01	1103.76	1135.94	981.18	1202.70	1118.57
2025-10-01	1096.70	1128.56	974.12	1195.26	1111.53
2025-11-01	1090.95	1122.38	968.29	1188.98	1105.39
2025-12-01	1086.32	1117.26	963.50	1183.71	1100.06

Conversely, the Okesha Feeder is projected to have the lowest load requirements, with values ranging from 1,100.30 kVA to 963.50 kVA over the same period.

This declining trend might be attributed to several factors, including:

I. Anticipated improvements in energy efficiency

ii. Projected changes in consumer behaviour such as more reliance in renewable energy sources

iii. Expected technological advancements in load management

iv. Possible shifts in industrial and commercial activities within the distribution network

The model's high R^2 value and low error metrics suggest these predictions are reliable, though they should be regularly validated against actual measurements as they become available. The discussion of findings and implications of the CNN-based load forecasting model for the Ado-Ekiti, Nigeria 11kV Distribution are discussed below.

The implementation of the CNN-based load forecasting model for the Ado-Ekiti, 11kV Distribution Network has yielded several significant findings with far-reaching implications for distribution network planning and operations. The model's exceptional performance, achieving an R^2 value of 0.9420 and MAPE of 10.0535%, demonstrates the potential of deep learning approaches in power distribution network planning and management.

The strong correlation observed among the feeders (correlation coefficients 0.75-0.92) reveals a crucial characteristic of the network's load behaviour. This synchronicity in load patterns across different geographical areas suggests that the network experiences coordinated demand fluctuations, likely driven by common factors such as business hours, weather conditions, and seasonal variations. Such understanding is vital for network operators as it implies that peak demands are likely to occur simultaneously across the network, requiring careful capacity planning and load management strategies.

The forecasted declining load trend for 2025 presents both opportunities and challenges for network management. This predicted trend, showing a consistent decrease across all feeders, may reflect anticipated improvements in energy efficiency, changes in consumer behaviour, or potential shifts in industrial and commercial activities within the distribution network's service area. The Ajilosun Feeder's sustained higher load profile, ranging from 1,324.35 kVA to 1,183.71 kVA, compared to other feeders, indicates potential areas for load balancing and infrastructure optimization.

The model's ability to capture both temporal and spatial aspects of load variations provides network operators with a powerful tool for proactive decision-making. The improved accuracy achieved through hyperparameter tuning, demonstrated by the significant reduction in RMSE from 0.1730 to 0.0490, enables more reliable long-term planning and resource allocation. This enhancement in prediction accuracy has substantial implications for maintenance scheduling, infrastructure investment planning, and operational efficiency.

The hierarchical load distribution pattern among feeders, consistently showing Ajilosun feeder with the highest demand and Okesha feeder with the lowest, suggests underlying socio-economic or infrastructural factors influencing energy consumption patterns. This understanding can inform targeted infrastructure development and customer engagement strategies. Furthermore, the right-skewed distribution observed in load patterns, particularly in Ajilosun and Adebayo feeders, indicates the need for robust contingency planning to handle occasional high-demand events.

The study successfully demonstrates the effectiveness of Convolutional Neural Networks (CNNs) in mid-term electrical load forecasting.

However, to better understand its strengths and weaknesses, a comparison with other models discussed in the literature review is necessary. Table 4 presents the comparative analysis based on key performance metrics.

