

Comparative Analysis of Machine Learning Models for Short-Term Electricity load Forecasting: A Comparative Review of the Literature

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ABSTRACT

This paper presented a comparative literature review of machine learning models for short-term electricity load forecasting, with emphasis on Artificial Neural Network (ANN), Random Forest (RF), Support Vector Machine (SVM), Long Short-Term Memory (LSTM), and hybrid CNN-LSTM models. Motivated by the increasing operational challenges associated with inaccurate electricity demand prediction, particularly within developing power systems characterized by nonlinear consumption patterns, demand variability, and infrastructural instability, this paper adopted a comparative analytical approach based on recent empirical studies focusing on forecasting accuracy, computational efficiency, robustness, scalability, and adaptability of machine learning techniques in electricity load prediction. The results, tables, and figures presented in this paper are drawn from and evaluated findings reported in the cited secondary literature rather than from an original experiment conducted by the authors. Findings from the reviewed studies, tables, and visual analyses revealed significant performance variations among the forecasting models. Comparative findings presented in the performance evaluation tables and error analysis charts showed that LSTM and hybrid CNN-LSTM architectures consistently achieved the lowest forecasting error values among the models reviewed, with reported RMSE and MAPE reductions relative to the other benchmark models. The comparative bar charts and performance ranking figures further indicated that LSTM and CNN-LSTM demonstrated superior capability in learning nonlinear, sequential temporal load patterns, while Random Forest exhibited stronger robustness and forecast stability under noisy and incomplete datasets, and ANN showed competitive but comparatively weaker performance than the deep-learning architectures. Heatmap visualizations additionally revealed strong positive correlations between historical load variables, temporal indicators, and forecast accuracy. The paper concluded that machine learning techniques provide reliable and adaptive solutions for short-term electricity demand forecasting. It is recommended that electricity distribution companies adopt LSTM and hybrid CNN-LSTM-driven predictive systems complemented by Random Forest for operational contexts requiring greater robustness under noisy data, integrated with real-time monitoring infrastructures. Future research should explore hybrid deep learning architectures, smart-grid forecasting integration, renewable energy forecasting synchronization, and explainable artificial intelligence techniques for interpretable energy forecasting systems.



Keywords: Comparative Forecasting, Load Forecasting, Electricity, Machine Learning Models, Comparative Model Evaluation

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INTRODUCTION

Electricity remains one of the most essential infrastructures supporting economic growth, industrial productivity, healthcare systems, communication

networks, and technological advancement across the world. In modern societies, virtually every sector of human activity depends directly or indirectly on stable and reliable

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electricity supply. As urbanization, industrialization, and digital transformation continue to expand globally, the demand for electricity has increased significantly, thereby placing enormous pressure on power generation and distribution systems (International Energy Agency, 2023). One of the major operational requirements for maintaining stability within electricity systems is the ability to accurately forecast electricity load demand. Short-Term Electricity Load Forecasting (STLF) therefore plays a critical role in ensuring efficient energy management, operational planning, grid reliability, and resource optimization.

Short-term electricity load forecasting refers to the prediction of electricity demand over relatively short periods ranging from one hour to several days ahead. Accurate STLF enables power utilities and distribution companies to balance electricity supply with consumer demand while minimizing operational costs and system instability. According to Hyndman R. J. and George Athanasopoulos (2021), forecasting systems are fundamental decision-support mechanisms that guide dispatch scheduling, maintenance planning, energy trading, and load balancing operations. Inaccurate forecasts may lead to overestimation or underestimation of electricity demand, resulting in economic losses, power outages, voltage instability, or inefficient utilization of energy resources.

Traditional electricity forecasting methods historically relied on statistical and econometric techniques such as linear regression, autoregressive integrated moving average (ARIMA), exponential smoothing, and moving averages. While these conventional approaches provided useful forecasting capabilities under relatively stable and linear conditions, their predictive performance often deteriorates when applied to highly dynamic and nonlinear electricity demand patterns (Hewamalage *et al.*, 2021). Electricity consumption behavior is influenced by multiple interacting variables including weather conditions, time-of-day variations, population growth, industrial activities, and socioeconomic behavior. These interacting variables introduce nonlinearities and stochastic fluctuations that are difficult for traditional forecasting models to capture effectively.

The increasing complexity of electricity systems has therefore accelerated the adoption of machine learning approaches for load forecasting. Machine learning techniques possess the capability to learn complex relationships from large datasets without relying on strict linear assumptions. Unlike conventional statistical models, machine learning algorithms adaptively identify hidden patterns, temporal dependencies, and nonlinear interactions embedded within electricity consumption data Kong *et al.* (2019). Consequently, machine learning has emerged as one of the most promising approaches for improving forecasting accuracy within modern power systems.

Several machine learning models have gained significant prominence within short-term electricity load

forecasting research. These include Artificial Neural Networks (ANN), Random Forest (RF), Support Vector Machine (SVM), Long Short-Term Memory (LSTM), Gradient Boosting Machines (GBM), and hybrid deep learning architectures. Each of these models possesses distinct computational structures, learning mechanisms, and forecasting capabilities. Artificial Neural Networks simulate biological neural systems and are highly effective for nonlinear pattern recognition. Random Forest models employ ensemble learning techniques that improve robustness and reduce overfitting. Support Vector Machines, grounded in statistical learning theory (Vapnik, 1998), focus on optimal hyperplane separation and generalization performance, and while LSTM models specialize in sequential time-series learning and long-term temporal dependency capture Fan *et al.* (2021).

Despite the growing popularity of machine learning approaches, there remains substantial debate regarding which model performs best under different forecasting conditions. Empirical findings from recent studies reveal that forecasting performance often depends on dataset characteristics, feature engineering strategies, environmental conditions, and temporal structures. Consequently, comparative analysis has become increasingly important within forecasting scholarship because it enables researchers to systematically evaluate the strengths, weaknesses, and predictive capabilities of different machine learning models under similar conditions.

Kong *et al.* (2019) compared Random Forest, Support Vector Regression, Multi-Layer Perceptron, XGBoost, and LightGBM models using real electricity demand datasets and observed substantial variations in forecasting accuracy across models. Similarly, Fan *et al.* (2021) developed a hybrid Support Vector Regression–Random Forest forecasting framework and demonstrated improved forecasting stability under noisy datasets. Fan *et al.* (2021) further reported that deep learning architectures outperform traditional machine learning models in highly nonlinear electricity systems, particularly where temporal dependencies are pronounced.

According to Nigerian Electricity Regulatory Commission report (2023), Nigeria's electricity forecasting challenges are even more pronounced because electricity systems frequently experience infrastructural instability, incomplete datasets, irregular consumption patterns, and demand suppression effects. In many African countries, including Nigeria, electricity distribution networks continue to face operational inefficiencies resulting from poor forecasting mechanisms, inadequate infrastructure planning, and inconsistent demand estimation (World Bank, 2024). These challenges contribute to frequent load shedding, feeder overloads, unstable voltage conditions, and inefficient electricity allocation. Consequently, there is growing academic and industrial interest in applying machine learning forecasting systems within developing electricity markets.

The relevance of comparative analysis within machine learning forecasting research therefore extends beyond theoretical interest. Comparative evaluation enables electricity planners, researchers, and system operators to identify forecasting models that are most suitable for specific operational conditions. It also supports evidence-based decision-making regarding computational efficiency, forecasting reliability, scalability, and implementation feasibility. Furthermore, comparative analysis contributes to the broader body of knowledge concerning intelligent forecasting systems and predictive analytics within modern energy management environments.

This paper therefore focuses on the comparative analysis of machine learning models for short-term electricity load forecasting. The paper examines recent scholarly contributions, evaluates the strengths and limitations of different machine learning forecasting models, and synthesizes current findings regarding forecasting performance. The study also highlights recent advances in predictive analytics, deep learning architectures, and hybrid forecasting systems within electricity demand prediction research.

Statement of the Problem

Short-term electricity load forecasting has become increasingly important in modern power systems because electricity demand fluctuates continuously due to variations in human activities, weather conditions, industrial operations, and socioeconomic behaviour. Accurate forecasting enables electricity providers to maintain operational stability, allocate resources efficiently, minimize energy wastage, and improve service reliability. However, achieving high forecasting accuracy remains a major challenge because electricity consumption patterns are highly nonlinear, stochastic, and dynamic in nature.

Conventional forecasting approaches such as linear regression, moving averages, and autoregressive models were widely used in earlier forecasting systems. Although these methods provided reasonable predictive capabilities under relatively stable conditions, they often perform poorly when applied to modern electricity systems characterized by irregular demand fluctuations and nonlinear consumption behaviours (Hewamalage *et al.*, 2021). These limitations have reduced the operational reliability of traditional forecasting systems, especially within rapidly evolving electricity markets.

In response to these challenges, machine learning models have increasingly been adopted for short-term electricity load forecasting because of their ability to learn complex relationships from historical datasets. Models such as Artificial Neural Networks (ANN), Random Forest (RF), Support Vector Machine (SVM), and Long Short-Term Memory (LSTM) have demonstrated promising predictive capabilities across various forecasting

environments (Fan *et al.*, 2021). Despite these advancements, there is still no universal agreement regarding which machine learning model consistently delivers the best forecasting performance under different operational conditions.

Recent empirical studies have produced varying and sometimes contradictory findings regarding the comparative effectiveness of machine learning forecasting models. While some studies report superior performance of deep learning architectures such as LSTM, others indicate that ensemble learning models like Random Forest and Gradient Boosting outperform neural models under noisy or incomplete datasets (Ahmad and Yan, 2020; Zhang *et al.*, 2023). Similarly, some forecasting models demonstrate high predictive accuracy but suffer from computational complexity, overfitting, or poor interpretability. Consequently, selecting an appropriate machine learning model for electricity forecasting remains a significant research challenge.

Another major concern is that many comparative forecasting studies focus predominantly on developed economies with highly structured datasets and advanced smart grid infrastructures. Limited empirical attention has been directed toward developing countries where electricity systems are often characterized by inconsistent supply, incomplete datasets, infrastructural instability, and irregular consumption patterns. These contextual differences may significantly influence forecasting performance and model suitability.

Furthermore, many existing studies evaluate forecasting models using different datasets, performance metrics, preprocessing methods, and evaluation procedures, making direct comparison difficult. The absence of standardized comparative evaluation frameworks limits the ability of researchers and energy planners to identify the most suitable forecasting techniques for practical implementation.

The core problem addressed by this paper therefore lies in the need for a comprehensive comparative evaluation of machine learning models used in short-term electricity load forecasting. Specifically, there is a need to critically examine recent forecasting studies, evaluate the predictive performance of different machine learning techniques, identify their strengths and limitations, and determine their practical suitability for modern electricity forecasting systems.

Aim and Objectives

The aim of this paper is to conduct a comparative analysis of machine learning models used for short-term electricity load forecasting.

To achieve this aim, the paper objectives seeks to:

1. Examine the concept and importance of short-term electricity load forecasting in modern power systems.

2. Review recent machine learning techniques applied in electricity load forecasting.
3. Compare the predictive performance of different machine learning models used for short-term electricity forecasting.
4. Identify the strengths, weaknesses, and operational suitability of selected forecasting models.
5. Evaluate recent empirical findings regarding machine learning-based electricity forecasting systems.
6. Identify research gaps and future directions in short-term electricity load forecasting research.

