*Journal of Engineering, Emerging Technologies and Applied Sciences*

*Volume: 03 Issue: 01 | March, 2026* Access point: **https://www.ndu.edu.ng/jeetas**

# Stacked Hybrid Ensemble Learning for Enhanced Short-Term Load Forecasting in Developing Power Grids

*Ezekiel N. Aneke[1], Nnamdi Ahuchaogu[2], Mike O. Ikpeama[3]

[1] *State University of Medical and Applied Sciences, Enugu*
[2, 3] *Department of Electrical and Electronic Engineering, Abia State University,*

*Email: ezekiel.aneke@sumas.edu.ng

## ABSTRACT

*Accurate short-term load forecasting (STLF) is critical for reliable and cost-effective power system operation, particularly in developing countries with fragile grids and volatile demand. This paper presents a hybrid ensemble forecasting framework that integrates linear regression, feedforward neural networks (NN), and a stacked meta-model learner for enhancing the accuracy of electricity demand predictions. Using hourly load, amperage, and weather data collected from load data from Geometric integrated limited, Aba, Nigeria, over a seven-month period (September 2024–March 2025), the hybrid approach is benchmarked against traditional methods including linear regression, neural networks, and Elman Recurrent Neural Networks (ERNN). The hybrid model consistently achieved superior performance across multiple statistical measures, recording the lowest RMSE (0.2608), MAE (0.1994), and MAPE (14.80%), while explaining 70.8% of variance in actual load ($R^2 = 0.7079$). Visual analysis of historical (Weeks 38–39) and future forecasts (Week 14) further confirmed its capacity to capture peak/off-peak variations more effectively than the baseline models. The results demonstrate that ensemble learning through stacked generalization offers robust advantages in contexts characterized by nonlinear load dynamics, climatic variability, and data irregularities. The findings provide a practical forecasting tool for utilities in Nigeria and other emerging economies, where accurate STLF is crucial for demand-side management, operational planning, and economic dispatch.*

***Keywords* — Short-term load forecasting, hybrid ensemble learning, neural networks, linear regression, Nigeria power systems.**

## 1. INTRODUCTION

Power system instability and operational uncertainty remain significant challenges in emerging electricity networks. Developing grids such as Nigeria's transmission system are characterized by voltage fluctuations, reactive power imbalance, weak bus sensitivity, and intermittent supply conditions. These technical deficiencies negatively impact system reliability, economic dispatch, and operational planning.

Voltage stability concerns within the Nigerian grid have been extensively analyzed, revealing structural weaknesses and sensitivity issues across critical buses (Aneke et al., 2021). Such instability characteristics further justify the need for intelligent and predictive load forecasting frameworks capable of supporting proactive decision-making and improving grid resilience. Accurate short-term load forecasting (STLF) therefore plays a vital role in enhancing energy management, operational scheduling, and system stability in volatile power environments.

Short-term load forecasting (STLF), typically covering time horizons from one hour to one week, is a cornerstone of modern power system operations (Bunn & Farmer, 2013). Reliable STLF enables operators to balance supply and demand, schedule generation economically, reduce operating costs, and avoid outages or blackouts. In liberalized electricity markets, it further supports competitive bidding and price optimization. However, the task of forecasting short-term loads is notoriously difficult due to the complex interplay of influencing factors such as weather, calendar variables, socioeconomic activities, and consumer behavior (Wu et al., 2020).

Traditional statistical models such as autoregressive integrated moving average (ARIMA), exponential smoothing, and linear regression have long been employed for STLF. While these models are computationally efficient and interpretable, they often fail to capture nonlinearities in load behavior, especially under volatile conditions typical of developing regions. In contrast, machine learning and computational intelligence approaches such as artificial neural networks (ANNs), recurrent neural networks (RNNs), and fuzzy systems are better suited for handling nonlinear and stochastic patterns (Liu et al., 2022). However, these models may suffer from overfitting, lack of transparency, and computational intensity.

The Elman Recurrent Neural Network (ERNN), for example, has been widely applied to capture temporal dependencies in load data (Shezi, 2015). While effective in learning sequential patterns, ERNN often underperforms in environments with abrupt load fluctuations or incomplete feature sets, leading to flattened forecasts and poor peak load tracking. These limitations necessitate hybridization approaches that combine the complementary strengths of linear and nonlinear models.

Hybrid ensemble learning, particularly through stacked generalization, offers a promising solution. By training base models (e.g., linear regression and neural networks) and then integrating their outputs using a meta-model, ensemble systems can dynamically adjust to varying load conditions. This approach mitigates the weaknesses of individual models while leveraging their strengths. Such methods have been shown to outperform standalone models in diverse forecasting tasks, yet their application in Nigeria's power systems remains limited.

This study therefore develops and evaluates a hybrid ensemble forecasting model for STLF in Aba, Nigeria a high-demand commercial hub with diverse load characteristics. The key contributions of this work include, development of a hybrid ensemble model combining linear regression, feed forward neural networks, and a meta-model trained using boosted regression trees. Comparative benchmarking against traditional models (linear regression, neural network, ERNN) using multiple accuracy metrics, case study application in Aba, Nigeria, providing practical insights into forecasting performance under real-world African grid conditions, and demonstration of operational benefits, showing how hybrid modeling reduces forecasting errors and enhances peak demand tracking.

By addressing the limitations of existing models and contextualizing the solution within Nigeria's distribution grid, this paper contributes both to the methodological advancement of STLF and to the broader literature on energy management in developing regions.

## 2. Short-Term Load Forecasting and Hybrid Forecast Model

Short-term load forecasting (STLF) refers to predicting electricity demand for horizons ranging from one hour to one week. It plays an indispensable role in power system planning and operation, supporting tasks such as unit commitment, generation dispatch, reserve allocation, and electricity market transactions (Bunn & Farmer, 2013). Unlike long-term load forecasting, which informs infrastructure expansion, or medium-term forecasts, which guide fuel purchasing and maintenance scheduling, STLF directly influences operational reliability and cost minimization (Feinberg et al., 2003).