Table 4: Comparative Analysis

Study & Model	Forecasting Horizon	RMSE	MAPE (%)	R^2 Value	Key Strengths	Key Weaknesses
Proposed CNN Model (This Study)	12 months	0.0490	10.05	0.9420	Captures spatial-temporal dependencies; High accuracy after hyperparameter tuning	High computational cost; No external variables considered (e.g., weather, economy)
Edoka et al. (2023) - LSTM	Short-term (100 time steps)	19.759	1.0	Not reported	Performs well for short-term load variations	Limited generalization due to dataset size
Ashigwuike et al. (2020) - ANN	Medium-term	Not reported	0.197	Not reported	Considers socio-economic factors	Does not incorporate real-time forecasting
Okelola et al. (2021) - ANN	Short-term (1 week)	0.51	Not reported	Not reported	Effective for short-term load forecasting	Overfitting risk due to excessive dependence on training data

Abdulsalam (2016) - RNN	Long-term (decades)	Not reported	Not reported	0.72	Suitable for long-term forecasting	Accuracy reduces significantly over time
Kong et al. (2024) - PCA-XGBoost-LSTM Hybrid	Short-term	67% lower RMSE than CNN alone	3.69% lower MAPE than CNN	Not reported	Feature selection and boosting improve accuracy	Does not integrate economic & social factors
Zghair& Issa (2025) - DNN with Simulated Annealing Optimization	Varying datasets	96.3% Accuracy	Not reported	Not reported	Highly optimized, hybrid CNN-DNN approach	High computational cost
Wang et al. (2025) - GAN for Small-Sample Forecasting	Short-term	Not reported	Not reported	Not reported	Effective when data is insufficient	Requires high computational resources

From the analysis of Table 4, the CNN model in this study outperforms many ANN and RNN-based models in terms of RMSE and MAPE, showcasing its ability to capture complex load dependencies. However, hybrid models like PCA-XGBoost-LSTM and DNN-based optimization models (Zghair& Issa, 2025) show potential for even better results.

CNN-based models require high computational resources, making them less feasible for real-time deployment compared to ANN-based models, which are faster and simpler. Furthermore, while CNN performs well for mid-term forecasting, LSTM and GAN-based models are better suited for short-term predictions, while RNNs can handle long-term forecasting but with reduced accuracy.

Additionally, many of the reviewed models incorporate additional socio-economic, weather, and policy-related variables, whereas this study relies solely on historical load data.

4. Conclusion

This research has successfully demonstrated the effectiveness of CNN architecture in mid-term electrical load forecasting for distribution networks. The developed model's high accuracy and reliability make it a valuable tool for distribution network planning and operations. The comprehensive analysis of load patterns and their correlations has provided crucial insights into network behaviour and interdependencies. The study succeeds in achieving highly accurate predictions, evidenced by the R^2 value of 0.9420, validates the chosen methodology and establishes a robust framework for future load forecasting applications. The identification of synchronized load patterns and their implications for network management represents a significant contribution to the field of distribution network planning.

The research also highlighted the importance of proper model tuning and data preprocessing in achieving reliable forecasts. The significant improvement in prediction accuracy through hyperparameter optimization demonstrates the potential for further enhancements in load forecasting techniques. These findings contribute to the broader understanding of deep learning applications in power distribution systems and provide a foundation for future research in this field.

Based on the technical findings of this research, it is recommended that the distribution company implements an automated data collection and model validation system. This should include regular model updates to incorporate new data, integration of weather and economic indicators into the forecasting framework, and establishment of systematic retraining protocols to maintain the model's high accuracy. These technical improvements will ensure the continued reliability and effectiveness of the load forecasting system.

From an operational perspective, the development of dynamic maintenance schedules informed by the predicted load patterns is crucial. The distribution company should establish comprehensive contingency plans for managing high-demand periods, implement strategic load balancing mechanisms between feeders, and introduce targeted energy efficiency programmes based on the identified consumption patterns across different network areas. At the strategic level, it is recommended that the distribution company fully integrates the forecasting model's outputs into their planning processes. This integration should drive infrastructure upgrade decisions, inform the development of comprehensive load management strategies, and guide the establishment of collaborative relationships with major consumers to better manage demand patterns. For future research and development, efforts should focus on exploring the integration of additional environmental and economic variables into the model, investigating hybrid approaches that combine CNN with other forecasting techniques, and developing enhanced capabilities for short-term load prediction. These advancements will further improve the model's accuracy and broaden its applicability for distribution network planning.

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