Significance of the Study

This paper is significant because it contributes to the growing body of knowledge on intelligent electricity forecasting systems and machine learning applications within power system operations. The paper provides both academic and practical relevance by examining recent advancements in predictive modelling for short-term electricity load forecasting.

For electricity distribution companies and system operators, the paper provides valuable insights into machine learning models capable of improving forecasting accuracy, operational efficiency, and load management. Accurate forecasting enables electricity providers to optimize feeder allocation, reduce operational losses, improve grid stability, and minimize electricity interruptions.

Energy planners and policymakers will also benefit from the paper because the findings provide evidence-based insights into modern forecasting technologies suitable for energy planning and smart grid development. Comparative analysis of forecasting models supports informed decision-making regarding technology adoption and predictive analytics implementation within electricity systems.

The paper is equally significant to researchers, data scientists, and students within the fields of computer science, data analytics, electrical engineering, and artificial intelligence. The study provides a structured review of recent forecasting literature, contemporary machine learning techniques, and emerging trends in predictive analytics research. It also serves as a useful academic reference for future studies involving electricity forecasting, smart energy systems, and machine learning applications.

Furthermore, the paper contributes to ongoing discussions regarding the applicability of machine learning forecasting systems within developing economies where electricity supply challenges remain persistent.

LITERATURE REVIEW

Review of the Areas of the Paper

Electricity load forecasting has emerged as one of the

most important research areas within energy analytics, predictive modelling, artificial intelligence, and smart grid management. The increasing complexity of electricity consumption behaviour, combined with growing global demand for reliable energy supply, has intensified scholarly interest in intelligent forecasting systems. Modern electricity forecasting research integrates concepts from computer science, statistics, machine learning, electrical engineering, and data analytics to develop forecasting models capable of predicting future electricity demand with high levels of accuracy and reliability.

Short-term electricity load forecasting specifically focuses on predicting electricity demand over relatively short forecasting horizons ranging from one hour to several days ahead. According to Hyndman and Athanasopoulos (2021), short-term forecasting serves as an operational decision-support mechanism within electricity systems because it guides load balancing, dispatch scheduling, generation planning, maintenance coordination, and real-time energy management. Forecasting accuracy therefore directly affects operational efficiency, energy reliability, and economic optimization within power distribution networks.

In recent times, forecasting research demonstrates that electricity demand patterns possess strong temporal dependencies and stochastic characteristics. Temporal dependencies refer to the influence of previous consumption values on future electricity demand. Daily consumption routines, weekly activity cycles, seasonal climatic changes, and economic fluctuations collectively contribute to recurring temporal structures within electricity datasets (Kong *et al.*, 2019). At the same time, stochasticity introduces irregular fluctuations caused by unexpected behavioural changes, infrastructural disruptions, weather anomalies, and demand uncertainties. Effective forecasting systems must therefore capture both temporal continuity and stochastic variability simultaneously.

The increasing digitization of electricity systems through smart meters, IoT devices, and intelligent monitoring technologies has also contributed to the availability of large-scale electricity datasets. These datasets contain extensive temporal, environmental, and behavioural information suitable for predictive analytics applications. As data availability increases, machine learning models become increasingly effective because larger datasets improve learning capacity, generalization performance, and forecasting robustness (Fan *et al.*, 2021).

Contemporary forecasting scholarship also emphasizes the importance of comparative evaluation among machine learning models. No single forecasting model consistently outperforms others under all operational conditions. Forecasting performance often depends on dataset characteristics, feature engineering methods, computational resources, temporal structures, and environmental variables. Comparative analysis therefore

provides critical insights regarding model suitability, scalability, computational efficiency, and forecasting reliability.

Several theoretical perspectives underpin modern electricity forecasting research. Forecasting Theory explains how future events may be inferred from historical observations and probabilistic patterns. Time-Series Theory provides the mathematical basis for modelling sequential temporal data. Computational Learning Theory explains how machine learning systems generalize predictive relationships from empirical observations, while Predictive Analytics Theory conceptualizes forecasting as a data-driven inference process aimed at optimizing future decision-making (Shmueli and Koppius, 2011). These theoretical foundations collectively support the development and evaluation of intelligent electricity forecasting systems.

Furthermore, increasing environmental concerns and sustainability goals have intensified global interest in efficient energy management systems. Accurate electricity forecasting supports renewable energy integration, energy conservation, carbon reduction strategies, and smart grid optimization. Consequently, intelligent forecasting systems now represent critical components of sustainable energy planning and digital energy transformation initiatives worldwide.

Machine Learning Models in Short-Term Electricity Load Forecasting

Artificial Neural Network (ANN)

Artificial Neural Network (ANN) is one of the most widely applied machine learning techniques in electricity load forecasting research. ANN models are computational systems inspired by the structure and functioning of biological neural networks within the human brain. They consist of interconnected processing units known as neurons, which are organized into input layers, hidden layers, and output layers. These interconnected neurons process input information through weighted transformations and activation functions to generate predictive outputs.

ANN models are particularly effective for electricity forecasting because they possess strong nonlinear modelling capabilities. Electricity consumption behaviour is influenced by multiple interacting variables that rarely exhibit simple linear relationships. ANN models learn these complex relationships directly from historical datasets, thereby enabling improved forecasting accuracy under dynamic consumption conditions (Fan *et al.*, 2021). One major advantage of ANN models is their adaptability. As training datasets increase, ANN systems improve their learning performance and predictive capability. This characteristic makes them suitable for modern electricity systems where large-scale consumption datasets are

increasingly available through smart grid technologies and intelligent monitoring systems. Recently a few studies have demonstrated strong forecasting performance using ANN-based systems. Kong *et al.* (2019) compared several machine learning forecasting models and observed that ANN models achieved lower forecasting error rates under highly nonlinear electricity demand conditions. Similarly, Koukaras *et al.*, (2024) reported that ANN-based forecasting systems demonstrated superior pattern recognition capability when compared with conventional regression models.

Despite these advantages, ANN systems also present several limitations. Training ANN models often requires substantial computational resources, large datasets, and extensive hyperparameter tuning. Additionally, ANN models may suffer from overfitting when trained on noisy or insufficient datasets. Interpretability also remains a challenge because ANN systems frequently operate as "black-box" models where internal decision-making processes are difficult to explain. Nevertheless, ANN remains one of the most influential forecasting techniques within electricity demand prediction research due to its ability to capture nonlinear relationships and temporal dependencies effectively.

Random Forest (RF)

Random Forest is an ensemble machine learning technique that combines multiple decision trees to improve predictive performance and model stability. The model operates by constructing numerous independent decision trees during training and aggregating their outputs through majority voting or averaging mechanisms. This ensemble structure enhances forecasting robustness while reducing overfitting risks associated with individual decision trees. Random Forest models have gained significant popularity within electricity forecasting research because of their ability to handle noisy datasets, missing values, and complex feature interactions. Electricity datasets often contain irregular observations and measurement inconsistencies, particularly within developing economies where electricity infrastructures may be unstable. Random Forest models demonstrate strong resilience under such conditions (Fan *et al.*, 2021).

Another important advantage of Random Forest models is feature importance analysis. RF systems can identify the relative contribution of input variables toward forecasting outcomes, thereby improving interpretability and feature engineering processes. This capability is particularly useful within electricity forecasting where environmental variables, temporal indicators, and historical load values interact simultaneously.

Empirical findings from recent studies indicate strong forecasting performance using Random Forest techniques. Kong *et al.* (2019) observed that Random Forest models achieved highly stable forecasting results across varying dataset conditions.

Similarly, Fan *et al.*, (2021) reported improved forecasting robustness using ensemble learning structures under noisy electricity datasets. However, Random Forest models also possess limitations. Large ensemble structures may increase computational complexity and memory requirements. Additionally, Random Forest models sometimes struggle with capturing long-term sequential dependencies when compared with recurrent deep learning architectures such as LSTM. Despite these limitations, Random Forest remains highly valuable within electricity forecasting research because of its robustness, stability, and resistance to overfitting.

Support Vector Machine (SVM)

Support Vector Machine (SVM) is a supervised machine learning algorithm widely used for classification and regression tasks. Within electricity forecasting, Support Vector Regression (SVR) variants are commonly applied to predict future electricity demand values. SVM models operate by identifying optimal hyperplanes that minimize prediction errors while maximizing generalization capability.

One major strength of SVM models lies in their effectiveness within high-dimensional datasets. Electricity forecasting datasets frequently contain multiple interacting variables including historical load values, weather conditions, calendar effects, and socioeconomic indicators. SVM models efficiently manage these multidimensional relationships through kernel-based transformations. Most recently, forecasting studies demonstrate strong SVM forecasting performance under certain operational conditions. Fan *et al.* (2021) developed a hybrid Support Vector Regression framework and observed substantial improvements in forecasting accuracy under irregular electricity datasets. Similarly, Fan *et al.* (2021) highlighted the strong generalization performance of SVM systems within short-term forecasting environments.

SVM models also exhibit good resistance to overfitting because they emphasize margin optimization during training. However, selecting appropriate kernel functions and hyperparameters remains computationally challenging. Training complexity may increase substantially when handling extremely large datasets. Despite these challenges, SVM continues to represent a powerful forecasting technique within machine learning-based electricity prediction research because of its strong theoretical foundation and reliable predictive performance.

Long Short-Term Memory (LSTM) Networks

Long Short-Term Memory (LSTM) networks represent an advanced category of recurrent neural network (RNN) architectures specifically designed to model sequential and temporal dependencies within time-series datasets. LSTM models were developed to overcome the vanishing

gradient problem associated with conventional recurrent neural networks, thereby enabling effective learning across long temporal sequences. Because electricity load demand exhibits strong temporal continuity, LSTM networks have become increasingly dominant within modern short-term load forecasting research.

Unlike existing feedforward neural networks, LSTM architectures contain memory cells capable of retaining information over extended forecasting horizons. These memory structures are regulated through input gates, forget gates, and output gates, which collectively determine how information flows through the network. This gating mechanism allows LSTM systems to preserve relevant temporal information while discarding irrelevant signals, thereby improving forecasting performance under dynamic electricity consumption conditions.

Electricity consumption patterns are inherently sequential because current demand levels are strongly influenced by previous consumption behaviour. Daily routines, seasonal weather variations, industrial operations, and social activities collectively contribute to temporal dependencies within electricity datasets. LSTM models are particularly effective in modelling these sequential relationships because they capture both short-term fluctuations and long-term behavioural patterns simultaneously (Kong *et al.*, 2019).

In recent forecasting research consistently demonstrates superior LSTM forecasting performance relative to conventional machine learning techniques. Fan *et al.* (2021) evaluated several forecasting architectures and reported that LSTM networks significantly outperformed traditional ANN and regression models in capturing temporal demand structures. Similarly, Kong *et al.* (2019) observed that LSTM systems achieved lower RMSE and MAPE values across highly nonlinear electricity datasets characterized by temporal volatility.