Electric loads are inherently stochastic and influenced by numerous variables, including weather conditions, time-of-day, calendar effects (weekends, holidays), economic activities, and consumer behavior. In developing regions such as Nigeria, the challenge is compounded by frequent grid instabilities, irregular demand surges, and incomplete data availability (Okolobah & Ismail, 2013). These conditions make traditional forecasting tools inadequate, driving the need for advanced modeling techniques that can handle nonlinearities and volatile dynamics.

The load profile of a region is shaped by cyclical patterns and contextual drivers. For example, residential loads tend to exhibit pronounced morning and evening peaks, while commercial centers have higher daytime demand (Ellen, 2015). Seasonal variations further affect electricity usage, with heating or cooling demands altering consumption patterns (Joshi, 2015). Figure 1 demonstrate typical load profiles across residential and commercial usage. Accurately modeling these variations is crucial for minimizing forecasting errors and ensuring efficient grid operations.

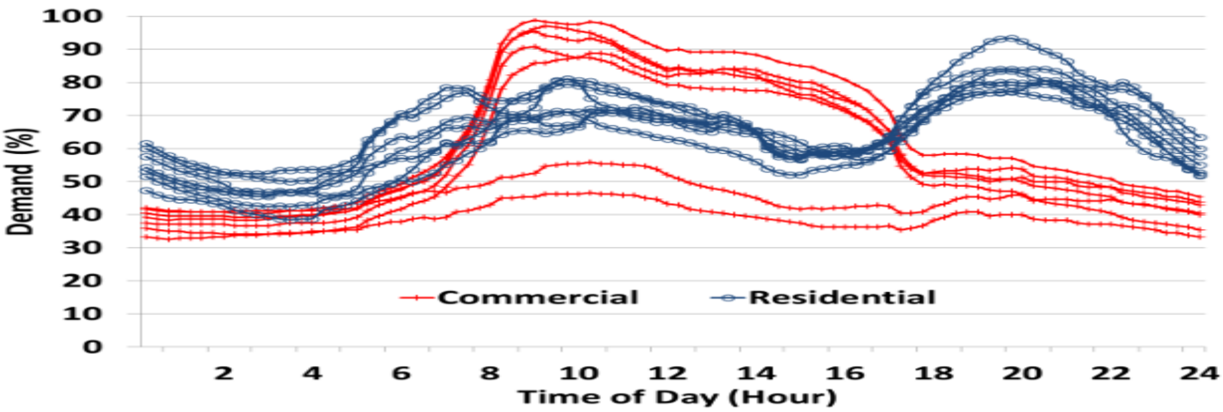

*Figure 1: Daily load profiles - commercial and residential - for one week (Joshi, 2015)*

Hybrid and ensemble models for short-term load forecasting (STLF) have gained prominence because they address the shortcomings of single-model approaches, particularly in volatile and data-rich grid environments. Recent studies have demonstrated that combining decomposition methods, deep learning architectures, and meta-learners significantly improves predictive performance, robustness, and interpretability.

Wen et al. (2024) proposed a deep learning-driven hybrid model that integrates Gated Recurrent Units (GRU), Temporal Convolutional Networks (TCN), and attention mechanisms to capture nonlinear and long-term dependencies in power load series. Tested on datasets such as GEFCom2014 and ERCOT, the model reduced mean absolute percentage error (MAPE) by 39% and improved computational efficiency by almost half compared with baseline models. This architecture highlights the value of combining recurrent and convolutional structures with attention to dynamically focus on influential input features, making it particularly effective for complex load patterns. Guo et al. (2024) advanced hybrid ensemble modeling by developing a stacking-based framework where artificial neural networks (ANNs), XGBoost, LSTM, and BiLSTM serve as base learners, and Lasso regression acts as a meta-learner. By incorporating exogenous factors such as temperature, rainfall, and electricity prices, the model consistently outperformed individual models and simpler hybrids on datasets from Spain and Australia. The study demonstrated that stacking not only enhances predictive accuracy but also stabilizes forecasts across diverse conditions, addressing weaknesses in earlier hybrid attempts that relied on simplistic error-weighted averaging. Similarly, Shin et al. (2024) combined variational mode decomposition (VMD) with Random Vector Functional Link (RVFL) networks to propose a hybrid model that is both accurate and computationally efficient. Using Australian Energy Market Operator (AEMO) data, their VMD-RVFL method surpassed benchmark models like VMD-SVR and VMD-ELM in both RMSE and MAPE, while requiring shorter computation time. By reducing non-stationarity through decomposition and leveraging RVFL's fast closed-form training, the model proved suitable for real-time applications, addressing a critical gap in operational feasibility for utility companies.

Yang et al. (2025) focused on very short-term load forecasting (VSTLF) by developing an interpretable hybrid model that combines convolutional neural networks (CNNs) and bidirectional LSTM (BiLSTM). Beyond accuracy improvements, the model incorporated Shapley Additive Explanations (SHAP) to quantify feature contributions, improving transparency for grid operators. Experiments revealed that the CNN-BiLSTM hybrid outperformed state-of-the-art baselines, while interpretability features made it more applicable in decision-critical environments such as real-time dispatch. Ullah et al. (2024) provided a comprehensive review and simulation study of CNN-LSTM hybrids applied to STLF. Their work demonstrated that CNNs excel at extracting high-dimensional features, while LSTMs capture sequential dependencies. On Pakistan's NTDC dataset, their hybrid achieved RMSE of 538.71 and MAPE of 2.72 in single-step forecasts, outperforming standalone CNNs, LSTMs, and regression models. The study highlighted how hybridization enhances generalization across different horizons, proving effective for both short-term and 24-hour ahead predictions.

Machine learning approaches, particularly Artificial Neural Networks (ANNs), have gained widespread acceptance in power system modeling due to their ability to capture nonlinear relationships and complex system dynamics. ANN-based models have demonstrated strong predictive capabilities in applications such as voltage stability assessment, fault diagnosis, and reactive power control. For example, Aneke, Eneh, and Iyidobi (2023) applied ANN-based control strategies for voltage stability enhancement using a controlled STATCOM device in a stressed multi-bus network. Their findings confirmed that intelligent learning algorithms can significantly improve system stability under fluctuating operating conditions. These results support the integration of ANN components within hybrid ensemble frameworks for short-term load forecasting, where nonlinear load behavior and dynamic grid responses must be accurately modeled.

