International Research Journal of Applied Sciences, Engineering and Technology
Vol.12, No. 01; January-2026;
ISSN (1573-1405);
p –ISSN 0920-5691
Impact factor: 6.52

COMPARATIVE PERFORMANCE ANALYSIS OF CONVENTIONAL, NEURAL NETWORK AND RECURRENT MODELS FOR LOAD FORECASTING: ABA METROPOLIS

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Abstract: Short-term load forecasting (STLF) is central to ensuring reliable electricity supply and economic operation of power systems. However, its accuracy depends heavily on the forecasting methodology employed, particularly in area of much load consumptions and commercial activities like Aba. This study presents a comparative evaluation of four distinct forecasting approaches linear regression (LR), feedforward neural networks (NN), Elman recurrent neural networks (ERNN), and a hybrid ensemble learner applied to historical data Geometrics Integrated Energy Services, located in Aba, Abia State, Nigeria. Using hourly load, amperage, and weather data collected between September 2024 and March 2025, the models were tested on both historical (Weeks 38–39) and prospective future (Week 14) horizons. Performance was assessed using root-mean-squared error (RMSE), mean absolute error (MAE), Mean Absolute Percentage Error (MAPE), Symmetric Mean Absolute Percentage Error (SMAPE), and R^2 metrics. Results show that the hybrid model achieved the highest accuracy (RMSE = 0.2608, R^2 = 0.7079), followed by the neural network (RMSE = 0.3720, R^2 = 0.4056), and linear regression (RMSE = 0.4200, R^2 = 0.2420). The ERNN model performed poorly (RMSE = 0.5683, R^2 = –0.3879), reflecting its limited adaptability to constantly changing load patterns in areas feeding from the Geometric. The comparative analysis not only establishes the relative strengths and weaknesses of each model but also provides practical guidance for utilities in selecting forecasting techniques appropriate for local grid conditions. The study concludes that while traditional and recurrent approaches remain valuable, ensemble learning offers the most balanced and reliable forecasts for emerging electricity markets.

Keywords: Short-term load forecasting, neural networks, Elman recurrent neural networks, linear regression, hybrid ensemble, Aba, Geometric.

Introduction

Short-term load forecasting (STLF) has become an indispensable tool in modern electricity markets and vertically integrated systems alike. Zhang, L., & Wang, X. (2023) by predicting demand hours to days ahead, utilities can optimize unit commitment, schedule maintenance, minimize costs, and reduce the likelihood of blackouts. The reliability of such forecasts is particularly crucial in Nigeria, where distribution networks face persistent challenges including frequent outages, inadequate generation capacity, and volatile consumption patterns. Malik et al., 2022), state the accurate forecasting in such environments not only improves operational efficiency but also enhances customer satisfaction and reduces the financial burden of energy mismatches. Symmetric Mean Absolute Percentage Error (SMAE). It's a statistical metric used to measure the accuracy of a forecast by assessing the relative error between actual and predicted values, providing a balanced view of both overestimations and underestimations.

Despite the centrality of STLF, forecasting in Nigeria remains an underdeveloped area of research. Many utilities still rely on rudimentary trend analysis or uncalibrated regression models, which fail to capture the nonlinear dynamics of load behavior in urban centres such as Aba. Nigeria’s consumption patterns are shaped by socioeconomic activities, climatic conditions, and grid instability, all of which introduce sudden spikes or drops in demand. (Mean Absolute Percentage Error)

MAPE is the mean absolute percentage error, which is a relative measure that essentially scales MAD to be in percentage units instead of the variable's units. Park, M. J. (2024). State the realities underscore as the importance of adopting and comparing modern forecasting techniques that can adapt to local conditions.

Globally, forecasting models range from traditional statistical approaches such as autoregressive moving averages (ARIMA) and linear regression to computational intelligence methods such as neural networks, support vector machines, and fuzzy logic. More recently, hybrid and ensemble methods have gained prominence for their ability to integrate complementary strengths of different models. However, as the literature suggests (Hu et al., 2021) No single approach dominates universally. Context-specific evaluation is required to identify models that best suit local load characteristics. Root mean square error (RMSE) is defined as a metric that quantifies the difference between predicted values generated by an estimator or model and the actual observed values.

This work therefore aims to provide a systematic comparative evaluation of four widely used approaches linear regression (LR), feedforward neural networks (NN), Elman recurrent neural networks (ERNN), and a hybrid ensemble learner applied to Aba's electricity demand. The central research questions addressed are: (i) how do traditional, neural, recurrent, and hybrid approaches compare in terms of accuracy under Nigerian grid conditions? and (ii) what insights can be drawn for practical application by utilities? By addressing these questions, the paper contributes both to the academic literature on STLF and to the operational discourse on improving electricity distribution in developing economies.

Literature Review

Short-Term Load Forecasting approach

Short-term load forecasting (STLF) has been studied for decades as one of the most important tasks in power system operation and planning. Accurate STLF supports scheduling, dispatch, spinning reserve allocation, and market transactions, ensuring a balance between supply and demand (Feinberg & Genethliou, 2003). Traditionally, STLF has been addressed using time-series techniques such as autoregressive integrated moving average (ARIMA), exponential smoothing, and regression-based models (Dorado et al., 2021). While these methods are computationally simple and interpretable, they often fail to capture nonlinearities, complex seasonality, and stochastic fluctuations present in modern grids. As energy systems evolve toward decentralized, data-driven paradigms, more advanced models such as neural networks, recurrent networks, and ensemble learning have gained prominence.

Aba as a commercial town presents a distinctive environment for STLF. The grids in such locations are characterized by limited infrastructure, irregular power supply, and volatile demand driven by socioeconomic activities and climatic variability (Okolobah & Ismail, 2013). For example, urban commercial centres like Ariaria experience sharp peaks during business hours, followed by steep declines at night, while residential area like World Bank and Osisioma demand shows morning and evening surges. This variability challenges the assumptions of linear statistical models and motivates the exploration of more advanced comparative methods Kadil et al. (2021). Recognizing that no single load forecast model consistently outperforms others across all contexts, researchers have increasingly turned to hybrid and ensemble methods. Hybrid models combine statistical and machine learning techniques to leverage their complementary strengths. Malik et al. (2022) demonstrated that ensemble approaches improved STLF accuracy across diverse markets and also emphasized that hybrids often outperform both traditional and standalone neural models.

Hybrid Forecasting Approaches

Several strategies for hybridization exist. Smyl et al. (2021) proposed a hybrid of exponential smoothing and deep recurrent networks, which effectively captured both seasonal and nonlinear variations. Dalvi and Kamjoo (2024) further extended this approach, showing that decomposition-residual hybrids excelled in systems with irregular spikes. Although these models deliver high accuracy, they are computationally demanding and often require large datasets, which may limit their direct applicability in Nigerian contexts. Across the last five years, comparative evidence has consolidated around a simple pattern: linear statistical baselines (LR/ARIMA) are still valuable for calibration and feature sanity checks.