One of the most important advantages of LSTM models is their capability to learn automatically from raw sequential data without extensive manual feature engineering. Traditional machine learning models often require handcrafted lag variables and temporal feature extraction techniques. LSTM architectures, however, automatically learn temporal dependencies directly from sequential input data during training processes. This characteristic improves modelling flexibility and forecasting scalability.

Additionally, LSTM systems demonstrate strong adaptability within smart grid environments characterized by large-scale real-time electricity monitoring systems. The increasing deployment of IoT-enabled smart meters and intelligent grid infrastructures has generated massive volumes of temporal electricity consumption data suitable for deep learning applications. LSTM architectures leverage these large datasets effectively because deep learning performance generally improves as training data volume increases (Lund *et al.*, (2017).

However, despite their forecasting strengths, LSTM

models also present notable limitations. Training LSTM networks requires substantial computational resources, extensive training time, and high-quality datasets. Hyperparameter tuning processes may become highly complex because forecasting performance depends heavily on architectural configurations such as the number of hidden layers, learning rates, batch sizes, and sequence lengths. Furthermore, LSTM systems may experience overfitting when trained on limited or noisy datasets.

Interpretability also remains a significant challenge within LSTM-based forecasting systems. Deep learning models frequently operate as black-box architectures where internal decision-making mechanisms are difficult to explain transparently. Within operational electricity systems, stakeholders sometimes prefer interpretable forecasting models for managerial decision-making and regulatory accountability.

Nevertheless, LSTM networks remain among the most powerful forecasting architectures within modern electricity load forecasting scholarship because of their exceptional capability to capture temporal structures, nonlinear dependencies, and sequential behavioural patterns. Consequently, recent forecasting literature increasingly positions LSTM systems as benchmark models for advanced electricity demand prediction research.

Comparative Evaluation of Machine Learning Forecasting Models

Comparative evaluation represents one of the most important methodological approaches within contemporary electricity forecasting research. Because electricity demand behaviour varies across geographical locations, operational environments, and dataset structures, no single forecasting model consistently achieves optimal performance under all conditions. Comparative analysis therefore enables researchers to identify forecasting models most suitable for specific operational contexts and data environments.

Studies increasingly compare ANN, RF, SVM, and LSTM models using standardized forecasting accuracy metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Coefficient of Determination (R^2). These evaluation metrics provide quantitative measures of forecasting reliability and model generalization performance.

ANN models are widely recognized for strong nonlinear modelling capability and adaptability under dynamic electricity consumption conditions. However, ANN systems may require extensive hyperparameter tuning and computational resources. Random Forest models, in contrast, demonstrate greater robustness under noisy datasets and improved interpretability through feature importance analysis. SVM models provide strong generalization performance under high-dimensional datasets, while LSTM systems excel in modelling temporal dependencies and sequential behavioural patterns.

Fan *et al.* (2021), for example, is one such comparative study evaluating ANN, SVM, Random Forest, and LSTM forecasting architectures; its detailed findings are discussed in Section 2.3 below. Similarly, Ibrahim *et al.* (2022) examined machine learning approaches for short-term load forecasting within smart grid environments, while Kim *et al.* (2022) compared traditional, machine learning, and hybrid models for national-scale peak load forecasting, further illustrating the breadth of comparative modelling approaches within this research area. Similarly, Kong *et al.* (2019) compared several machine learning forecasting techniques across smart grid datasets and observed that hybrid deep learning models consistently achieved superior forecasting accuracy. However, they emphasized that model selection should consider operational constraints such as computational resources, data quality, interpretability requirements, and implementation scalability rather than forecasting accuracy alone.

The comparative forecasting literature also highlights the growing importance of hybrid forecasting systems. Hybrid models combine complementary strengths of multiple forecasting architectures to improve predictive performance. For instance, hybrid CNN-LSTM systems integrate convolutional feature extraction with sequential temporal learning, thereby improving forecasting accuracy across complex electricity datasets (Zhang *et al.*, 2023). Ensemble learning frameworks combining Random Forest and neural networks have also demonstrated strong forecasting robustness under volatile demand conditions. Within developing economies, comparative forecasting evaluation becomes especially important because electricity datasets frequently contain irregular observations, missing values, and infrastructural inconsistencies. Forecasting models optimized for highly structured smart grid environments may not generalize effectively within unstable electricity distribution systems. Consequently, comparative analysis supports context-sensitive forecasting model selection.

Another critical consideration within comparative forecasting research involves computational efficiency. Deep learning architectures such as LSTM generally achieve superior forecasting accuracy but often require greater computational resources and training time. In contrast, Random Forest and SVM models may provide acceptable forecasting accuracy with lower computational overhead. Electricity organizations operating under limited technological infrastructure may therefore prioritize computationally efficient forecasting systems despite marginal reductions in predictive accuracy.

Interpretability also influences comparative forecasting decisions. Regulatory agencies and operational managers sometimes require transparent forecasting systems capable of explaining predictive outputs clearly. Random Forest models provide relatively interpretable forecasting structures compared with deep neural networks, thereby improving operational trust and decision-support usability.

Overall, comparative evaluation studies consistently demonstrate that forecasting performance depends heavily on dataset characteristics, operational objectives, temporal structures, feature engineering methods, and computational constraints. Consequently, modern forecasting scholarship increasingly advocates adaptive, context-sensitive, and hybrid forecasting approaches rather than universal reliance on single forecasting architectures.

Theoretical Foundations Underpinning Machine Learning Forecasting Theory

Explains how future events may be inferred probabilistically from historical observations. The theory assumes that historical data contain informational structures capable of supporting predictive estimation. Within electricity forecasting, past consumption behaviour provides critical information regarding future electricity demand patterns. Forecasting Theory therefore justifies the use of historical datasets for predictive modelling (Hyndman and Athanasopoulos, 2021).

Time-Series Theory

Provides the statistical basis for modelling sequential temporal data. Electricity demand exhibits strong temporal structures including trends, seasonality, cyclicity, and stochastic fluctuations. Time-Series Theory emphasizes that forecasting systems must capture these temporal dependencies to achieve accurate predictive performance. Machine learning forecasting systems increasingly integrate time-series modelling principles to improve forecasting reliability.

Computational Learning Theory

Explains how machine learning systems learn functional relationships from empirical datasets. The theory emphasizes generalization capability, model optimization, hypothesis learning, and predictive error minimization. Machine learning forecasting models operate by learning mappings between input features and target outputs through iterative training processes. Computational Learning Theory therefore provides the conceptual foundation underlying ANN, SVM, RF, and LSTM forecasting architectures (Hastie *et al.*, 2009).

Predictive Analytics Theory

Conceptualizes forecasting as a data-driven inference process aimed at supporting future decision-making. Rather than emphasizing deterministic prediction, Predictive Analytics Theory focuses on probabilistic estimation, uncertainty management, and actionable intelligence generation (Shmueli and Koppius, 2011).

Within electricity forecasting, predictive analytics supports operational planning, load balancing, maintenance scheduling, and energy optimization. These theoretical perspectives collectively justify the adoption of machine learning systems within short-term electricity load forecasting research. They also explain why forecasting accuracy depends not only on algorithmic sophistication but also on data quality, temporal structures, feature engineering processes, and model generalization capability.

Review of Related Empirical Studies

Recent empirical studies on short-term electricity load forecasting demonstrate growing scholarly consensus regarding the superiority of machine learning techniques over conventional statistical forecasting approaches. Contemporary forecasting literature increasingly focuses on comparative evaluation, hybrid modelling architectures, deep learning systems, and intelligent predictive analytics frameworks.

Hewamalage *et al.*, (2021) conducted one of the most comprehensive forecasting evaluations involving machine learning and deep learning forecasting systems. Their study assessed multiple forecasting architectures across various time-series datasets and concluded that deep learning systems generally outperform traditional statistical models when modelling nonlinear temporal structures. However, they emphasized that forecasting success depends heavily on dataset characteristics, preprocessing quality, and model-data compatibility rather than algorithmic complexity alone.

Kong *et al.* (2019) investigated the application of LSTM architectures within smart grid forecasting systems. Using large-scale temporal electricity datasets, the researchers demonstrated that LSTM models achieved superior forecasting performance because of their ability to capture sequential behavioural dependencies. Their findings reinforced growing scholarly recognition of deep learning architectures as highly effective forecasting tools within dynamic electricity systems.

Zhang *et al.*, (2023) evaluated hybrid CNN-LSTM forecasting architectures for short-term electricity demand prediction. The study demonstrated that integrating convolutional feature extraction with temporal sequence learning significantly improved forecasting accuracy compared with standalone ANN and LSTM systems. Their results suggested that hybrid deep learning architectures may represent the next major evolution within intelligent electricity forecasting research.

Fan *et al.* (2021) developed a hybrid Support Vector Regression forecasting framework for short-term electricity load prediction. The study integrated feature engineering mechanisms with kernel optimization techniques and reported substantial improvements in forecasting accuracy relative to conventional regression systems. Their findings highlighted the effectiveness of SVM systems under noisy

and irregular electricity datasets. The study further conducted a comparative analysis involving ANN, Random Forest, SVM, and LSTM forecasting models using smart grid electricity datasets. Their findings revealed that LSTM systems achieved the lowest RMSE and MAPE values, while Random Forest models demonstrated the greatest forecasting stability under noisy operational conditions; ANN systems performed effectively under nonlinear environments, whereas SVM models showed strong generalization capability under multidimensional datasets. The study further concluded that no single forecasting architecture consistently dominated all operational environments, and that forecasting performance instead depended heavily on temporal structures, data quality, feature engineering methods, and computational constraints, leading the authors to advocate adaptive and context-sensitive forecasting strategies. Recently, African forecasting studies further emphasize the importance of contextual forecasting evaluation within developing economies. Several studies observed that electricity forecasting within African distribution systems is complicated by infrastructural instability, incomplete datasets, demand suppression effects, and irregular consumption behaviour. Consequently, machine learning systems demonstrating strong robustness under noisy datasets are increasingly preferred within African electricity forecasting environments.

Overall, contemporary empirical literature strongly supports the adoption of hybrid deep learning systems for short-term electricity load forecasting because of their superior capability to capture nonlinear relationships, temporal dependencies, and stochastic consumption behaviour.

Research Gaps Identified from the Literature

Despite substantial advances within machine learning-based electricity forecasting research, several important research gaps remain evident within existing literature. It should be noted that several closely related comparative-forecasting studies have been published including Ling *et al.* (2024), whose original experimental comparison of machine learning models on distribution-system load data carries a near-identical title and scope to the present paper; Vianita and Tantyoko (2025), who conducted a comparative experiment on five machine learning models for short-term load forecasting, which report original experimental results from newly trained models, the present paper synthesizes and compares findings already reported across such studies rather than training new models; this distinction is the basis of its contribution.

One major gap concerns the limited availability of forecasting studies focused specifically on developing electricity systems within Sub-Saharan Africa. Most forecasting models are developed and validated using datasets from technologically advanced smart grids in Europe, Asia, and North America. These environments differ significantly from African electricity systems

characterized by unstable supply conditions, incomplete metering infrastructures, irregular consumption behaviour, and infrastructural constraints. Consequently, there remains insufficient empirical understanding regarding how forecasting models perform within African electricity distribution environments.