## 3. METHODOLOGY

### 3.1. Study Design and Rationale

The methodology adopted in this study was guided by the dual objective of (i) assessing the limitations of conventional forecasting models, and (ii) demonstrating the robustness of a hybrid ensemble learning framework for short-term load forecasting (STLF). The study design therefore followed a structured workflow comprising six key stages: data collection, preprocessing, feature engineering, model development, hybrid ensemble construction, and evaluation. The staged design ensured consistency between baseline models (linear regression, feedforward neural networks, and Elman recurrent neural networks) and the proposed hybrid ensemble, enabling fair comparative benchmarking.

The choice of Aba, Nigeria, as the case study location reflects its unique role as a commercial hub with highly dynamic load behavior. Aba's distribution network is characterized by mixed residential, commercial, and light industrial consumption, making it an ideal testbed for forecasting models intended for deployment in volatile and resource-constrained environments. Figure 2 illustrates the structure of the Nigerian power grid, which provides the broader operational context within which the Aba distribution network operates.

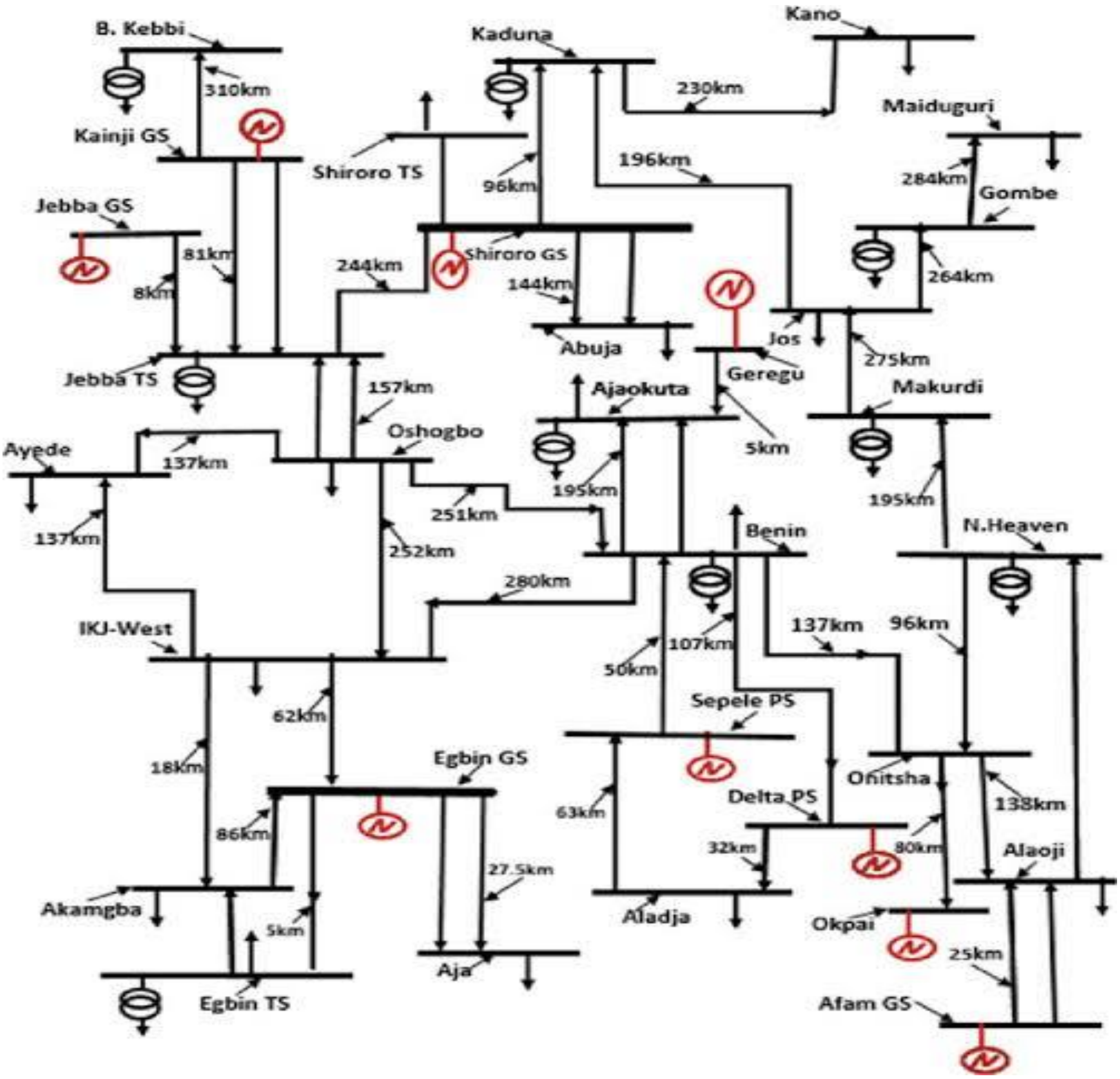

***Figure 2: The Nigerian Power Grid***

## 3.2. Data Collection

### *3.2.1. Data Source and Acquisition*

The dataset was obtained from Geometrics Integrated Energy Services, a utility company operating in Aba, Abia State, Nigeria. Load and operational variables were captured in real time using a supervisory control and data acquisition (SCADA) system, which monitored feeder and transformer lines at hourly resolution. Data logging included transformer amperage, casing temperature, load (in megawatts), and auxiliary weather variables such as dry bulb and dew point temperatures. Data were exported in Excel format and subsequently processed in MATLAB.

The dataset spanned seven months (September 2024 to March 2025), capturing diverse seasonal regimes relevant to southern Nigeria's tropical climate, which includes, late Wet Season (September–October), dry harmattan season (November–February), and early Wet Season Onset (March). This range ensured that the forecasting models were exposed to both climatic and behavioural variability, such as cooling loads during high temperatures and demand fluctuations during festive and holiday periods.