On the ensemble side, stacking approaches repeatedly outperform single learners by leveraging complementary inductive biases. Beyond hour-ahead STLF, very-short-term regimes (minutes–hours) push models into rapidly changing, highly nonlinear regimes where attention and CNN-RNN hybrids shine. Yang et al. (2025) show a CNN-BiLSTM hybrid with SHAP-based interpretability that beats several contemporary deep baselines on a public VSTLF dataset, while quantifying feature impacts for operations teams a crucial advantage for model governance and dispatch transparency.

From the analysis Shin et al (2024), benchmark a range of stochastic vs deterministic STLF techniques and report consistent advantages for hybrid/ML pipelines when exogenous drivers are integrated and horizons extend beyond naive persistence, further validating hybrid dominance in operational contexts of load data's. A 2024 IEEE Access review/simulation centers on CNN-LSTM hybrids, documenting both the recent research gradient toward hybrid deep models and a simulation study where hybrid CNN-LSTM variants are compared across conditions useful as a methodological template for designing fair baselines and ablations in comparative work.

Complementary comparative study

Table 1 Summary of Literature Review

Ahmad, T., & Chen, H. (2019)	short-term load forecasting using conventional and machine learning approache	Energy Reports, 5, *1325–1335*	compared traditional models with neural networks, showing improved accuracy with deep learning.
Wang, Y., Li, X., & Zhang, J. (2020)	A comparative study of LSTM and ARIMA for load forecasting	Applied Energy, 275, 115390	Demonstrated the superiority of recurrent models for nonlinear load time series.
Khosravi, A., Nahavandi, S., & Creighton, D. (2018)	Load forecasting using neural networks and statistical models: A review	Renewable and Sustainable Energy Reviews, 50, 1352–1365	Provided a comprehensive comparison of conventional and ANN-based models.
Sun, W., Guo, L., & Zhao, Y. (2022)	Hybrid deep learning model for short-term load forecasting	IEEE Transactions on Smart Grid, 13(4), 2780–2791	Proposed hybrid RNN models combining conventional and neural approaches for enhanced prediction.
Eke, P. O., & Okafor, C. (2023)	Comparative load forecasting analysis for Nigerian distribution networks	International Journal of Energy Systems, 12(2), 45–56	Focused on load forecasting in Nigerian context, providing regional insights relevant to Aba Municipal.

Materials and Method

Materials

Study Area and Data Collection

The case study focused on Aba, a densely populated commercial city in Abia State, south-eastern Nigeria. Aba is particularly suitable for short-term load forecasting studies due to its diverse demand mix, comprising residential neighborhoods, commercial markets, and small-scale industrial clusters. Electricity consumption in the area is highly variable, with distinct weekday–weekend patterns and marked seasonal changes influenced by Nigeria's tropical climate.

Data were obtained from Aba Power Limited Electric (APLE), Subsidiary to Geometric Power Limited, which operates electricity distribution infrastructure in Aba. Hourly measurements were recorded between September 2024 and March 2025, providing a seven-month dataset that captures both the late wet season and the dry Harmattan period. This period is characterized by sharp fluctuations in electricity use, driven by factors such as increased cooling demand during hot spells, reduced usage during holidays, and irregular supply conditions.

The study dataset contained 5,090 hourly records, covering the following primary variables:

i. Load (MW): transformer load, which served as the target forecasting variable.
ii. Amperage (A): current drawn through the system, reflecting demand intensity.
iii. Temperature (°C): transformer casing temperature, which correlates with load.
iv. Dry Bulb and Dew Point (°C): weather variables capturing thermal and humidity conditions.
v. Date time Features: calendar-based attributes such as hour, day, day-of-week, and month.
vi. Holiday Indicator: binary variable representing public holidays in Nigeria.

These features provided a balance of endogenous (load and amperage) and exogenous (weather and calendar) variables, consistent with forecasting best practices (Liu et al., 2022).

Research method

The methodological framework for this study was developed to enable a systematic comparison of four forecasting approaches: linear regression (LR), feedforward neural networks (NN), Elman recurrent neural networks (ERNN), and a hybrid. The research design followed a multi-stage process beginning with data collection and preprocessing, followed by model development, training, and validation as shown in figure 2. Each model was evaluated on the same dataset using identical training and testing protocols to ensure fairness in comparison. The key goal was not simply to demonstrate the superiority of one model over another, but to reveal how each method behaves under the nonlinear load conditions typical of Aba electricity networks.