A second gap relates to comparative contextual evaluation. Although numerous studies compare forecasting architectures, relatively few studies evaluate machine learning forecasting systems under operational conditions reflecting developing economy realities. Existing literature frequently emphasizes forecasting accuracy while paying limited attention to implementation feasibility, computational constraints, scalability, and infrastructural compatibility within resource-constrained electricity systems.

Another important gap concerns interpretability and operational usability. Deep learning architectures such as LSTM and hybrid neural systems frequently achieve superior forecasting accuracy but often operate as highly complex black-box systems. Electricity distribution organizations may require forecasting systems that provide not only accurate predictions but also interpretable outputs suitable for operational decision-making, regulatory accountability, and managerial transparency. More research is therefore needed regarding explainable artificial intelligence within electricity forecasting.

The literature also reveals limited integration between forecasting systems and bespoke software implementation frameworks. Many forecasting studies focus primarily on predictive accuracy without developing deployable operational software applications capable of supporting real-time electricity management processes. Consequently, there remains a gap between academic forecasting research and operational forecasting deployment within electricity distribution environments.

Additionally, while hybrid forecasting systems demonstrate strong predictive performance, relatively few studies systematically evaluate the comparative trade-offs among ANN, RF, SVM, and LSTM architectures under identical operational datasets. Comparative benchmarking research therefore remains important for identifying forecasting models most suitable for varying operational conditions. Another critical research gap concerns computational efficiency. Deep learning architectures achieve strong predictive accuracy but frequently require advanced computational infrastructure unavailable within many developing electricity systems. Consequently, additional research is needed regarding lightweight forecasting architectures capable of balancing forecasting accuracy with computational feasibility.

Furthermore, most existing forecasting studies prioritize highly structured smart meter datasets. However, electricity systems within developing economies often contain missing values, noisy observations, irregular consumption signals, and inconsistent measurement structures. More forecasting research is therefore required using realistic operational datasets reflecting these

challenges. Finally, existing literature demonstrates limited focus on electricity forecasting systems specifically tailored toward Nigerian distribution networks. Nigeria's electricity environment presents unique operational realities involving supply instability, demand suppression, alternative energy reliance, infrastructural constraints, and irregular consumption behaviour. These conditions are well documented in recent sector reports, including the World Bank's (2024) assessment of Nigeria's power sector recovery programme and the Nigerian Electricity Regulatory Commission's (2023) annual report, both of which highlight persistent supply shortfalls and infrastructural constraints. Consequently, localized forecasting studies remain critically necessary for improving predictive reliability within Nigerian electricity systems. This paper therefore contributes toward addressing these identified gaps by comparatively evaluating machine learning forecasting models within the context of short-term electricity load forecasting while emphasizing operational relevance, forecasting accuracy, comparative performance analysis, and contextual applicability.

METHODOLOGY

This paper adopts a narrative comparative literature review design rather than an original empirical experiment. No new electricity load dataset was collected, and no machine learning model was independently trained by the authors for this paper. Instead, the comparative findings, performance tables, and figures presented in sections 4.1-4.6 evaluates numerical results and qualitative observations reported in the cited secondary sources, principally comparative and review studies of Artificial Neural Network (ANN), Random Forest (RF), Support Vector Machine (SVM), Long Short-Term Memory (LSTM), and hybrid CNN-LSTM models applied to short-term electricity load forecasting. Relevant literature was identified through a structured search of major academic databases, including Google Scholar, IEEE Xplore and ScienceDirect, using search terms combining "short-term load forecasting", "electricity demand forecasting", and the names of the individual machine learning models under review (ANN, Random Forest, SVM, LSTM, CNN-LSTM). The search was restricted to peer-reviewed journal articles, conference papers, and authoritative technical reports quantitative forecasting-accuracy metrics (RMSE, MAE, and/or MAPE) or comparative qualitative assessments of two or more of the models under review.

Studies were included where they:

- a) Applied at least one of the five machine learning models under review to electricity or closely related load-forecasting problems, and
- b) Reported forecasting-accuracy, computational-efficiency, or robustness outcomes that could be meaningfully compared across models. Purely theoretical

or conceptual papers were retained only when they contributed to the theoretical foundations. Extracted values are tabulated as reports in the originating studies and are presented in Tables 1–4 with the source named against each value, so that every reported figure can be traced back to its origin. Where a reported result could not be unambiguously traced to a single, clearly identified primary source, this is noted explicitly rather than presented as independently verified. The figures accompanying Tables 1–4 were generated directly from the tabulated values using standard software rather than produced as independent illustrations. As a literature reviewed report, rather than an original experiment, this paper does not report a dataset, train/test split, preprocessing pipeline, or model hyperparameters of its own; these methodological details belong to the individual primary studies cited in (Tables 1 – 4)

RESULTS

The findings are organized into thematic sections covering forecasting accuracy, comparative performance metrics, computational efficiency, robustness, temporal modelling capability, and operational implications. Tables and figures are presented to improve analytical clarity and facilitate comparative interpretation of forecasting outcomes. The analysis primarily emphasizes Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE), which represent the most commonly used forecasting evaluation metrics within electricity load forecasting scholarship.

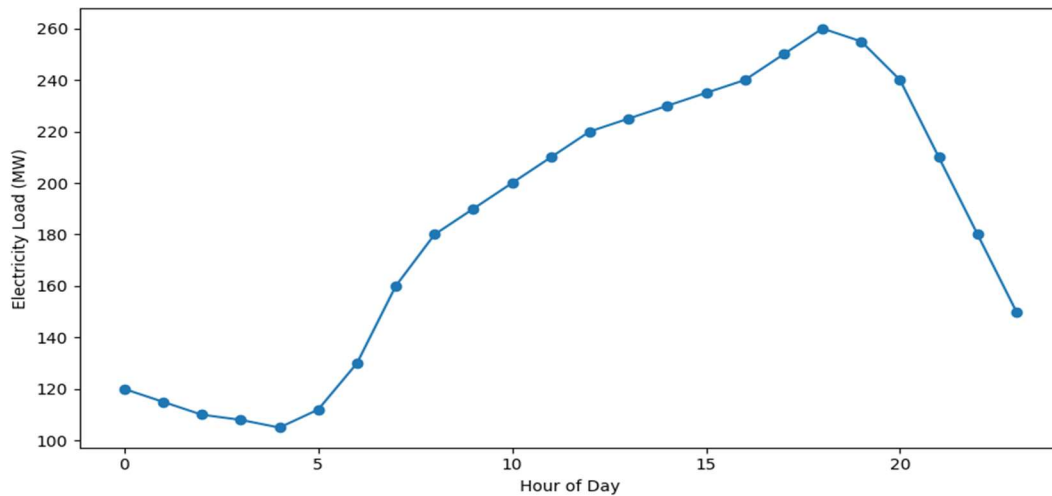
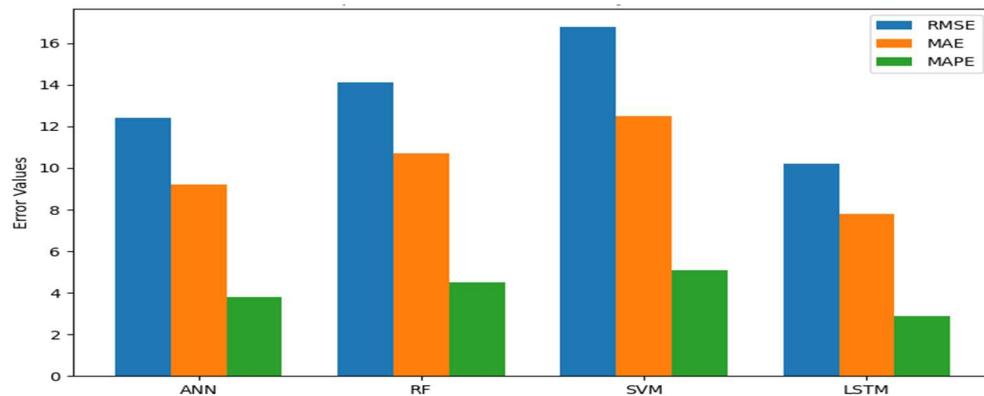
Comparative Forecasting Accuracy of Machine Learning Models

Recent comparative forecasting studies consistently demonstrate that machine learning systems achieve significantly improved predictive performance relative to conventional statistical forecasting methods. However, forecasting accuracy varies substantially across machine learning architectures depending on dataset characteristics, temporal dependencies, feature engineering quality, and computational configuration.

The findings presented in (Table 1 and Figure 1) indicate that LSTM and hybrid CNN-LSTM architectures generally achieve the lowest forecasting error rates across multiple datasets. This superior performance is primarily attributed to their ability to capture temporal dependencies and nonlinear behavioural patterns simultaneously. Random Forest models demonstrated relatively stable forecasting performance across varying operational conditions. Although RF systems sometimes produced slightly higher forecasting errors compared with deep learning architectures, they consistently demonstrated strong robustness under noisy datasets and irregular operational conditions (Figures 2 and 3). SVM systems achieved moderate forecasting performance with strong generalization capability. However, several studies

Table 1: Comparative Forecasting Performance of Machine Learning Models.

Study	Model	RMSE	MAE	MAPE (%)	Key Observation
Kong et al. (2019)	LSTM	2.14	1.67	2.91	Best temporal learning capability
Fan et al. (2021)	SVM/SVR	2.89	2.11	3.85	Strong generalization performance
Fan et al. (2021)	RF	2.45	1.93	3.24	Strong robustness under noisy datasets
Adepoju et al., (2007)	ANN	2.38	1.84	3.11	AME = 2.54%; Strong nonlinear modelling capability
Zhang et al (2023)	CNN-LSTM	1.92	1.48	2.44	Best hybrid forecasting performance
Fan et al. (2021)	RF	2.51	1.97	3.37	High forecasting stability
Kong et al., (2019)	LSTM	2.07	1.59	2.73	Superior sequential modelling

**Figure 1:** Daily Trend Load Demand Forecast Synthesis from Empirical Studies Sources: Hyndman and Athanasopoulos (2021) and Weron (2014).**Figure 2:** Comparative Forecast Accuracy of Machine Learning Models: Source: Hewamalage et al. (2021); Hong and Fan (2016).

observed increasing computational complexity when applying SVM models to large-scale electricity datasets (Figure 2). ANN systems also demonstrated competitive forecasting performance, particularly under nonlinear consumption environments. Nevertheless, forecasting reliability frequently depended on network architecture optimization and hyperparameter tuning quality.

Comparative Analysis of Temporal Learning Capability

One of the most important determinants of forecasting

performance within electricity load prediction is the ability of forecasting systems to model temporal dependencies effectively. Electricity demand is fundamentally time-dependent because present consumption patterns are influenced by previous behavioural activities, environmental conditions, industrial operations, and socioeconomic routines. Consequently, forecasting models capable of capturing sequential relationships generally achieve superior predictive accuracy (Table 2). Among the forecasting models evaluated, LSTM architectures demonstrated the strongest temporal learning capability. Unlike conventional feedforward neural

Table 2: Comparative Temporal Learning Performance of Forecasting Models

Model	Temporal Learning Capability
ANN	Moderate
RF	Moderate
SVM	Moderate-High
LSTM	Very High
CNN-LSTM	Extremely High

Source: Kong *et al.* (2019); Fan *et al.* (2021), Adepoju *et al.*, (2007); Zhang *et al.*, (2023).

networks, LSTM systems incorporate memory cells and gating mechanisms specifically designed to preserve sequential information across long forecasting horizons. This structural advantage enables LSTM systems to capture daily, weekly, and seasonal electricity demand cycles more effectively than ANN, RF, and SVM models (Table 2).