In terms of geographic and climatic context, Aba lies in southeastern Nigeria with a high-density population and active commercial sector. The city's tropical wet-and-dry climate is characterized by temperatures ranging from 25 °C to 34 °C, humidity levels averaging 70–90%, significant rainfall in wet months, and Volatile consumption driven by small-scale manufacturing, cold storage, and household air-conditioning.

## 3.3. Dataset Features and Structure

The merged dataset contained **5,090 hourly records**, each representing a snapshot of the system's operational and environmental state. The primary variables are summarized in **Table 1**.

***Table 1: Dataset Primary variables***

| Date time | Amperage | Temperature | Load | Hour | Day | Day Of Week | Month | Dry Bulb (°C) | Dew Point (°C) |
|---|---|---|---|---|---|---|---|---|---|
| … | … | … | | | … | | | | … |
| … | | | | | … | | | … | … |

Key features included:

- Date time: Hourly timestamp of each observation.
- Load (MW): Transformer load, serving as the dependent forecasting variable.
- Amperage (A): Transformer line current, used as a proxy for demand intensity.
- Temperature (°C): Transformer casing temperature.
- Dry Bulb & Dew Point: Weather data indicating thermal comfort and humidity.
- Calendar Variables: Hour, Day, Day of Week, Month.
- Holiday Indicator: Boolean flag for Nigerian public holidays.

To enhance model learning, additional lag features were engineered to capture autoregressive behavior:

- Previous Day Load (t–24),
- Previous Week Load (t–168),
- Previous Day/Week Amperage and Temperature.

## 3.4. Preprocessing and Feature Engineering

### *3.4.1. Data Cleaning*

Raw SCADA logs were screened for missing values, duplicates, and irregular timestamps. Gaps were interpolated using nearest-neighbour filling for continuous features, while categorical variables (e.g., holiday) were manually validated. Outliers caused by sensor errors were smoothed using a rolling median filter.

### *3.4.2. Normalization*

To ensure uniform learning across variables with different scales, all continuous features were normalized using z-score scaling:

$$X_{norm} = \frac{X - \mu}{\sigma}$$

Where μ and σ represent the mean and standard deviation, respectively. This pre-processing was particularly critical for neural networks, which are sensitive to scale discrepancies.

## 3.5. Model Development

### *3.5.1. Linear Regression Model*

The linear regression model served as the baseline statistical approach. It assumes a linear relationship between load (dependent variable) and predictor features:

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

Where $\hat{Y}_{Linear}$ is the Forecasted Load, $X_i$ is the independent input features (calendar, weather, lag), $\beta_i$ is the Model coefficients, $\beta_0$ is the model intercept, and $\epsilon$ is the residual error. While regression models are simple and interpretable, they are constrained by their inability to model nonlinear patterns in load behavior. This limitation motivated the development of nonlinear and hybrid approaches.

## 3.6. Hybrid Ensemble Model (Stacked Generalization)

The central contribution of this study is the **hybrid ensemble model**, constructed through stacked generalization. The hybrid integrates the outputs of linear regression and NN models as meta-features for a second-level learner. The overall architecture and workflow of the proposed hybrid ensemble framework are illustrated in Figure 3.

The ensemble is mathematically represented as:

$$\hat{Y}_{Meta} = g\left(\hat{Y}_{Linear}, \hat{Y}_{NN}\right) \qquad (2)$$

Where $\boldsymbol{g}(\cdot)$ denotes the meta-model function, trained using gradient boosted regression trees (GBRT).

The hybrid workflow includes, train base models (LR and NN), generate forecasts from each base model, concatenate outputs into a meta-feature matrix, train GBRT meta-learner on this matrix, and produce final hybrid forecasts. By learning "when to trust" each base model, the hybrid framework combines trend-following strength of regression with nonlinear adaptability of neural networks. Table 2 presents the training algorithm for the hybrid model.

***Table 2: Algorithm for the hybrid model***

Algorithm: Adaptive Hybrid Forecasting (Load)

```
Input: Feature matrix X (13 inputs), Target Y
Output: Hybrid prediction Y_H

1. Normalize(X)
2. Train Linear Regression → Y_LR = predict(linModel, X)
3. Train Neural Network → Y_NN = net(X')'
4. Create meta features Z = [Y_LR, Y_NN]
5. Train Meta-model → Y_H = predict(metaModel, Z)
```