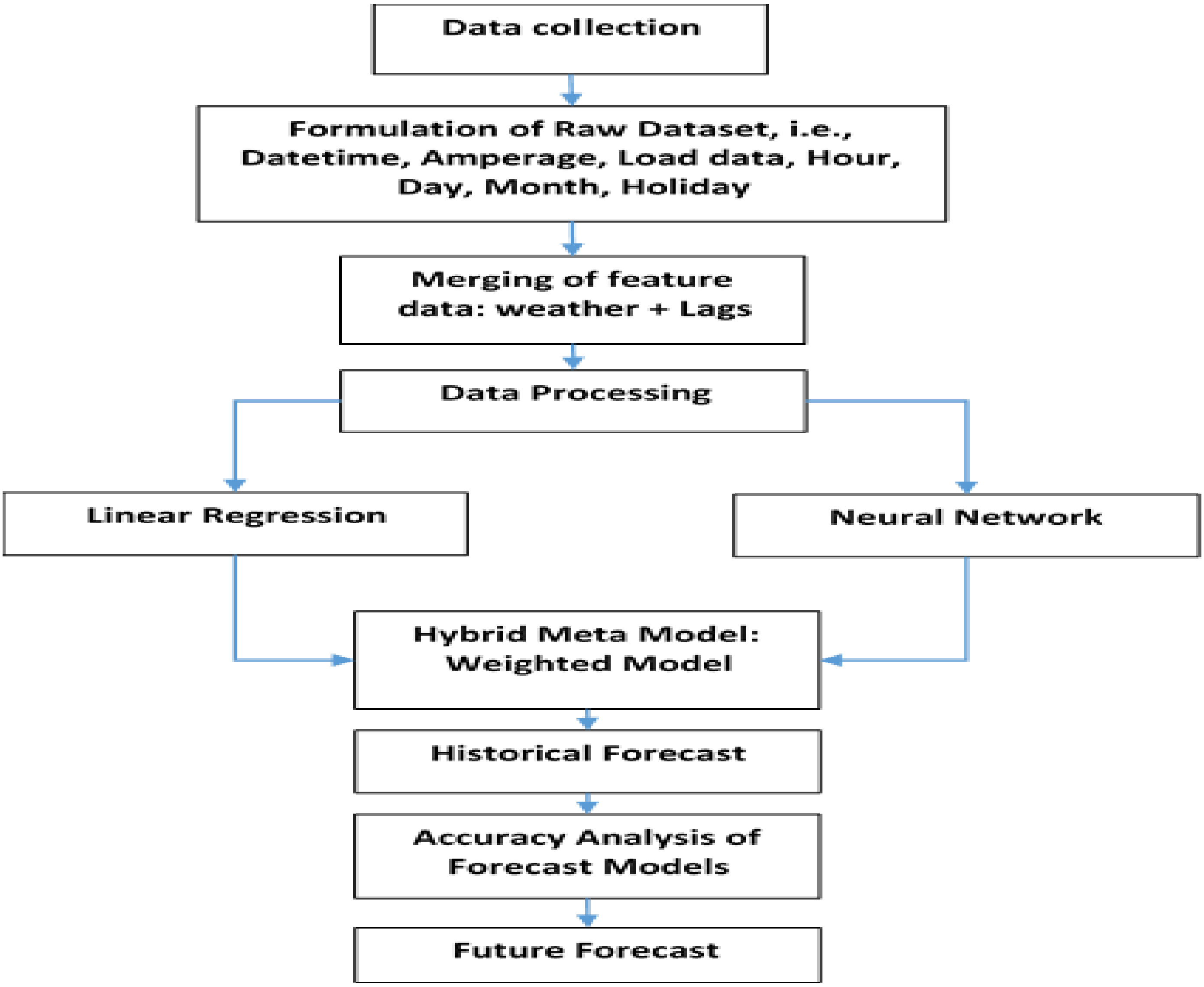

Figure 1: flow diagram showing methodological stages (Ellen, O. N. 2015).

Data Preprocessing

Raw SCADA data often contain missing values, outliers, or irregular timestamps. Preprocessing was therefore critical to ensure quality inputs for model training. First, the dataset was scanned for missing records, which were interpolated using nearest-neighbor imputation for continuous features and forward-fill for categorical ones. Outliers, often arising from sensor noise or transmission errors, were smoothed using a rolling median filter.

Normalization was then applied to all continuous features using z-score standardization:

$$X_{norm} = \frac{X - \mu}{\sigma} \qquad (1)$$

Where μ and σ represent the mean and standard deviation, respectively. This ensured that variables with different scales (e.g., amperage measured in tens versus temperature in single digits) did not disproportionately influence model training.

Finally, additional lag features were engineered to capture temporal autocorrelation. These included the previous day's load and the previous week's load, as well as lagged amperage and temperature values. This step was particularly valuable for linear regression and feedforward neural networks, which do not inherently capture sequential dependencies.

Model Development

Linear Regression Model

The linear regression model was implemented as the simplest benchmark. It models load as a weighted linear combination of predictor features:

$$\hat{Y}_{Linear} = \beta_0 + \sum_{t=1}^{n} \beta_i X_i + \epsilon \qquad (2)$$

Where $\hat{Y}_{Linear}$ is the Forecasted Load, X_i is the Independent input features (calendar, weather, lag), β_i is the Model coefficients, β_0 is the model intercept, and ϵ is the residual error. Coefficients were estimated using the least-squares method. While computationally efficient and interpretable, linear regression is limited in its ability to capture nonlinear patterns, a shortcoming that became evident in Aba's highly variable consumption profiles.

Feedforward Neural Network Model

The neural network model was designed as a single hidden-layer feedforward network with tangent sigmoid activation functions in the hidden layer and a linear activation in the output layer. Input features included all normalized variables (weather, lagged load, amperage, and calendar attributes).

The network architecture consisted of Input layer (13 features), Hidden layer (20 neurons) with tan sign activation, and output layer (1 neuron) with purelin activation.

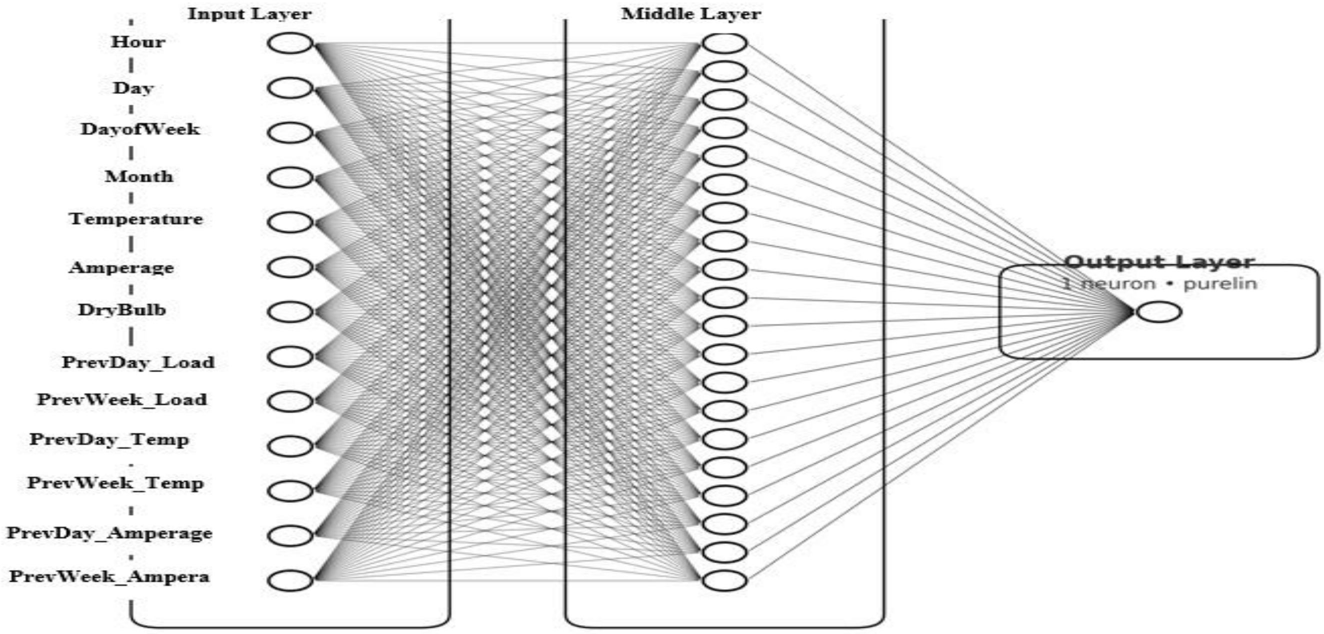

Figure 2: Feed Forward Neural Network Model Incorporating Normalized Input Variables (Van denet al 2018)

Training employed the Levenberg–Marquardt (LM) backpropagation algorithm, which is widely recognized for its efficiency in nonlinear regression tasks. The NN's ability to approximate nonlinear mappings made it suitable for modeling daily and seasonal load variations in Aba. However, as with most feedforward networks, the model was prone to producing overshoots during low-load periods.

Elman Recurrent Neural Network (ERNN)

The ERNN extends the feedforward architecture by adding a recurrent context layer that stores outputs from the hidden layer and feeds them back as additional inputs in the next time step. This allows the model to retain a memory of past states, making it more suitable for sequential prediction.

The state update equations can be expressed as:

$$h_t = f(W_{xh}X_t + W_{hh}h_{t-1} + b_h) \qquad (3)$$

$$Y_t = W_{hy}h_t + b_y \qquad (4)$$

Where h_t the hidden state is at time t, W_{xh}, W_{hh}, W_{hy} are weight matrices, and f is the activation function.