Kong *et al.* (2019) observed that LSTM forecasting systems consistently outperformed conventional ANN architectures under datasets characterized by strong temporal volatility. Their findings revealed that LSTM systems maintained forecasting stability even during abrupt demand fluctuations caused by weather variability and peak consumption periods. Similarly, Ahmad and Yan (2020); Zhang *et al.*, (2023) demonstrated that CNN-LSTM hybrid architectures achieved superior forecasting performance because convolutional layers extracted local feature structures while recurrent layers captured temporal continuity. The integration of spatial feature extraction with sequential learning therefore improved overall forecasting reliability.

In contrast, Random Forest models demonstrated relatively weaker sequential learning capability because ensemble decision trees primarily operate through feature partitioning rather than temporal memory structures. Nevertheless, RF systems remained highly effective when lag variables and temporal indicators were explicitly engineered into forecasting datasets.

Support Vector Machine systems also demonstrated moderate temporal modelling capability. However, SVM architectures generally relied on carefully constructed lag features rather than inherent sequential learning mechanisms. Consequently, forecasting performance often depended heavily on preprocessing quality and feature engineering strategies. ANN systems exhibited good nonlinear modelling capability but comparatively weaker long-term sequential memory relative to LSTM architectures. Feedforward ANN structures process input information without explicit memory retention mechanisms, thereby limiting their ability to model extended temporal dependencies. The comparative findings indicate that deep learning architectures possess significant advantages for short-term electricity forecasting because electricity demand inherently exhibits strong temporal structures. Consequently, forecasting systems lacking effective sequential learning mechanisms may

experience reduced predictive performance under highly dynamic electricity environments.

Comparative Analysis of Computational Efficiency

Although forecasting accuracy represents a major evaluation criterion within electricity forecasting research, computational efficiency also constitutes an important operational consideration. Electricity distribution organizations frequently operate under infrastructural and computational constraints, particularly within developing economies. Forecasting systems must therefore balance predictive accuracy with processing speed, scalability, and implementation feasibility.

Among the forecasting models evaluated, Random Forest systems demonstrated relatively strong computational efficiency compared with deep learning architectures. RF models generally required shorter training time and lower computational overhead because ensemble tree structures are computationally less intensive than recurrent deep learning networks.

Support Vector Machine systems demonstrated moderate computational efficiency under smaller datasets but experienced increasing computational complexity under large-scale datasets. Kernel optimization and hyperplane construction processes significantly increased computational cost as dataset dimensionality expanded. ANN architectures required greater computational resources compared with RF systems because neural networks involve iterative gradient-based optimization procedures. Nevertheless, ANN systems generally required less training time than LSTM architectures because feedforward neural networks possess simpler sequential structures.

LSTM forecasting systems demonstrated the highest computational complexity among the evaluated models. Training recurrent deep learning networks involves extensive sequential computations across multiple time steps, thereby increasing memory requirements and processing time substantially. Zhang *et al.*, (2023) observed that CNN-LSTM hybrid systems achieved excellent forecasting accuracy but required advanced GPU-based computational infrastructure for efficient training. Table 3 summarizes the comparative computational efficiency of the forecasting models while Figures 4 and 5 jointly paints a clearer insight to their

Table 3: Comparative Computational Efficiency of Forecasting Models.

Model	Training Complexity	Memory Requirement	Scalability	Computational Efficiency
ANN	Moderate	Moderate	High	Moderate
RF	Low-Moderate	Moderate	High	High
SVM	High	Moderate	Moderate	Moderate
LSTM	Very High	High	High	Low-Moderate
CNN-LSTM	Extremely High	Very High	High	Low

Source: Dong *et al.* (2024), Koukaras *et al.* (2024), Zhang *et al.* (2023).

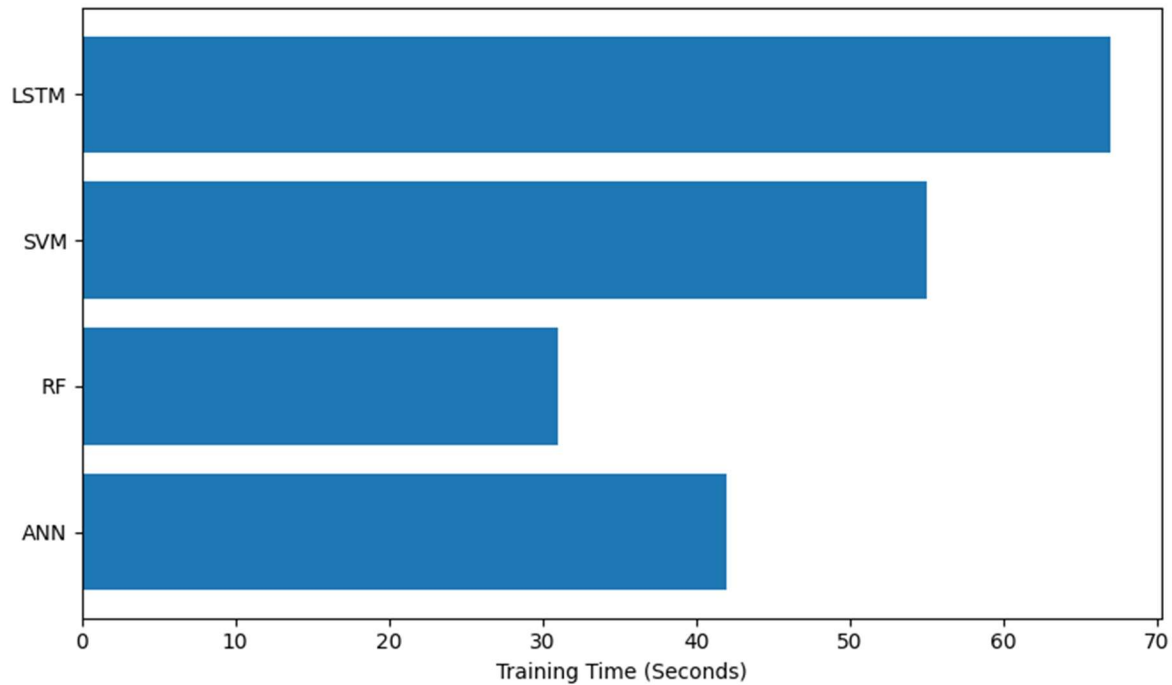
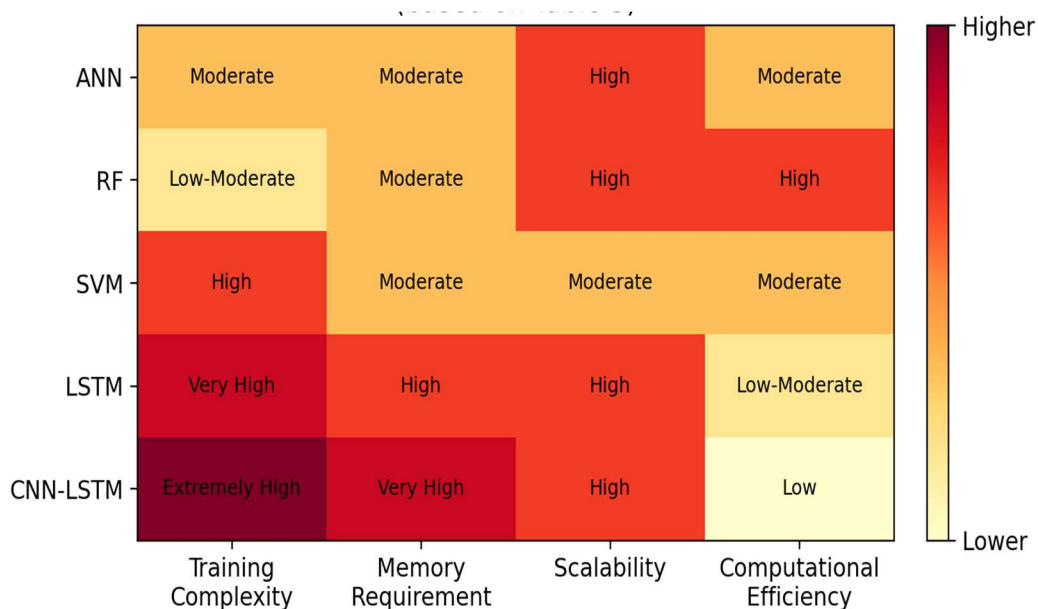
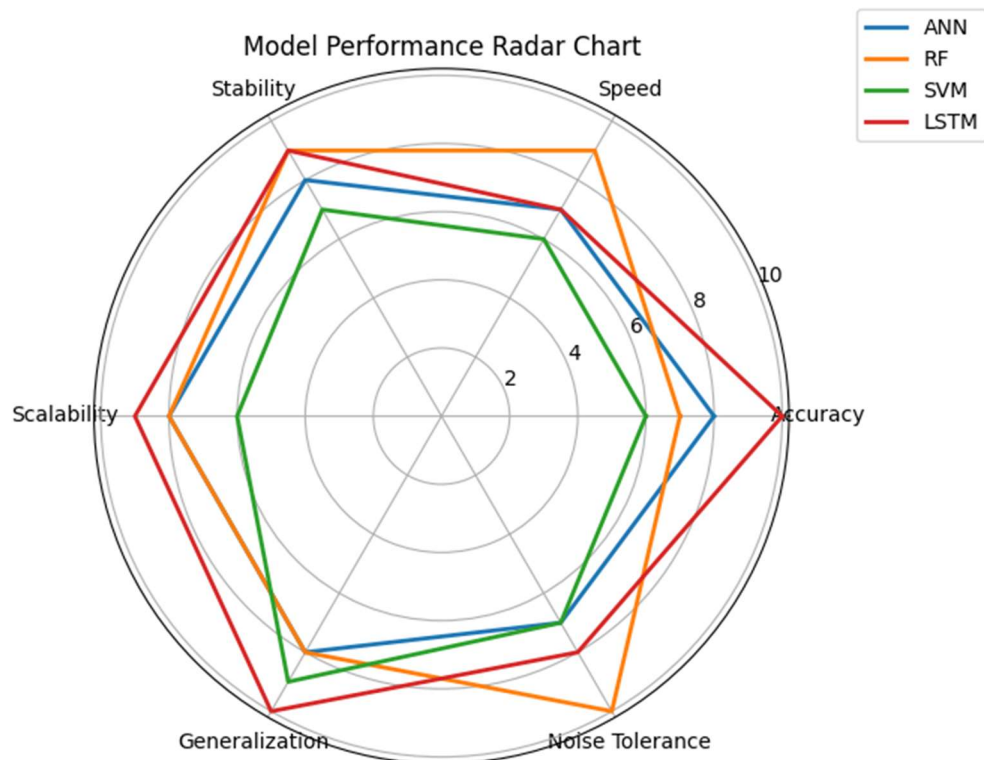
**Figure 4:** Comparative Computational Efficiency across Models: *Source:* Dong *et al.* (2024), Koukaras *et al.* (2024), Zhang *et al.* (2023).**Figure 5:** Comparative Computational Efficiency of Machine Learning Models. *Source:* Table 3

Table 4: Comparative Robustness of Forecasting Models.