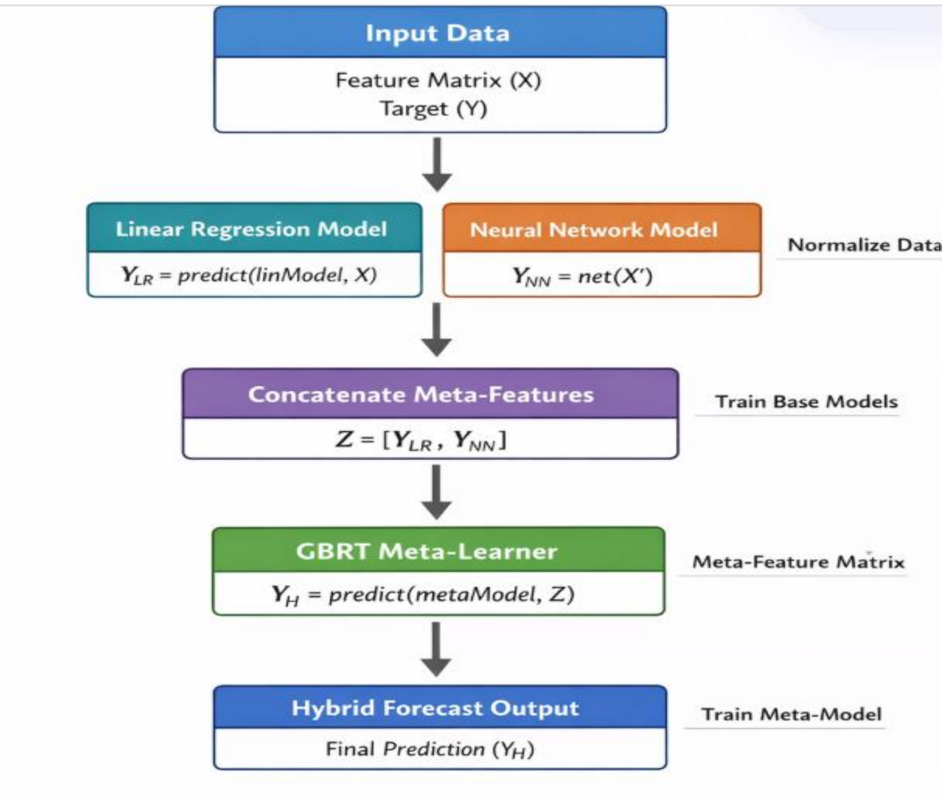

***Figure 3: Flow chart diagram showing the Hybrid Ensemble Mode***

### 3.6. Model Evaluation and Accuracy Metrics

To ensure rigorous benchmarking, five standard performance metrics were applied:

**1.** Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2} \qquad (3)$$

Where, $\hat{y}_i$ is predicted load value, $y_i$ is actual load value, and $N$ is the number of observations. Penalizes large deviations, critical for peak demand tracking.

2. Mean Absolute Error (MAE):

$$MAE = \frac{1}{N}\sqrt{\sum_{i=1}^{N}|\hat{y}_i - y_i|} \qquad (4)$$

Represents average deviation in MW, offering interpretable error magnitudes.

3. Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{100}{N}\sum_{i=1}^{N}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \qquad (5)$$

Captures proportional accuracy, though sensitive to near-zero loads.

4. Coefficient of Determination ($R^2$):

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(\hat{y}_i - y_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \qquad (6)$$

Measures proportion of variance explained by the model.

These metrics were selected for their complementary perspectives, collectively ensuring robust model assessment (Zhang & Wang, 2023).

### 3.7. Experimental Setup

The models were implemented in MATLAB R2024a and trained on a workstation with Intel i7 processor, 16GB RAM, and Windows 11 OS. Dataset division followed an **80/20 split**, with 80% used for training and 20% reserved for testing.

Forecast evaluations were conducted over selected weekly horizons of h**istorical forecasts:** Weeks 38–39 (Sept 2024), and f**uture forecasts:** Week 14 (April 2025). This setup enabled both retrospective validation and prospective assessment of model generalizability.

## 4. RESULTS AND DISCUSSION

### 4.1. Historical Forecast Analysis: Week 38 (September 15–21, 2024)

Week 38 provides the first and required validation window for evaluating the forecasting models against actual observed load. The week includes both weekday and weekend patterns, offering a representative benchmark of Aba's residential and commercial consumption dynamics.

The LR model tracked the general shape of the load curve but struggled to capture sharp morning and evening peaks. On September 16, the evening peak was underpredicted by 0.35 MW, reflecting the model's limited nonlinear adaptability (figure 3). The NN model performed better, particularly in capturing dynamic changes. For example, on September 17, the NN accurately modeled the late evening rebound, with deviations within ±0.2 MW. However, occasional overshooting was observed during transitions, such as around 6 PM on September 18 (see figure 4). The Hybrid consistently outperformed both LR and NN. On September 18, when actual load peaked at 1.95 MW, the Hybrid predicted 1.92 MW, resulting in an error margin of less than 2%. The Hybrid maintained smooth transitions, avoiding the overshooting of NN and the underfitting of LR. The ERNN model introduced in (Ellen, 2015) underperformed, exhibiting flatter curves and lagging behind during sharp rises. On September 19–20, actual peaks exceeded 2.0 MW, yet ERNN forecasts stagnated near 1.6 MW, underpredicting by 0.4 MW. This confirms ERNN's reduced sensitivity to rapid fluctuations (see figure 6).