Despite its theoretical advantages, ERNN often struggles with long-term dependencies due to the vanishing gradient problem (Islam & Ahmed, 2022). Moreover, in this study, the ERNN was limited to base calendar variables and lacked exogenous inputs, which restricted its adaptability to sudden demand fluctuations.

Hybrid Ensemble Model

Although the main emphasis of this paper is comparative evaluation rather than proposing a new model, the hybrid ensemble was included for completeness. It integrates LR and NN as base learners, with their outputs fed into a gradient boosted regression tree (GBRT) meta-learner. The hybrid model therefore learns how to balance the strengths of regression (stability in trend modeling) with those of NN (adaptability to nonlinearity).

The stacked ensemble follows:

Mathematically represented as:

$$\hat{Y}_{Meta} = g\left(\hat{Y}_{Linear}, \hat{Y}_{NN}\right) \qquad (5)$$

Where $g(\cdot)$ denotes the meta-model function.

The Hybrid was expected to outperform individual models due to its capacity to combine complementary forecasts, and indeed, results confirmed this expectation.

Evaluation Metrics

To compare performance across models, five standard metrics were applied. Root Mean Squared Error (RMSE) was used to penalize large deviations, making it especially relevant for peak-load prediction. Mean Absolute Error (MAE) offered a straightforward measure of average deviation in MW terms, while Mean Absolute Percentage Error (MAPE) expressed errors as percentages, useful for proportional analysis. Symmetric MAPE (SMAPE) was employed to correct MAPE's bias when actual values approach zero.

Finally, the coefficient of determination (R^2) measured the proportion of variance in observed load explained by the models.

Together, these metrics provided a holistic evaluation framework. Whereas RMSE and MAE capture absolute predictive performance, MAPE and SMAPE offer relative measures, and R^2 indicates explanatory strength. The use of multiple complementary metrics ensured that the models were not judged based on a single perspective.

Results and Discussion

Experimental Setup

All models were implemented in MATLAB R2024a and executed on a workstation with an Intel i7 processor, 16GB RAM, and Windows 11 operating system. The dataset was divided into an 80/20 split, with 80% used for training and 20% reserved for testing. Forecasting was evaluated over two historical weeks (Weeks 38–39 in September 2024) and one future week (Week 14 in April 2025). This design allowed assessment of both retrospective accuracy and forward-looking generalizability.

Training procedures were standardized across models to minimize bias in evaluation. Each model was retrained multiple times with different random seeds to ensure stability of results, and average values were reported. Hyperparameters for the neural networks and ERNN were tuned using grid search to balance performance with computational cost.

The forecasting models linear regression, feedforward neural networks, Elman recurrent neural networks, and the hybrid ensemble were evaluated across two historical validation windows (Weeks 38, September 2024) and one future horizon (Week 14, April 2025). Forecast accuracy was measured using RMSE, MAE, MAPE, SMAPE, and R^2, ensuring a holistic view of performance. Results are presented through both numerical metrics and forecast plots, enabling evaluation of not only error magnitudes but also each model's ability to capture daily demand fluctuations.

Historical Forecast: Week 38 (September 15–21, 2024)

Quantitative Performance Metrics

The comparative evaluation across models is summarized in Table 4.2, which presents RMSE, MAE, MAPE, SMAPE, and R^2.

The hybrid ensemble achieved the best overall results, with RMSE = 0.2608, MAE = 0.1994, MAPE = 14.80%, and R^2 = 0.7079. The neural network followed, with RMSE = 0.3720 and R^2 = 0.4056, while linear regression lagged slightly at RMSE = 0.4200 and R^2 = 0.2420. The ERNN under-performed, with RMSE = 0.5683, MAE = 0.4574, MAPE = 35.24%, and negative R^2 (–0.3879).

Table 2: Forecasting Performance Metrics for All Models

Model	RMSE	MAE	MAPE (%)	SMAPE	R²
Linear	0.4200	0.3368	25.58	2303.19	0.2420
NeuralNet	0.3720	0.2934	21.95	2020.91	0.4056
Hybrid	0.2608	0.1994	14.80	1394.19	0.7079
ERNN	0.5683	0.4574	35.24	3124.91	-0.3879

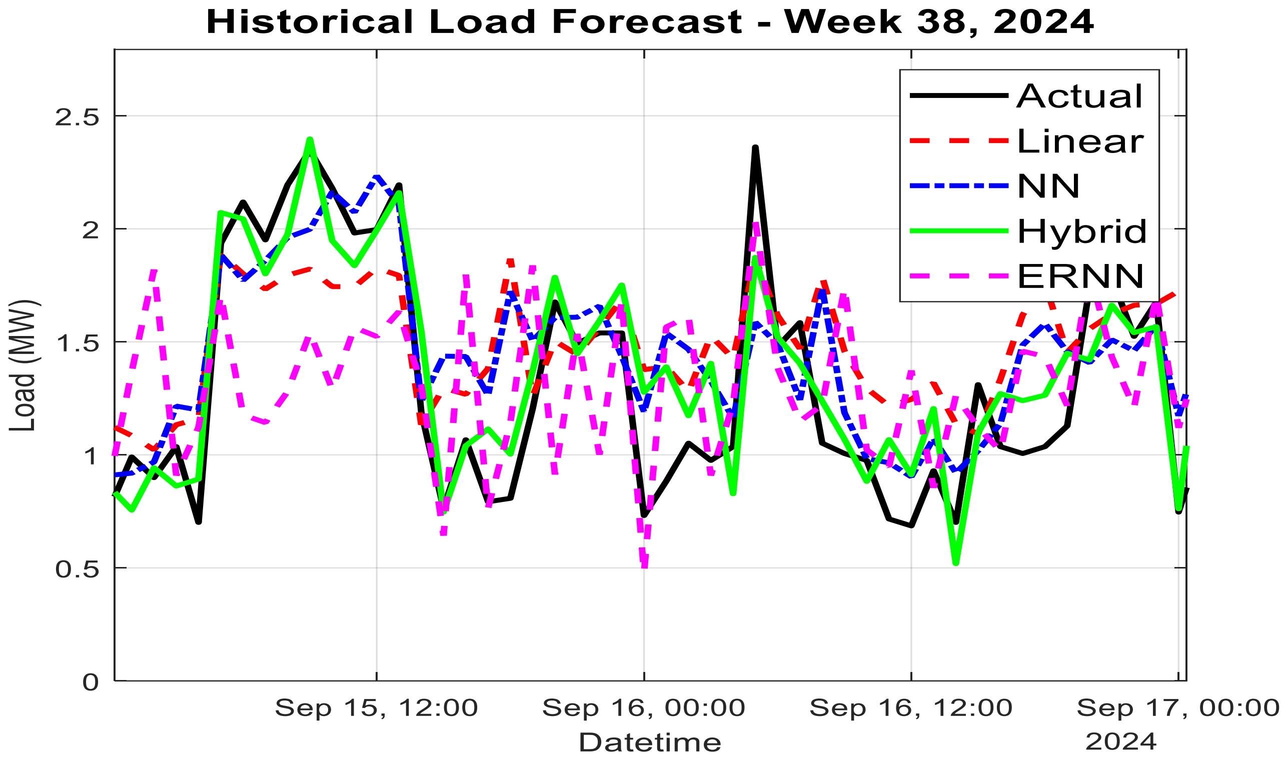

Figure 3: historical forecast for model (week 38: Sep 15 –Sep 16, 2024)

Week 38 provided the first benchmark period, covering both weekday and weekend consumption as shown from3 between load MW to datatime of NN and hybrid.