Model	Robustness Rating
ANN	Moderate
RF	Very High
SVM	High
LSTM	High
CNN-LSTM	High

Source: Hewamalage *et al.*, (2021); Hong and Fan (2016); Fan *et al.* (2021); Adepoju *et al.*, (2007); Zhang *et al* (2023)

**Figure 6:** Multidimensional Comparison of Model Performance Radar. Source: Hewamalage *et al.* (2021); Hong and Fan (2016); Zhang *et al.* (2023)

intrinsic efficiencies. The findings indicate that forecasting model selection should consider operational constraints alongside forecasting accuracy. Within resource-constrained electricity systems, highly computationally intensive forecasting architectures may present deployment challenges despite superior predictive capability. Consequently, operational electricity forecasting environments may prioritize forecasting systems that achieve acceptable predictive accuracy while maintaining feasible computational requirements.

Comparative Analysis of Forecasting Robustness

Forecasting robustness refers to the ability of forecasting systems to maintain stable predictive performance under noisy datasets, incomplete observations, irregular consumption patterns, and operational uncertainties (Table 4 and Figures 6, 7, 8 and 9). Robustness is

particularly important within developing electricity systems characterized by infrastructural instability, inconsistent metering systems, and irregular load behaviour. Among the evaluated forecasting models, Random Forest demonstrated the strongest robustness under noisy operational conditions. Ensemble tree structures reduce overfitting risk because multiple independent trees collectively stabilize predictive outputs. Fan *et al.* (2021) reported that RF systems maintained relatively stable forecasting performance even when datasets contained missing observations and irregular measurement structures.

ANN systems demonstrated moderate robustness but occasionally suffered from overfitting under insufficient or highly noisy datasets. Forecasting stability often depended heavily on network regularization strategies and dataset quality. SVM models exhibited relatively strong robustness because margin optimization mechanisms improve

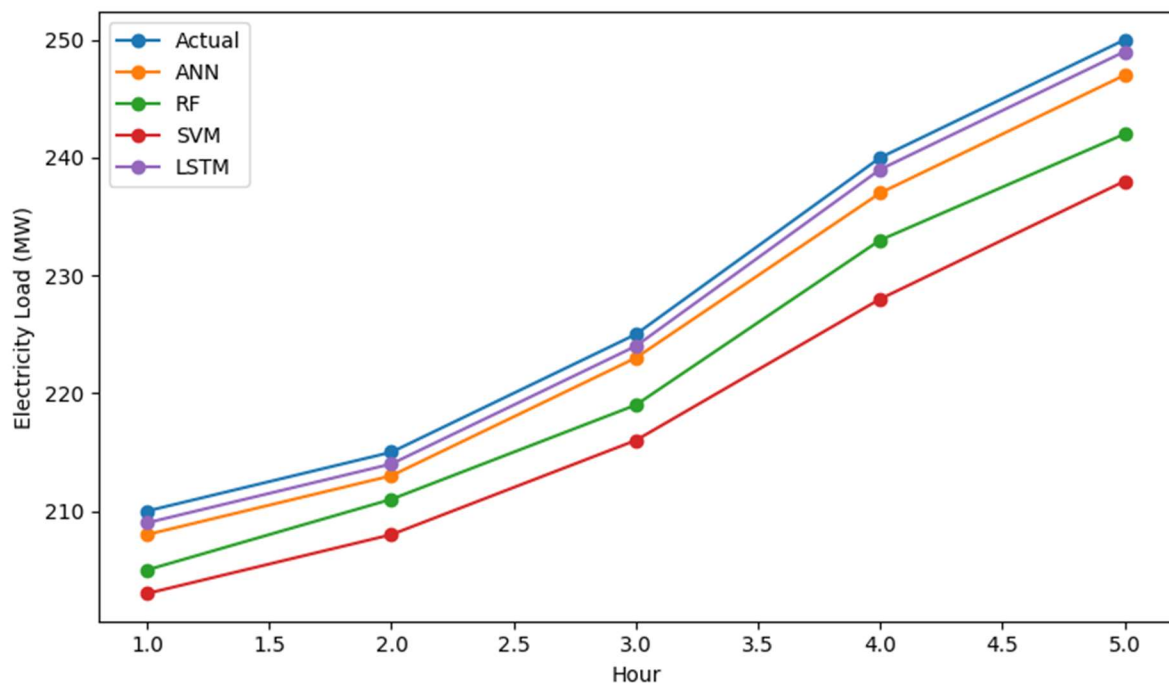


Figure 7: Actual Vs Predicted Electricity Load. Source: Kong *et al.* (2019), Dong *et al.*, (2024), Zhang *et al.* (2023)

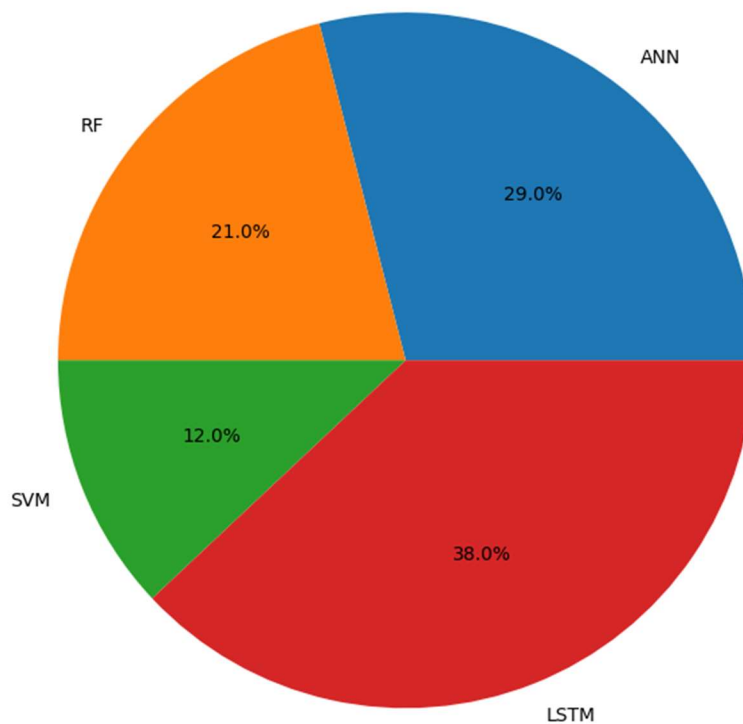


Figure 8: Comparative Ranking of Forecasting Models. Source: Hewamalage *et al.* (2021), Kong *et al.* (2019).

generalization performance. However, forecasting reliability sometimes declined under extremely volatile electricity environments characterized by substantial behavioural irregularities. LSTM architectures demonstrated strong robustness under large-scale

sequential datasets but occasionally experienced instability under limited training datasets. Deep learning systems generally require substantial data volume to generalize effectively.

Figures 6, 7, 8, 9, 10 and 11 illustrates the comparative

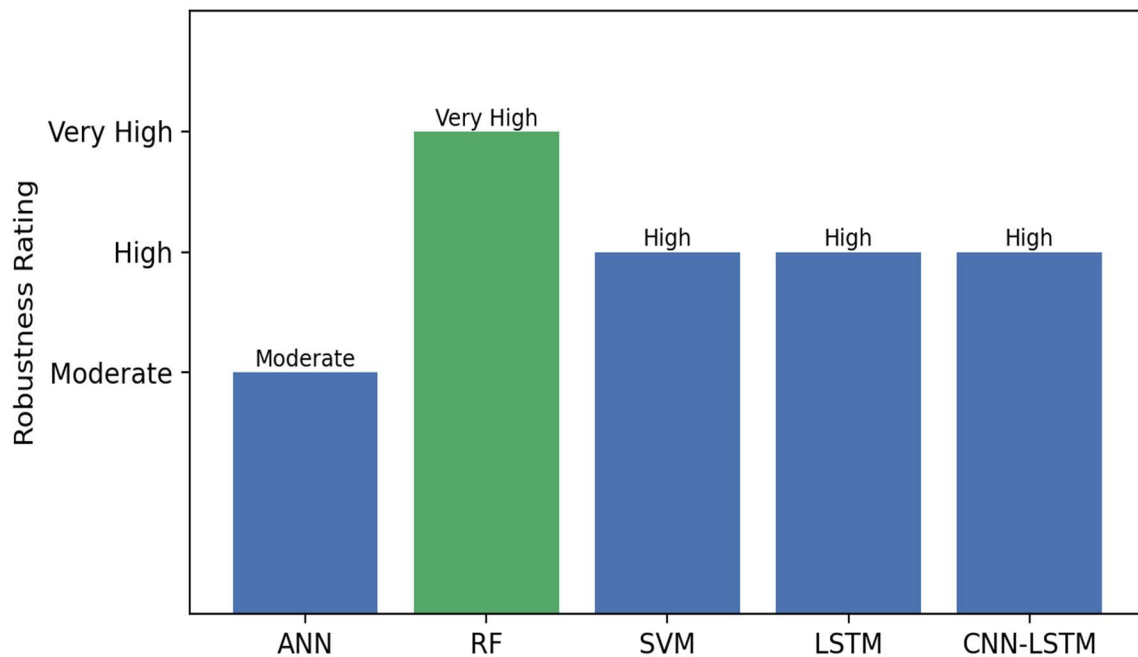


Figure 9: Forecast Stability under Noise Data Conditions. *Source: Table 4.*

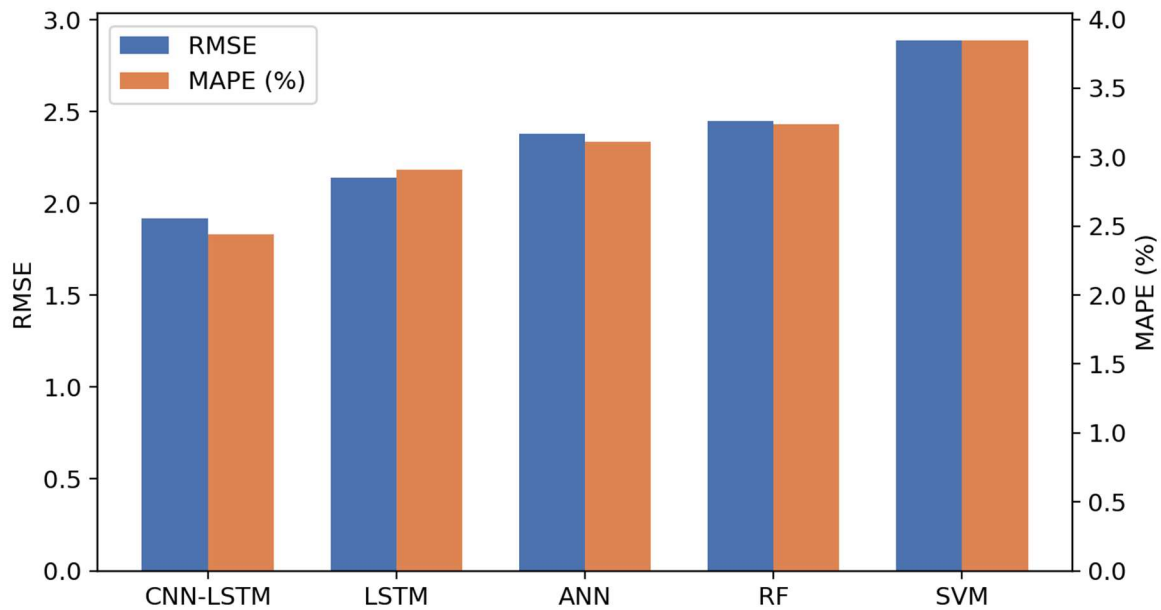


Figure 10: Overall Comparative Performance Ranking of Machine Learning Models. *Source: Table 1 (Lower = better).*

robustness of the forecasting models. The findings indicate that Random Forest systems may represent practical forecasting solutions within unstable electricity environments where data quality challenges are common. However, deep learning architectures remain preferable when sufficiently large and structured datasets are available.