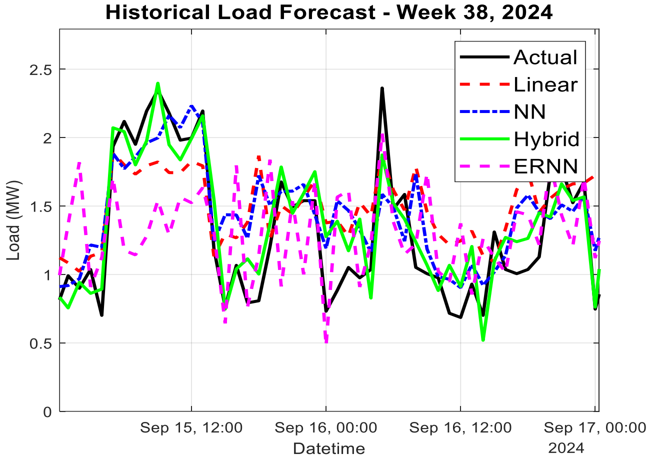

*Figure 3: historical forecast for model (week 38: Sep 15 – Sep 16, 2024)*

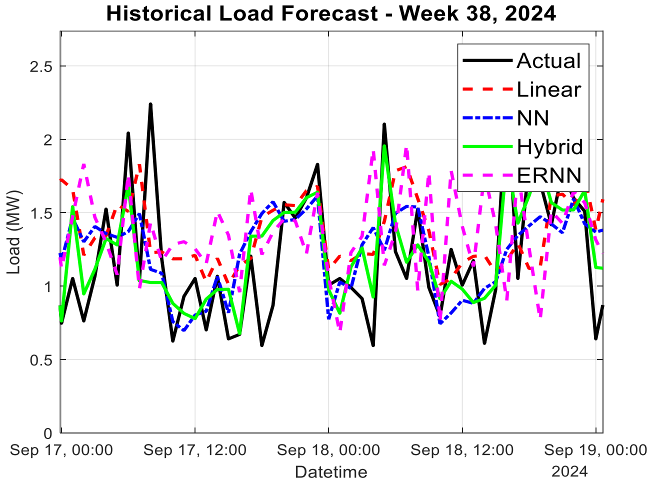

*Figure 4: historical forecast for model (week 38: Sep 17 – Sep 18, 2024)*

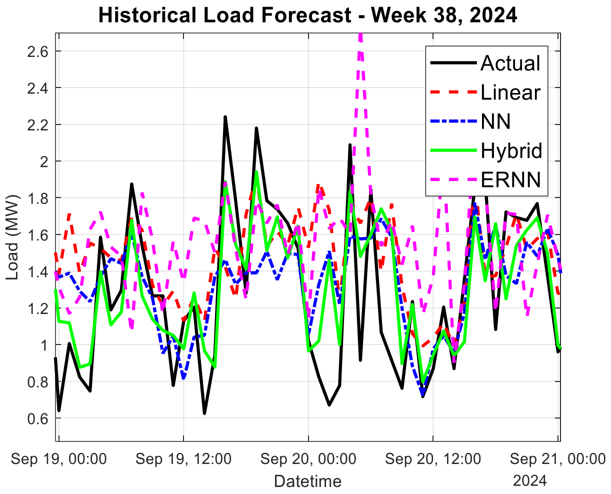

***Figure 5: historical forecast for model (week 38: Sep 19 – Sep 20, 2024)***

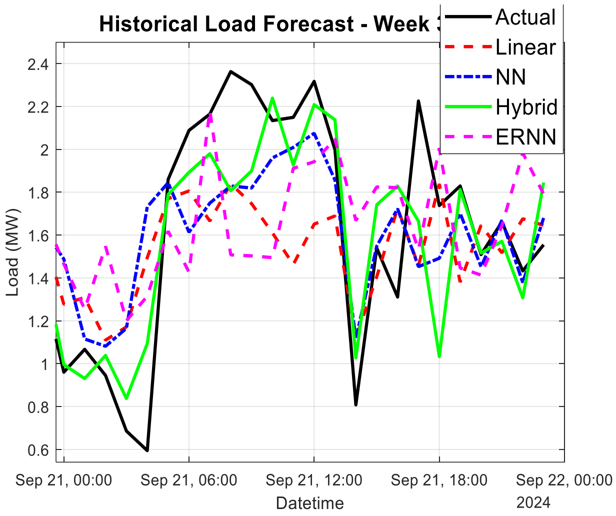

***Figure 6: historical forecast for model (week 38: Sep 21, 2024)***

## 4.2. Future Forecast Analysis: Week 14 (April 1–7, 2025)

Unlike historical analysis, future forecasts rely solely on the models' generalization capacity. This period coincides with early wet season onset, where climatic transitions drive unique load dynamics. Here, linear regression produced relatively flattened curves across the week (figure 7). On April 2, the model predicted values between 1.45 MW and 2.1 MW, underestimating morning surges typically seen between 6–9 a.m. The Neural Network becomes more responsive to daily fluctuations (figure 8). On April 5, NN forecasts rose from 2.0 MW at 4 a.m. to 2.45 MW at 10 a.m., aligning with expected commercial-hour demand. However, spurious spikes were noted during low-activity periods (2–4 a.m.). The hybrid model delivered the most realistic forecasts (figure 9), for example on April 5, it predicted a peak of 2.1 MW at 11 a.m. and a sharp dip to 1.05 MW at midnight, aligning with historical seasonal behavior. The Hybrid corrected anomalies present in NN outputs and avoided the flattening observed in LR, while the ERNN overestimated early-morning demand (figure 10), for example, on April 1, forecasts ranged from 3.5 MW at midnight to 1.25 MW by 6 a.m., far exceeding the expected load range. While ERNN occasionally mirrored Hybrid's trend, its outputs were unstable and unrealistic for the case study grid conditions.