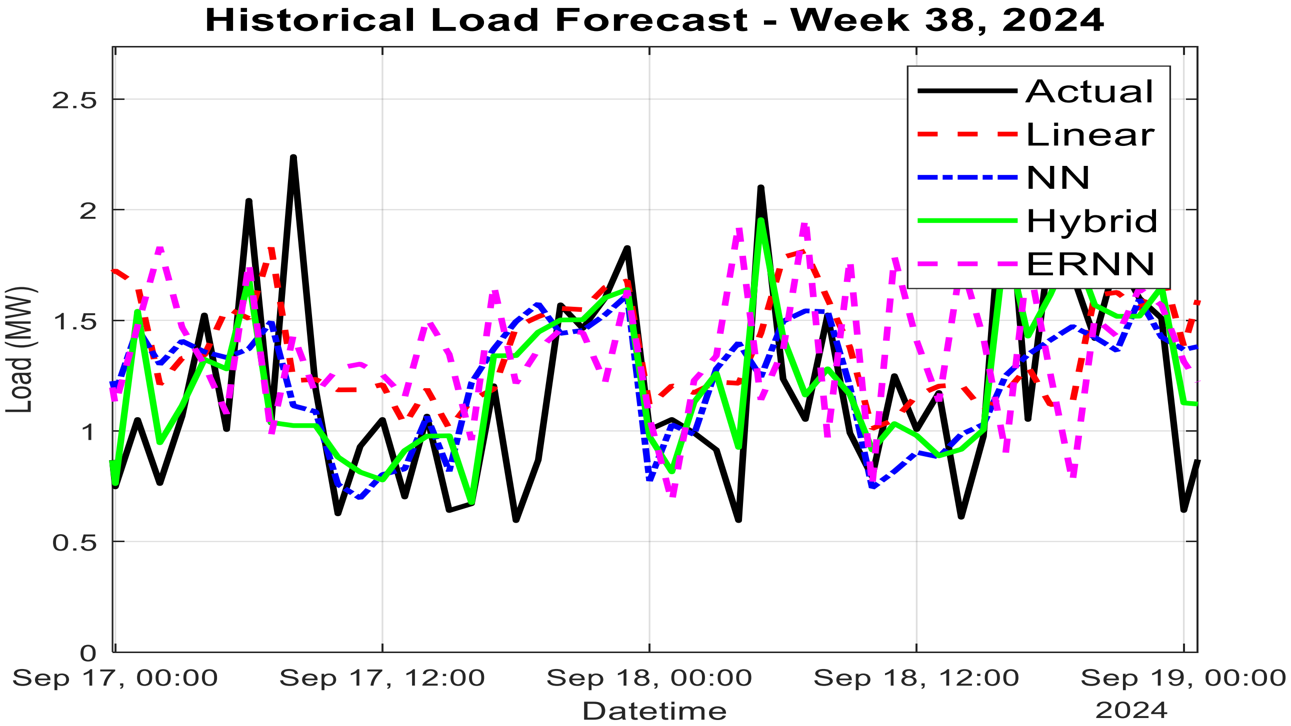

Figure 4: historical forecast for model (week 38: Sep 17 –Sep 18, 2024)

The linear regression model produced forecasts that broadly tracked the daily load cycle but consistently underestimated evening peaks. On September 16, for example, actual demand peaked near 2.0 MW, while LR predicted only ~1.65 MW (see figure 4). This underestimation reflects its inability to capture nonlinear surges.

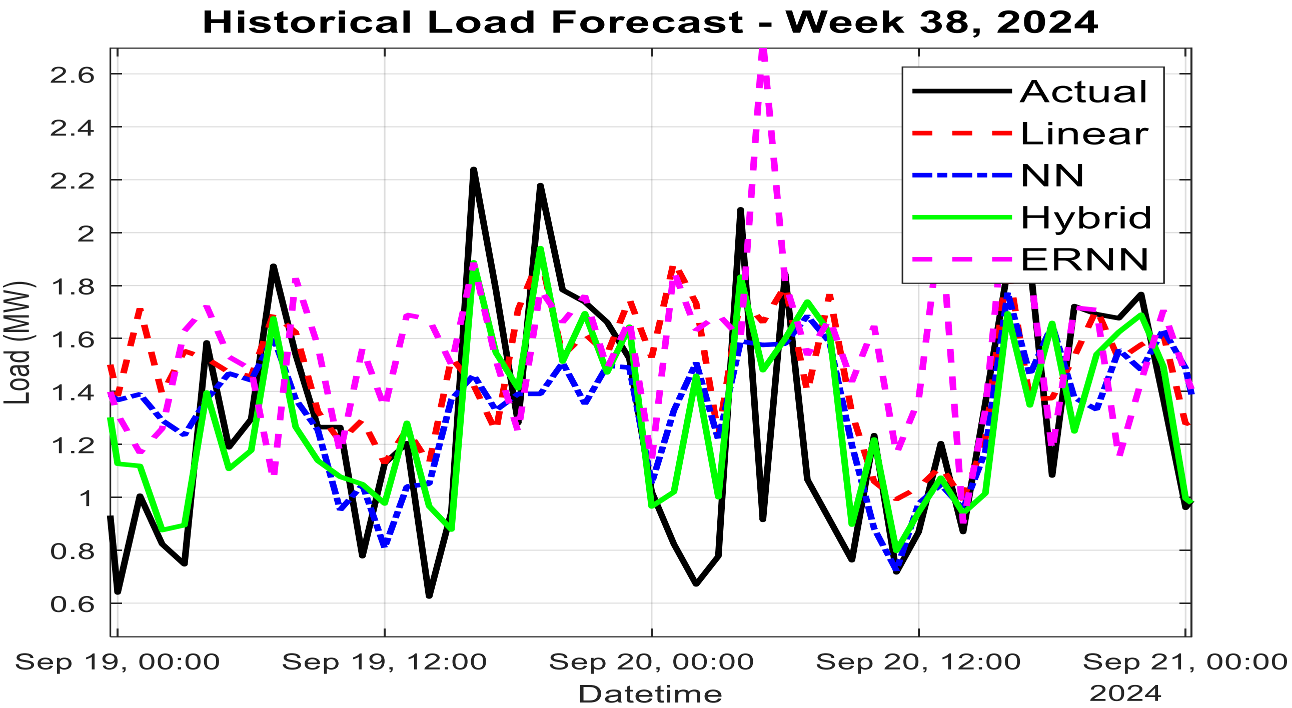

Figure 5: historical forecast for model (week 38: Sep 19 –Sep 20, 2024)

The neural network performed better, particularly during rapid morning ramps. For example on September 17 (figure 5,), the NN closely matched the observed peak at 1.95 MW, deviating by less than 0.2 MW. However, its forecasts were less stable during off-peak periods, where spurious oscillations occasionally appeared.