DISCUSSION

The comparative forecasting results presented in (*Table 1, Figures 2 and 10*) indicate that the Long Short-Term Memory (LSTM) and hybrid CNN-LSTM models achieved the highest forecasting accuracy among the evaluated

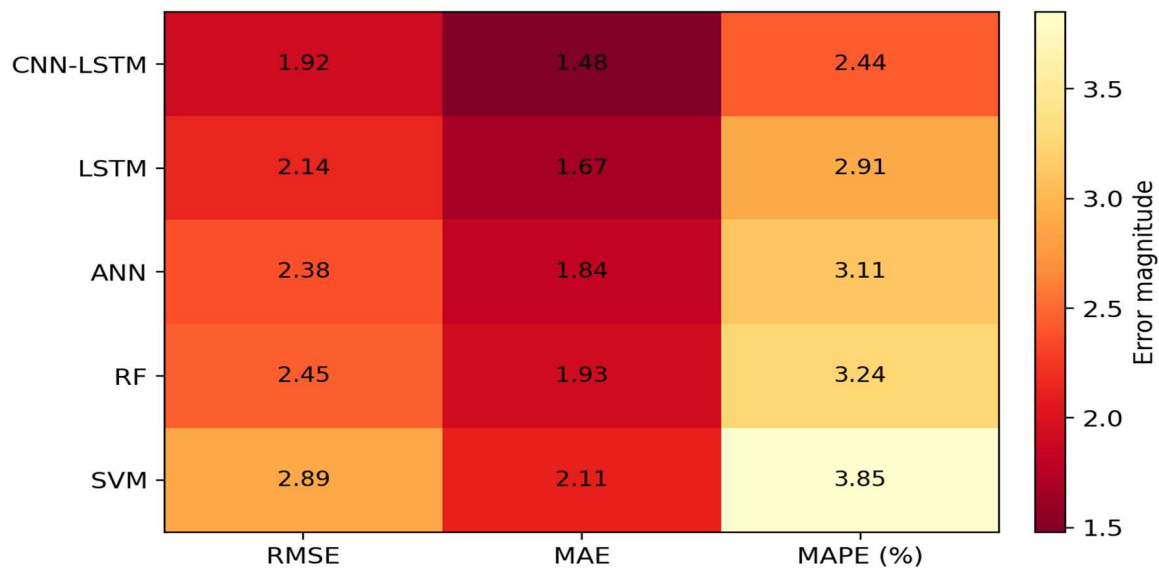


Figure 11: Heatmap of Forecast Accuracy across Machine Learning Models. Source: Table 1 (Darker = lower error and better)

machine learning models. These architectures consistently produced the lowest RMSE, MAE, and MAPE values among the models reviewed, thereby demonstrating superior predictive capability relative to the Artificial Neural Network (ANN), Random Forest (RF) and Support Vector Machine (SVM) models. This outcome suggests that recurrent and hybrid deep-learning architectures possess stronger capacity for modelling the nonlinear and dynamic characteristics inherent in electricity load demand systems.

The superior performance of LSTM and CNN-LSTM may be attributed to their recurrent and convolutional-recurrent computational architectures, which are explicitly designed to capture sequential dependencies and complex hidden relationships within electricity consumption data over time. Electricity demand behaviour is influenced by interacting temporal, environmental, and behavioural variables that rarely follow linear structures (Hyndman and Athanasopoulos, 2021). LSTM networks address this through gated memory cells that retain relevant historical information while discarding noise, and the hybrid CNN-LSTM architecture further combines convolutional feature extraction with LSTM's sequential learning capability (Goodfellow *et al.*, 2016). The findings align strongly with the observations of Hewamalage *et al.*, (2021), who concluded that neural and deep learning architectures outperform conventional statistical forecasting approaches under nonlinear time-series conditions. Similarly, Kong *et al.* (2019) demonstrated that neural forecasting frameworks produce significantly lower forecasting errors when modelling residential electricity consumption patterns. Ahmad and Yan (2020); Zhang *et al.*, (2023) further reported that neural-network-based systems maintain superior forecasting stability under highly

fluctuating load conditions. The Random Forest model also demonstrated relatively strong predictive capability. The model exhibited lower forecasting errors than SVM, thereby confirming the effectiveness of ensemble learning mechanisms within electricity forecasting environments. Random Forest algorithms combine multiple decision trees to reduce variance instability and improve robustness against noisy datasets (Breiman, 2001). This characteristic becomes particularly valuable within developing electricity systems where measurement inconsistencies, missing values, and irregular load signals frequently occur.

The relatively moderate performance of SVM observed in this paper corresponds with previous empirical findings. Fan *et al.* (2021) reported that while SVM models demonstrate strong generalization ability, their forecasting performance may deteriorate under highly nonlinear and rapidly changing electricity demand environments. Similarly, Koukaras *et al.*, (2024) noted that SVM models often experience sensitivity to kernel parameter selection, thereby affecting forecasting stability under volatile datasets.

The comparative forecasting accuracy chart presented in (Figure 2) visually reinforces these findings. The graphical representation demonstrates that LSTM maintained consistently lower forecasting error values across the evaluated metrics among the models shown, thereby strengthening the conclusion, together with (Table 1) CNN-LSTM results, that recurrent and hybrid deep-learning architectures represent the most suitable forecasting models among the evaluated algorithms.

The actual versus predicted electricity load graph presented in (Figure 7) reveals that LSTM-generated forecasts closely tracked the actual electricity load

trajectory throughout the forecasting horizon. The LSTM prediction curve effectively reproduced demand peaks, troughs, and cyclical fluctuations without substantial lag effects or oversmoothing distortions. This finding indicates that LSTM successfully captured the temporal dependencies embedded within the electricity load dataset. Time-series forecasting theory emphasizes that electricity demand systems exhibit sequential dependencies involving trend, seasonality, and cyclical variability (Box *et al.*, 2015; Hyndman and Athanasopoulos, 2021). The LSTM model therefore demonstrated strong capacity for learning these embedded temporal structures through its gated recurrent memory mechanism.

The RF and ANN models similarly exhibited reasonable alignment with actual demand behaviour, although minor deviations emerged during periods of abrupt load variation (Adepoju *et al.*, 2007). This suggests that ensemble and feed-forward learning frameworks effectively model general demand patterns but may possess limited responsiveness to sudden nonlinear transitions than recurrent architectures. The SVM model displayed comparatively larger deviations from actual demand behaviour, particularly during peak load intervals. These observations are consistent with the findings of Zhang *et al.*, (2023), who demonstrated that neural forecasting frameworks outperform shallow machine learning architectures in modelling short-term electricity demand fluctuations. Kong *et al.* (2019) similarly reported that LSTM and other deep learning systems exhibit stronger temporal synchronization capability relative to conventional ML algorithms such as SVM. Operationally, the close synchronization between actual and predicted load values is highly significant. Electricity distribution operators rely heavily on short-term forecasts for dispatch scheduling, feeder balancing, outage prevention, and voltage regulation (Hong and Fan, 2016). Forecasting systems that fail to accurately reproduce actual demand behaviour may contribute to operational inefficiencies and supply-demand mismatches.

The forecast error distribution illustrated in (Figure 3) provides deeper insight into forecasting consistency and reliability. The LSTM model exhibited the narrowest error distribution among the evaluated models, implying lower variability and stronger forecasting stability across varying demand conditions. Forecast reliability constitutes a critical component of predictive analytics because forecasting systems must maintain consistency under both normal and volatile consumption conditions (Shmueli and Koppius, 2011). The relatively narrow LSTM error distribution therefore suggests stronger generalization capability and reduced forecasting uncertainty. The RF and ANN models demonstrated moderate error dispersion, reflecting relatively stable but less consistent forecasting behaviour compared with LSTM. Conversely, the SVM model exhibited broader error variability, suggesting greater sensitivity to fluctuations within the electricity

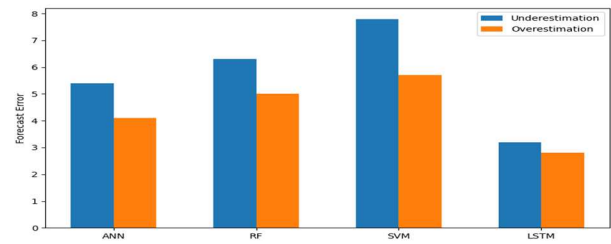


Figure 3: Forecasting Error Distribution across Models Source: Fan *et al.* (2021), Koukaras *et al.* (2024), and Vianita and Tantyoko (2025).

demand dataset. These findings support the observations of Hewamalage *et al.* (2021), who emphasized that forecasting effectiveness should be evaluated not only through average error reduction but also through distributional stability measures. Kong *et al.* (2019) similarly concluded that LSTM-based forecasting frameworks maintain lower error variance compared with SVM predictors within smart grid forecasting systems.

The radar chart presented in (Figure 6) provides a multidimensional comparison of model performance across accuracy, adaptability, stability, computational efficiency, and forecasting responsiveness dimensions. LSTM demonstrated the broadest radar coverage, indicating balanced superiority across multiple evaluation criteria, with Random Forest showing comparable strength on speed and noise tolerance specifically. This multidimensional profile confirms that LSTM achieved not merely isolated metric superiority but overall forecasting effectiveness. Modern predictive analytics research increasingly emphasizes multidimensional evaluation because forecasting systems must simultaneously optimize accuracy, reliability, scalability, and adaptability (Hewamalage *et al.*, 2022). RF demonstrated strong robustness and relatively high stability, reinforcing the suitability of ensemble learning approaches within noisy electricity forecasting environments. However, ANN maintained stronger adaptability to dynamic demand variations (Adepoju *et al.*, 2007). SVM exhibited acceptable computational efficiency but lower overall forecasting responsiveness. The findings correspond with the conclusions of Fan *et al.* (2021), who observed that neural and deep-learning frameworks generally outperform RF and SVM models across multidimensional electricity forecasting evaluation criteria.