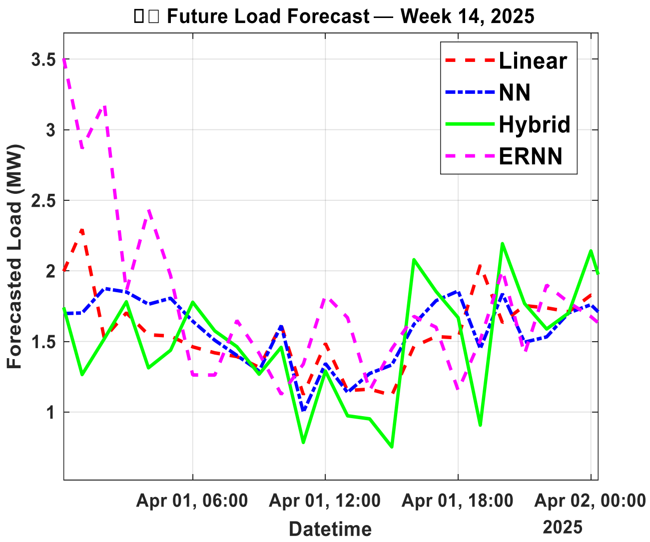

***Figure 7: Future forecast for model (week 14: Apr 01, 2025)***

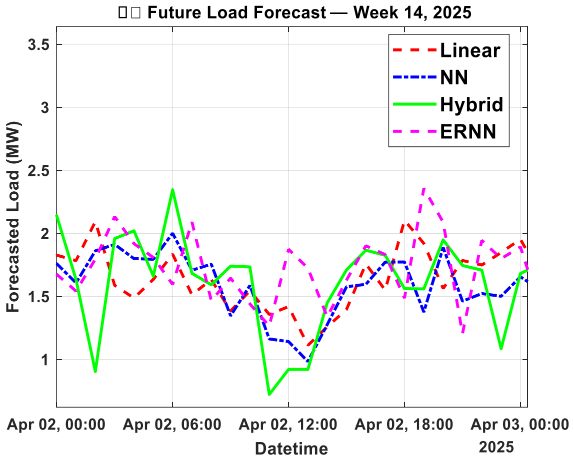

***Figure 8: Future forecast for model (week 14: Apr 02, 2025)***

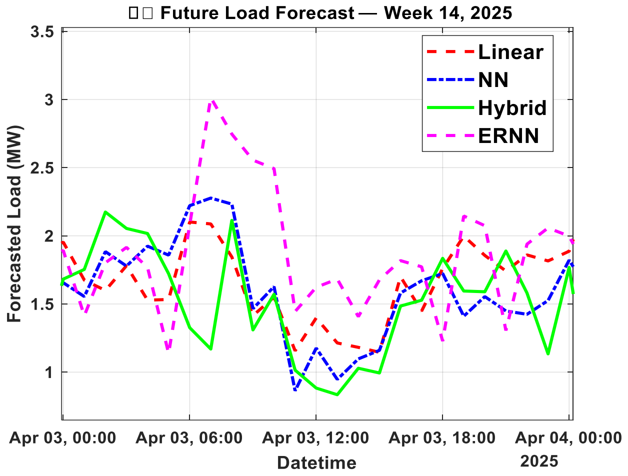

***Figure 9: Future forecast for model (week 14: Apr 03, 2025)***

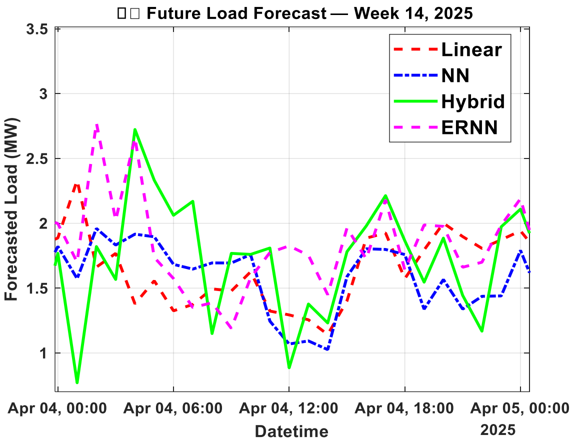

***Figure 10: Future forecast for model (week 14: Apr 04, 2025)***

### 4.5 Quantitative Performance Evaluation

The forecasting performance of all four models was evaluated using the statistical metrics described in Section 3. Results are presented in table 3. The hybrid model achieved the lowest RMSE (0.2608), MAE (0.1994), and MAPE (14.80%), with $R^2 = 0.7079$. This confirms its superior ability to capture both overall trends and short-term fluctuations. The neural network with RMSE = 0.3720 and $R^2 = 0.4056$. It successfully captured nonlinear behavior but lacked robustness in low-load conditions. The linear regression model Performed moderately, with RMSE = 0.4200 and $R^2 = 0.2420$. Its simplicity limited its predictive power in volatile load contexts. While the ERNN performed worst, with RMSE = 0.5683, MAE = 0.4574, MAPE = 35.24%, and $R^2 = –0.3879$. Its inability to incorporate the study variables and adapt to sudden fluctuations makes it less suitable for load forecast on the case study area.

***Table 3: Forecasting Performance Metrics for All Models***

| Model | RMSE | MAE | MAPE (%) | SMAPE | $R^2$ |
|---|---|---|---|---|---|
| Linear | 0.4200 | 0.3368 | 25.58 | 2303.19 | 0.2420 |
| Neural Net | 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 |

From the results of the case study area, we can conclude that by combining LR’s trend-following capability with NN’s nonlinear adaptability, the Hybrid achieved consistently superior accuracy. Its meta-model effectively learned when to rely on each base model, reducing overshooting and underfitting. The NN demonstrated improved accuracy over LR but occasionally produced unrealistic spikes, reflecting over-sensitivity to in load profiles that shouldn't, however, despite theoretical advantages in temporal modeling, ERNN performed poorly in this context. Its restricted feature set (hour, day, month) and lack of exogenous variables hindered adaptability. For utilities in Aba and similar contexts, Hybrid forecasting provides a more reliable tool for short-term planning. Its reduced error rates imply fewer mismatches between generation and demand, lowering operational costs and risk of outages.

## 5. CONCLUSION

This study addressed the challenge of accurate short-term load forecasting (STLF) in a developing power system using Aba, Nigeria as a case study. A hybrid ensemble framework combining linear regression and feedforward neural networks, integrated through a gradient-boosted meta-learner, was developed to overcome the limitations of conventional models.

The results showed that the hybrid model consistently outperformed benchmark models across validation and future projection periods, achieving the lowest forecasting errors (RMSE = 0.2608, MAE = 0.1994, MAPE = 14.80%) and explaining over 70% of load variance. Unlike individual models, it accurately captured both peak and off-peak demand patterns, demonstrating improved reliability and robustness in volatile grid environments.

Future research may extend this framework by incorporating advanced deep learning models such as LSTM, GRU, and Transformer architectures, integrating attention mechanisms for interpretability, applying signal decomposition techniques to better capture demand irregularities, and leveraging high-resolution smart meter and SCADA data for near real-time forecasting.

## REFERENCES

Aneke, E. N., Eneh, I. I., & Iyidobi, J. C. (2023). ANN-based voltage stability enhancement and voltage collapse reduction in stressed multi-bus network using controlled STATCOM. *ESP Journal of Engineering & Technology Advancements, 3*(1), 1–6.

Aneke, E. N., Ibekwe, B. E., Iyidobi, J. C., & Okafor, E. N. C. (2021). Voltage stability evaluation in the Nigeria 44-bus grid network using modal analysis. *Journal of Engineering Research and Reports, 20*(11), 80–89.

Bunn, D. W., & Farmer, E. D. (2013). *Comparative models for electrical load forecasting*. John Wiley & Sons.