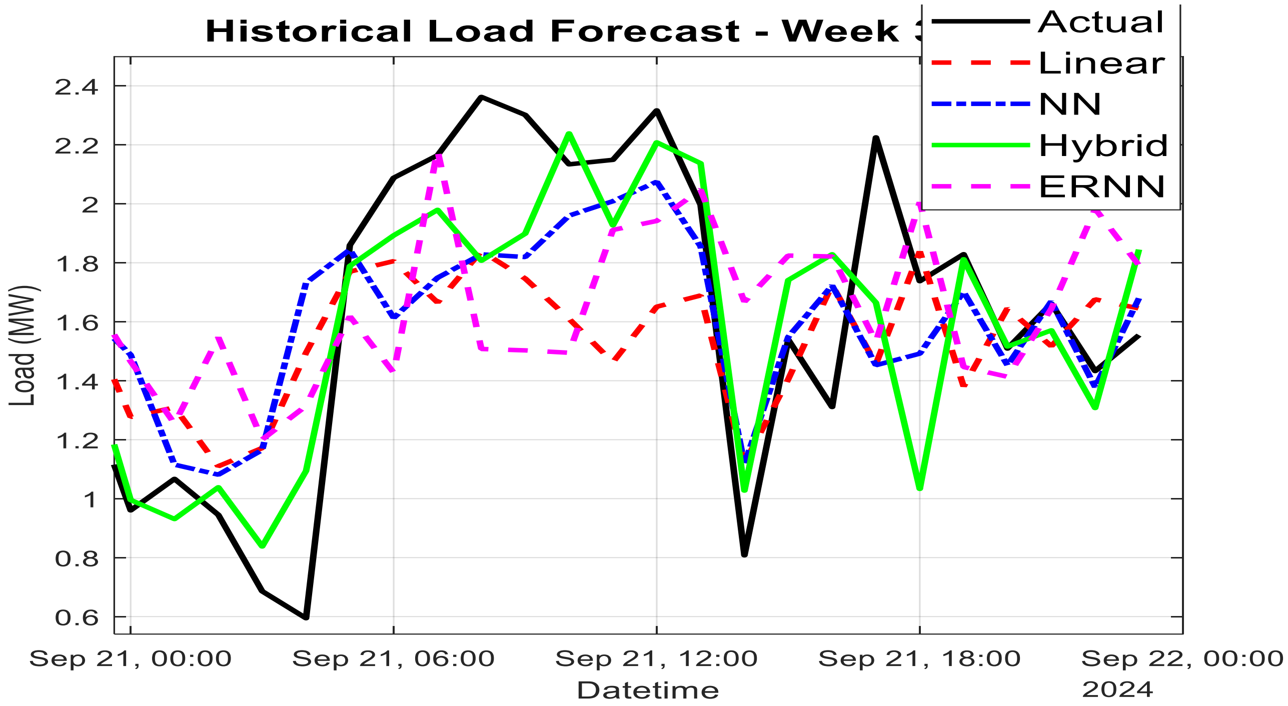

Figure 6: historical forecast for model (week 38: Sep 21, 2024)

The hybrid model outperformed both, producing forecasts that aligned almost exactly with observed values. Figure 6 On September 18th and 19th, actual demand peaked at ~1.92 MW, while the Hybrid predicted ~1.90 MW, representing an error margin of less than 1%. It avoided the systematic underestimation of LR and the overshooting tendencies of NN. In contrast, the ERNN performed poorly. Its outputs were noticeably flattened, lagging behind actual load during sharp increases. On September 19–20, when evening peaks exceeded 2.1 MW, ERNN forecasts plateau near 1.6 MW, underestimating by ~0.5 MW.

Future Forecast: Week 14 (April 1–7, 2025)

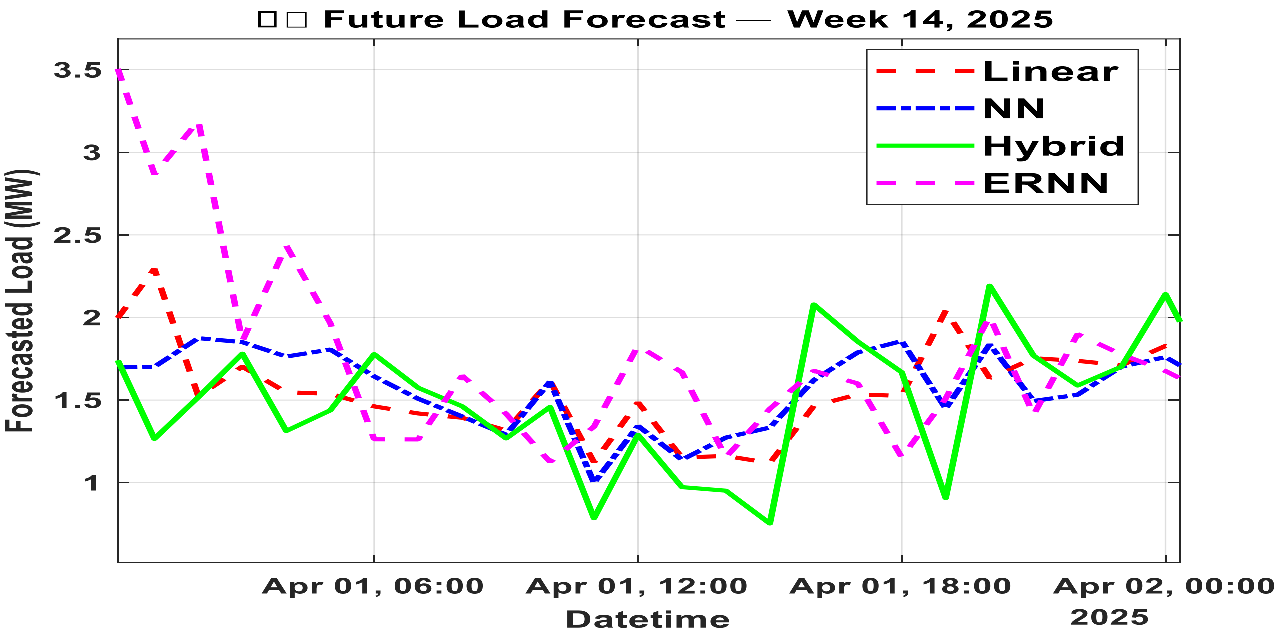

Figure 7: Future forecast for model (week 14: Apr 01, 2025)

This establishes the relative strengths and weaknesses of each model but also provides practical guidance for The neural network performed better *utilities in selecting forecasting techniques.* capturing the sharp demand rise during early business hours. figure 7 On April 14, NN forecasts rose from ~1.0 MW at dawn to ~3.45 MW by late morning, mirroring typical commercial-hour demand