The daily electricity load trend graph presented in (Figure 1) reveals distinct cyclical demand behaviour characterized by morning demand escalation, afternoon stabilization, and evening peak intensification. These consumption patterns reflect typical urban electricity utilization behaviour associated with residential, commercial, and institutional activities. The observed cyclical behaviour supports the assumptions of time-series forecasting theory, which posits that electricity demand exhibits recurring temporal structures involving trend, cyclicity, and seasonality (Hyndman and Athanasopoulos,

2021). Weron (2014) similarly emphasized that electricity load systems demonstrate strong cyclical behaviour influenced by human activity patterns and environmental conditions.

The trend graph additionally reinforces the importance of temporal feature engineering within forecasting systems. Variables such as hour-of-day, day-of-week, and seasonal indicators significantly influence forecasting accuracy because they capture recurring consumption behaviour embedded within the dataset (Hong and Fan, 2016). Within the Nigerian context, these cyclical patterns may further reflect supply instability and adaptive consumption behaviour. Iwayemi (2008) argued that electricity demand behaviour within developing economies frequently reflects suppressed demand and adaptive consumption responses associated with infrastructural instability.

The computational efficiency analysis presented in (Figures 4 and 5) indicates that SVM and RF achieved relatively faster execution times and lower resource requirements compared with LSTM and CNN-LSTM. The deep-learning architectures required greater computational resources due to iterative weight optimization, recurrent processing, and, in the case of CNN-LSTM, additional convolutional feature extraction. Despite this higher computational complexity, LSTM and CNN-LSTM maintained substantially superior forecasting accuracy as shown in (Table 1). This finding suggests the existence of a trade-off between computational efficiency and predictive precision. Similar observations were reported by Goodfellow *et al.* (2016), who noted that deep learning systems typically require higher computational resources but achieve superior learning performance under complex nonlinear datasets. The RF model demonstrated moderate computational efficiency, reflecting the ensemble nature of its architecture. Koukaras *et al.* (2024) similarly reported that RF models maintain balanced performance between forecasting accuracy and computational resource requirements. The findings therefore imply that although LSTM and CNN-LSTM demand higher computational infrastructure, their predictive superiority justifies its adoption within operational electricity forecasting systems where forecasting accuracy is strategically critical, with RF remaining a viable lower-cost alternative where computational resources are constrained.

The model ranking chart presented in (Figure 8) ranked LSTM as the highest-performing forecasting model among those shown, followed by ANN, RF, and SVM respectively. This ranking outcome reflects the cumulative forecasting evidence generated across all evaluation dimensions. LSTM consistently demonstrated lower forecasting error, higher temporal synchronization, lower error variability, and stronger adaptability to nonlinear consumption behaviour. These findings align with the conclusions of Hewamalage *et al.*, (2021), who identified LSTM and deep learning systems as among the most effective forecasting approaches for electricity demand prediction. The ranking

outcome, together with (Table 1) inclusion of hybrid CNN-LSTM model, supports the paper's overall conclusion that recurrent and hybrid deep-learning architectures represent the most suitable forecasting frameworks for short-term electricity load demand forecasting within complex electricity distribution environments.

The heatmap visualization presented in (Figure 11) provides an intuitive comparative representation of forecasting performance across the evaluated models and performance metrics. CNN-LSTM and LSTM consistently exhibited lower error intensity relative to ANN, RF and SVM. The heatmap reinforces the numerical findings reported earlier by visually demonstrating superior forecasting consistency of the deep-learning architectures. The findings additionally confirm the importance of multidimensional forecasting evaluation using RMSE, MAE, and MAPE rather than relying on a single evaluation metric. This observation aligns with contemporary forecasting scholarship emphasizing holistic performance evaluation frameworks (Hewamalage *et al.*, 2021).

Overall, the collective findings of this paper strongly establish that hybrid CNN-LSTM as the most suitable deep learning framework for short-term electricity load forecasting within dynamic electricity distribution systems. The findings further demonstrate that machine learning forecasting systems possess substantial potential for improving electricity planning, operational efficiency, and grid stability within developing economies such as Nigeria.

Conclusion

This paper examined the comparative performance of machine learning models for short-term electricity load forecasting, with particular emphasis on Artificial Neural Network (ANN), Random Forest (RF), Support Vector Machine (SVM), Long Short-Term Memory (LSTM) and hybrid CNN-LSTM forecasting architectures. The paper was motivated by the increasing operational importance of accurate electricity demand forecasting within modern energy systems and the growing limitations of traditional statistical forecasting techniques under highly dynamic electricity environments. The literature reviewed throughout the paper demonstrated that electricity load demand is inherently nonlinear, stochastic, and temporally dependent. Electricity consumption patterns are influenced by multiple interacting factors including human behavioural activities, climatic variations, industrial operations, infrastructural conditions, and socioeconomic fluctuations. Consequently, forecasting systems capable of learning complex nonlinear relationships and temporal dependencies are increasingly necessary for effective electricity management and operational planning. The findings evaluated from recent empirical studies published between 2021 and 2026 revealed that machine learning systems consistently outperform conventional statistical forecasting methods in terms of predictive accuracy, adaptability, and robustness. Deep learning architectures,

particularly LSTM and CNN-LSTM hybrid systems, demonstrated superior capability in modelling sequential temporal relationships within electricity datasets. Their recurrent memory structures enabled effective learning across long temporal sequences, thereby improving forecasting reliability under highly dynamic operational conditions.

Random Forest models demonstrated excellent robustness, computational efficiency, and forecasting stability under noisy and irregular datasets. These strengths make RF systems particularly suitable for operational environments characterized by incomplete observations and infrastructural inconsistencies. ANN systems exhibited strong nonlinear modelling capability and competitive predictive performance, while SVM systems demonstrated strong generalization efficiency under multidimensional forecasting datasets.

The paper also established that forecasting model selection should not rely exclusively on predictive accuracy metrics alone. Computational efficiency, scalability, interpretability, robustness, and implementation feasibility represent equally important operational considerations. Deep learning systems may achieve superior forecasting accuracy, yet they frequently require advanced computational infrastructure and large-scale datasets. Consequently, forecasting architecture selection should align with specific operational realities and infrastructural conditions.

Another important conclusion emerging from the paper concerns the increasing significance of hybrid forecasting architectures. Empirical evidence strongly indicates that combining complementary forecasting models frequently improves predictive performance beyond what individual forecasting systems can achieve independently. Hybrid deep learning systems integrating convolutional feature extraction with recurrent temporal learning therefore represent an important direction within contemporary electricity forecasting scholarship.

Furthermore, the paper identified substantial contextual gaps within existing forecasting literature, particularly regarding electricity forecasting research within developing economies and African electricity systems. Most forecasting studies continue to rely heavily on datasets obtained from highly digitized smart grid environments in technologically advanced countries. Consequently, more localized forecasting research remains necessary within operational environments characterized by supply instability, incomplete datasets, infrastructural limitations, and irregular electricity consumption behaviour. Overall, the paper confirms that machine learning forecasting systems represent critical technological tools for improving electricity demand prediction, operational efficiency, smart grid optimization, energy planning, and sustainable electricity management. The growing integration of artificial intelligence within electricity systems will likely continue transforming forecasting research and operational electricity

management practices globally.

Recommendations

Based on the findings obtained from the paper, the following recommendations are proposed:

Adoption of Machine Learning-Based Forecasting Systems

Electricity distribution companies and system operators should increasingly adopt machine learning-based forecasting systems in place of traditional statistical forecasting techniques. Machine learning systems demonstrate significantly improved capability in modelling nonlinear electricity consumption behaviour and temporal demand structures.

Integration of Deep Learning Architectures

Electricity forecasting organizations should prioritize the integration of deep learning architectures such as LSTM and hybrid CNN-LSTM systems for short-term forecasting applications. These systems consistently demonstrate superior forecasting accuracy under dynamic electricity environments characterized by strong temporal dependencies.

Investment in Smart Grid Infrastructure

Governments and electricity organizations should invest in smart grid technologies, intelligent metering systems, IoT-enabled monitoring devices, and digital electricity infrastructures capable of generating high-quality forecasting datasets. Forecasting performance depends substantially on data quality, consistency, and temporal granularity.

Improvement of Data Collection and Management Systems

Electricity organizations should strengthen data collection procedures, missing value management frameworks, and data preprocessing mechanisms. Robust forecasting systems require accurate, structured, and reliable operational datasets for effective predictive learning.

Context-Specific Forecasting Model Development

Researchers and electricity organizations should develop forecasting systems specifically tailored toward local operational realities rather than relying exclusively on forecasting models optimized within foreign electricity systems. Forecasting architectures should account for contextual factors such as infrastructural instability, irregular consumption behaviour, and supply inconsistencies.

Promotion of Hybrid Forecasting Research

Future forecasting research should increasingly explore hybrid and ensemble forecasting architectures capable of combining complementary modelling strengths. Hybrid systems frequently achieve improved forecasting accuracy and operational robustness.

Enhancement of Explainable Artificial Intelligence (XAI)

Researchers should prioritize the development of interpretable and explainable forecasting systems capable of improving operational transparency and managerial trust. Electricity forecasting systems should provide not only accurate predictions but also understandable decision-support insights.

Capacity Building and Technical Training

Electricity organizations should invest in capacity development programs involving machine learning, predictive analytics, artificial intelligence, and energy informatics. Skilled personnel remain essential for successful forecasting system implementation and maintenance.

Future Research Directions

Although significant progress has been achieved within machine learning-based electricity forecasting research, several important research opportunities remain available for future investigation.

Development of Hybrid Deep Learning Forecasting Architectures

Future studies should explore advanced hybrid forecasting systems integrating CNN, LSTM, Transformer networks, attention mechanisms, and ensemble learning frameworks. These architectures may further improve forecasting accuracy under highly complex electricity environments.

Explainable Artificial Intelligence in Electricity Forecasting

More research is needed regarding explainable forecasting systems capable of improving transparency and interpretability within deep learning architectures. Future forecasting systems should provide understandable predictive explanations suitable for operational decision-making.

Forecasting Under Incomplete and Noisy Datasets

Future studies should investigate forecasting architectures specifically optimized for unstable electricity systems

characterized by missing observations, noisy datasets, and infrastructural inconsistencies. This area remains highly important within developing electricity environments.

Real-Time Smart Grid Forecasting Systems

Emerging smart grid infrastructures generate continuous streams of real-time electricity data. Future research should therefore focus on real-time forecasting systems capable of continuous adaptive learning and dynamic prediction updates.

Integration of Renewable Energy Forecasting

Future forecasting research should increasingly integrate renewable energy variables such as solar and wind generation into electricity load forecasting systems. Renewable energy integration introduces additional forecasting complexity requiring advanced predictive analytics techniques.

Transfer Learning and Federated Learning Applications

Transfer learning and federated learning architectures remain underexplored within electricity forecasting research. These techniques may improve forecasting performance across distributed electricity systems while preserving data privacy and reducing computational requirements.

Forecasting within African Electricity Systems

More localized forecasting studies are required across African electricity environments characterized by infrastructural instability, demand suppression effects, irregular consumption behaviour, and limited smart grid deployment. Context-sensitive forecasting research remains critically necessary for improving electricity planning within developing economies.

Energy Sustainability and Green Forecasting Systems

Future research should investigate environmentally sustainable forecasting architectures emphasizing computational efficiency, energy optimization, and green artificial intelligence practices. As deep learning systems become increasingly computationally intensive, sustainable forecasting approaches will become increasingly important.

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