Chen, J., Zhang, Z., & Xu, T. (2021). Short-term load forecasting based on improved regression models: A case of nonlinear feature adjustments. *Energy Reports, 7*, 1231–1242. https://doi.org/10.1016/j.egyr.2021.01.087

Christian, T., & Taylor, J. W. (2000). Support vector machines for short-term load forecasting. *IEEE Transactions on Power Systems, 15*(2), 587–592. https://doi.org/10.1109/59.867131

Dalvi, S., & Kamjoo, A. (2024). Hybrid CEEMDAN-residual learning model for electricity load forecasting under volatile grid conditions. *Applied Energy, 352*, 121991. https://doi.org/10.1016/j.apenergy.2024.121991

Dorado, R., Tejada, J., & Cano, J. (2021). Advances in exponential smoothing techniques for electricity demand forecasting. *International Journal of Forecasting, 37*(4), 1234–1248. https://doi.org/10.1016/j.ijforecast.2020.11.007

Ellen, O. N. (2015). *Application of Elman recurrent neural networks in short-term load forecasting in Nigerian distribution grids* (Master's thesis, University of Nigeria, Nsukka).

Feinberg, E. A., & Genethliou, D. (2003). Load forecasting. In J. H. Chow (Ed.), *Applied mathematics for restructured electric power systems* (pp. 269–285). Springer.

Guo, F., Mo, H., Wu, J., Pan, L., Zhou, H., Zhang, Z., Li, L., & Huang, F. (2024). A hybrid stacking model for enhanced short-term load forecasting. *Electronics, 13*(14), 2719. https://doi.org/10.3390/electronics13142719

Hu, X., Chen, L., & Zhou, P. (2021). Comparative evaluation of hybrid models for short-term load forecasting. *IEEE Access, 9*, 117223–117235. https://doi.org/10.1109/ACCESS.2021.3107949

Islam, M. S., & Ahmed, K. (2022). A critical review of recurrent neural networks for time series forecasting. *Neural Computing and Applications, 34*(15), 12243–12259. https://doi.org/10.1007/s00521-022-06812-6

Joshi, K. (2015). Assessing the impact of plug-in hybrid electric vehicles on distribution network operations using time-series distribution power flow analysis. https://doi.org/10.1109/PEDES.2014.7042120

Kadil, A., Rahman, M., & Bensaid, H. (2021). ARIMA and ARMAX models for short-term load forecasting under uncertain conditions. *Energies, 14*(11), 3297. https://doi.org/10.3390/en14113297

Li, X., Zhou, Y., & Fang, H. (2020). Residential load forecasting considering seasonal variations and user behavior. *Energy and Buildings, 209*, 109702. https://doi.org/10.1016/j.enbuild.2019.109702

Li, Y., Sun, H., & Zhao, J. (2023). Hybrid decomposition-based forecasting for nonlinear load series using CEEMDAN and LSTM. *Energy, 278*, 127725. https://doi.org/10.1016/j.energy.2023.127725

Liu, Q., Wang, L., & Xu, F. (2022). Artificial neural networks for short-term load forecasting: A review of recent applications. *Sustainable Energy Technologies and Assessments, 52*, 102022. https://doi.org/10.1016/j.seta.2022.102022

Malik, M., Rashid, T., & Sharma, P. (2022). Hybrid ensemble approaches for improved electricity load forecasting: Comparative insights. *International Journal of Electrical Power & Energy Systems, 136*, 107669. https://doi.org/10.1016/j.ijepes.2021.107669

Okolobah, V. D., & Ismail, Z. (2013). Power sector reforms: Implications for sustainable electricity supply in Nigeria. *Journal of Energy in Southern Africa, 24*(2), 15–23. https://doi.org/10.17159/2413-3051/2013/v24i2a3135

Shezi, S. (2015). Application of Elman recurrent neural networks in short-term load forecasting. *South African Journal of Industrial Engineering, 26*(3), 123–134. https://doi.org/10.7166/26-3-1277

Shin, S. M., Rasheed, A., Park, K. H., & Veluvolu, K. C. (2024). Fast and accurate short-term load forecasting with a hybrid model. *Electronics, 13*(6), 1079. https://doi.org/10.3390/electronics13061079

Singh, S., & Dwivedi, A. (2020). Integrating evolutionary algorithms with neural networks for load forecasting. *Electric Power Systems Research, 189*, 106767. https://doi.org/10.1016/j.epsr.2020.106767

Smyl, S., Salinas, D., & Gasthaus, J. (2021). DeepAR and hybrid approaches for probabilistic load forecasting. *International Journal of Forecasting, 37*(2), 725–742. https://doi.org/10.1016/j.ijforecast.2020.05.006

Ullah, K., Ahsan, M., Hasanat, S. M., Haris, M., Yousaf, H., Raza, S. F., Tandon, R., Abid, S., & Ullah, Z. (2024). Short-term load forecasting: A comprehensive review and simulation study with CNN-LSTM hybrid approach. *IEEE Access, 12*, 111858–111872. https://doi.org/10.1109/ACCESS.2024.3440631

Van den Bossche, A., Kifayat, K., & Saeed, A. (2018). Fuzzy logic-based methods for anomaly detection in IoT and power networks. *Wireless Networks, 24*(3), 955–969. https://doi.org/10.1007/s11276-016-1390-2

Wen, X., Liao, J., Niu, Q., Shen, N., & Bao, Y. (2024). Deep learning-driven hybrid model for short-term load forecasting and smart grid information management. *Scientific Reports, 14*, 13720. https://doi.org/10.1038/s41598-024-63262-x

Wu, Q., Zhang, H., & Li, Y. (2020). Convolutional neural networks for short-term load forecasting in smart grids. *IEEE Transactions on Smart Grid, 11*(6), 5829–5840. https://doi.org/10.1109/TSG.2020.2998471

Yang, Z., Li, J., Liu, C., & Wang, H. (2025). Forecasting very short-term power load with hybrid interpretable deep models. *Systems Science & Control Engineering, 13*(1), 2486136. https://doi.org/10.1080/21642583.2025.2486136

Zhang, L., & Wang, X. (2023). Advances in hybrid ensemble methods for time series load forecasting. *Energy Reports, 9*, 811–827. https://doi.org/10.1016/j.egyr.2023.02.045

Zhang, Y., & Wang, Z. (2021). Attention-enhanced deep learning models for interpretable short-term load forecasting. *Applied Energy, 301*, 117457. https://doi.org/10.1016/j.apenergy.2021.117457