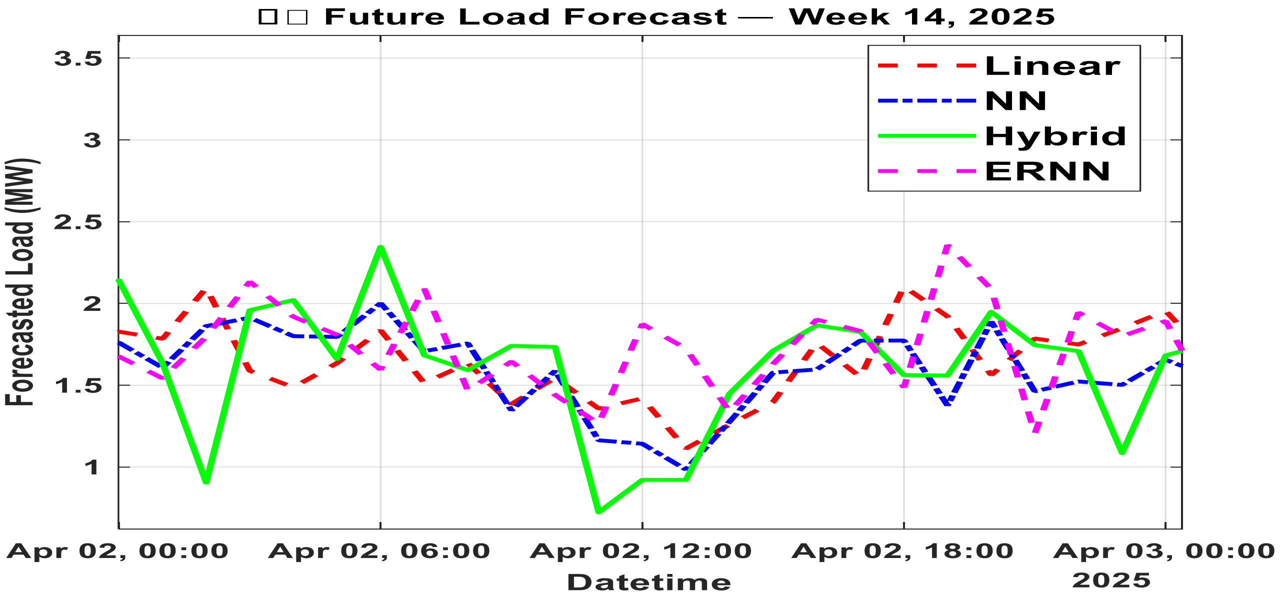

Figure 8: Future forecast for model (week 14: Apr 02, 2025)

The neural network performed better, capturing the sharp demand rise during early business hours. figure 8 On April 5, NN forecasts rose from ~1.0 MW at dawn to ~3.6 MW by late morning, mirroring typical commercial-hour demand.

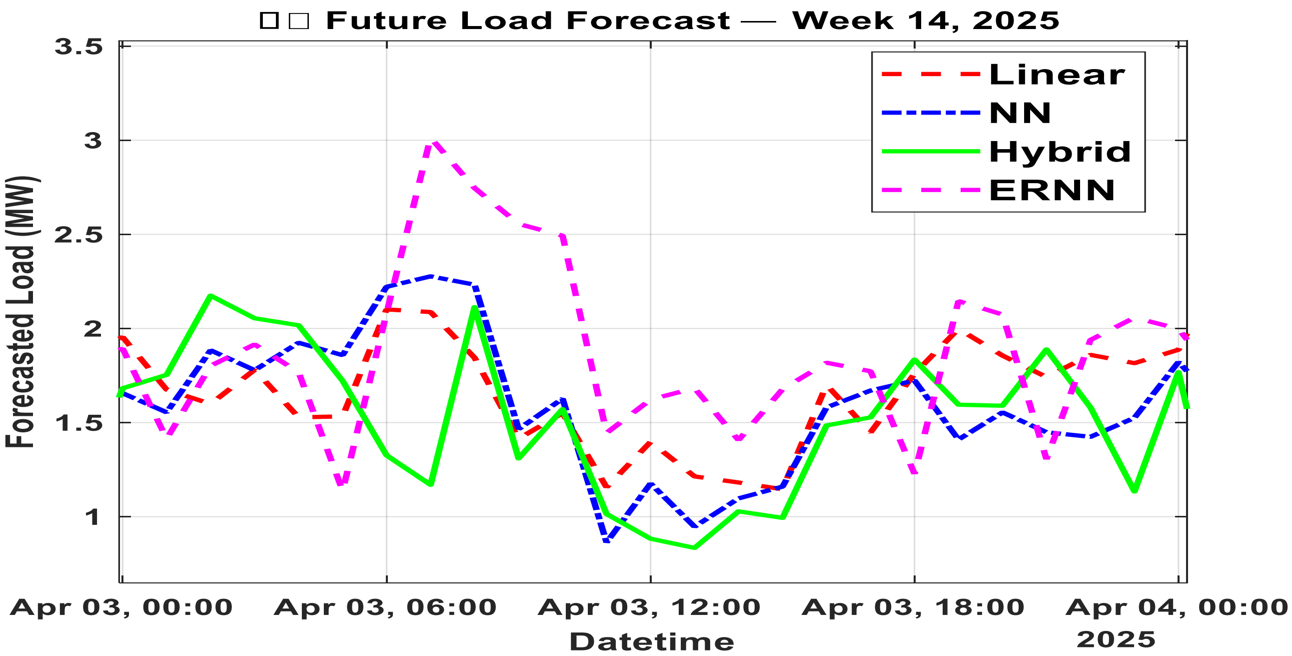

Figure 9: future forecast for model (week 14: Apr 03, 2025)

(see figure 9). However, instability persisted, with occasional unrealistic spikes during midnight hours. The hybrid model once more proved most robust. Also on April 5, it predicted a peak of 2.1 MW at 11 AM and a trough of 1.05 MW at midnight, both aligning with expected seasonal behavior. Its limited adaptability became evident in this forward-looking scenario as seen in figure 9.

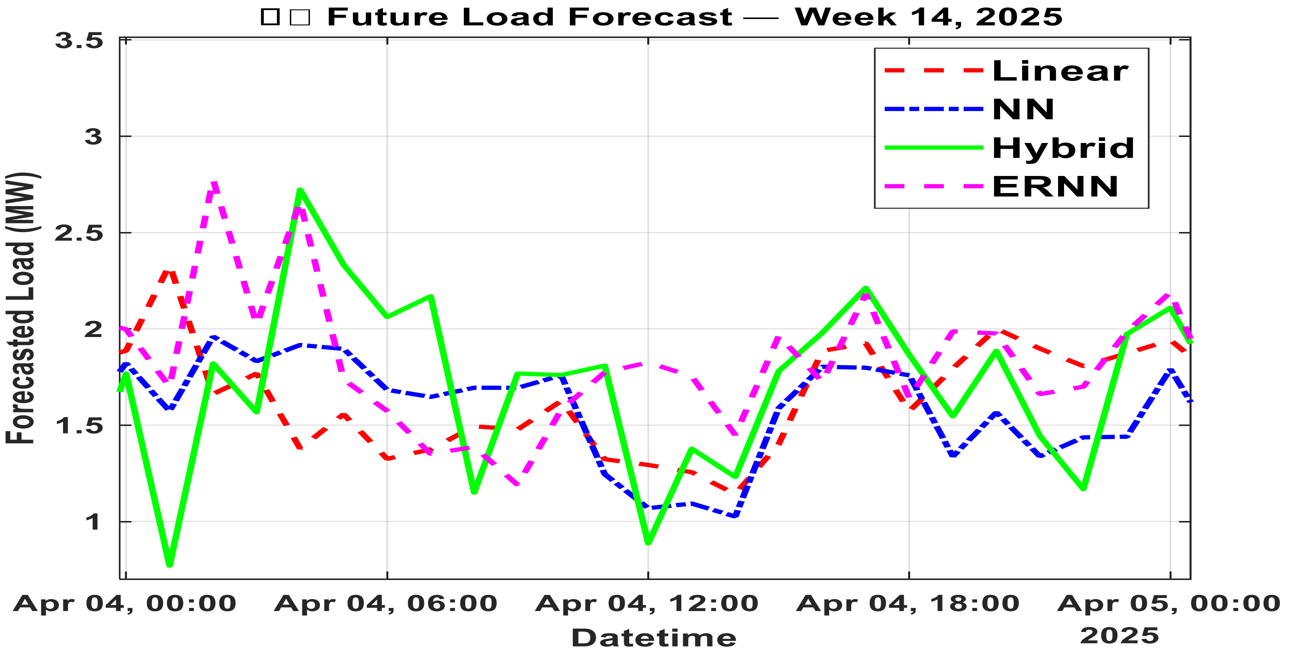

Figure 10: Future forecast for model (week 14: Apr 04, 2025)

The future forecast window tested each model's generalization ability under unseen conditions as seen figure 7. Linear regression again produced flattened curves. On April 2, its predicted peak was ~1.8 MW, while actual seasonal demand patterns suggested closer to 2.5 MW.

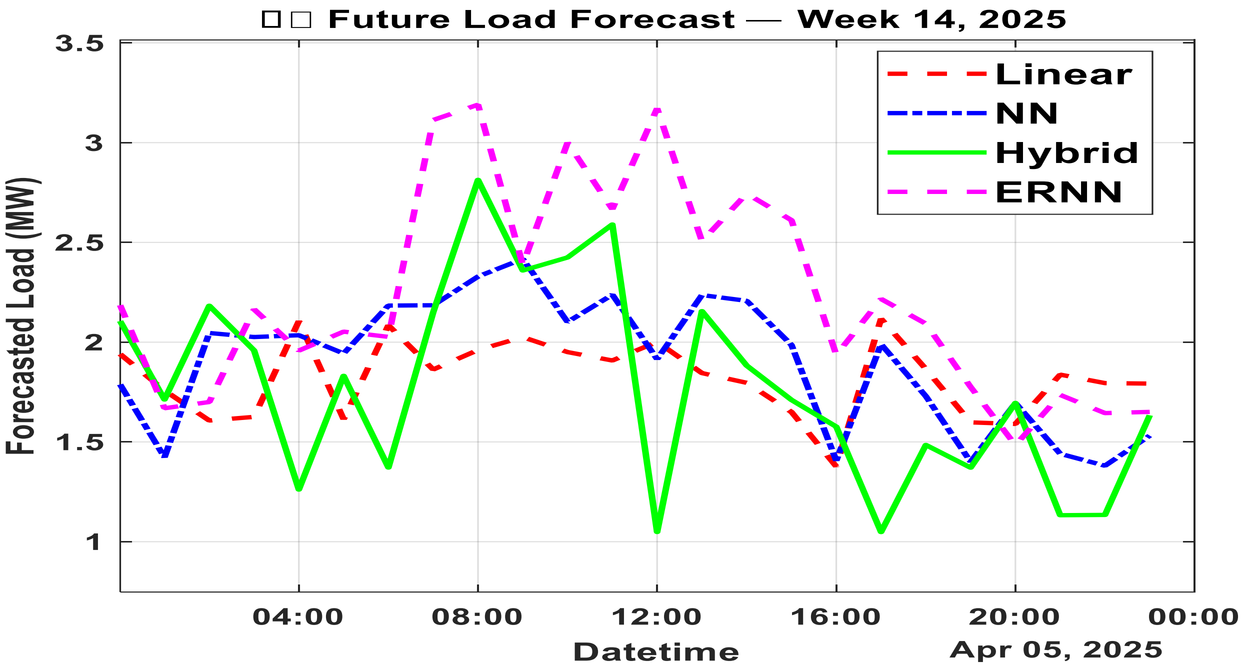

Figure 11: Future forecast for model (week 14: Apr 05, 2025)

ERNN forecasts were highly unstable. figure 10 On April 1, for instance, it predicted an implausible surge to 3.5 MW at midnight, before dropping abruptly to 1.2 MW by 6 AM. Such outputs deviate significantly from observed load patterns and confirm the ERNN's unsuitability for varying load with such selected features.

Conclusion and Recommendations

This study has undertaken a comparative evaluation of four forecasting models linear regression (LR), feed forward neural networks (NN), Elman recurrent neural networks (ERNN), and a hybrid ensemble applied to short-term load forecasting (STLF) in selected location areas in Aba, Nigeria. By analysing both historical (Weeks 38–39, September 2024) and future (Week 14, April 2025) forecasts, the research provides empirical evidence on the relative strengths and weaknesses of these approaches following steady variations in the load distribution system in Aba.

The results establish a clear performance hierarchy. The hybrid ensemble model consistently achieved the best results, with the lowest RMSE (0.2608), MAE (0.1994), and MAPE (14.80%) while explaining more than 70% of the variance in actual demand ($R^2 = 0.7079$). It successfully balanced the strengths of linear regression's stability and neural networks' nonlinear adaptability, producing forecasts that were both accurate and robust across different time horizons.

Despite these contributions to knowledge, limitations of the study must be acknowledged. The dataset covered seven months, capturing seasonal but not multi-year variability. Expanding the temporal coverage would enhance generalizability. Additionally, the models considered primarily weather and calendar variables, omitting socioeconomic drivers such as industrial activity indices or tariff changes, which could further improve forecasts. Finally, the hybrid framework, while effective, requires greater computational resources than regression or simple neural networks, raising questions about its scalability in utilities with limited IT infrastructure.

Based on these findings, several recommendations are made. Utility systems in Aba should prioritize the adoption of hybrid ensemble models for operational STLF, as these offer the best balance of accuracy and adaptability. Linear regression should remain in use as a baseline or fallback tool, particularly in contexts with constrained resources, while feedforward neural networks may be deployed where computational capacity allows. ERNN should be phased out in favor of more modern recurrent architectures such as LSTM or GRU, which are better suited for capturing temporal dependencies. Future research should explore advanced hybrid frameworks incorporating decomposition techniques (e.g., CEEMDAN), attention-based mechanisms for interpretability, and deep learning architectures for temporal modeling. As smart metering and advanced SCADA systems expand across Nigeria, the availability of higher-resolution data will further enhance the feasibility of such advanced models.

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