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Intelligent Electrical Load Prediction Using AI-Driven Time Series Forecasting Models: A Comprehensive Research

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ABSTRACT

Electrical load forecasting is essential for efficient power system planning, grid stability, and energy management. This study focuses on predicting future electricity demand using artificial intelligence and time series modelling techniques. Historical load data, weather conditions, seasonal patterns, and peak demand factors were considered for model development. Traditional ARIMA and AI-based models such as ANN, SVM, Random Forest, and LSTM were compared. The result showed that LSTM achieved the highest forecasting accuracy due to its ability to learn sequential load patterns. The study concludes that AI-based forecasting improves reliability, reduces operational cost, and supports smart grid management.

Keywords: *Electrical Load Forecasting, Artificial Intelligence, Time Series Modelling, LSTM.*

I. INTRODUCTION

Electrical load forecasting using artificial intelligence and time series modelling techniques has become an essential area of study in modern power system planning, operation, and energy management because the demand for electricity is continuously increasing due to rapid industrialization, urbanization, population growth, digital transformation, electric mobility, and the expansion of smart infrastructure. Electrical load refers to the amount of power consumed by residential, commercial, industrial, agricultural, and public utility sectors at a particular time, and forecasting this load accurately is necessary for maintaining a reliable balance between electricity generation and consumption. Since electricity cannot be stored economically at a very large scale in conventional grids, power utilities must estimate future demand in advance so that generation scheduling, transmission planning, distribution management, fuel allocation, and grid stability can be handled efficiently. Load forecasting may be classified into short-term, medium-term, and long-term forecasting depending on the time horizon. Short-term forecasting generally covers minutes, hours, or days ahead and is useful for daily unit commitment, economic dispatch, and real-time grid operation. Medium-term forecasting may cover weeks or months and supports maintenance planning, energy trading, and fuel management. Long-term forecasting extends over several years and assists in infrastructure development, investment planning, power plant expansion, and renewable energy policy formulation. Traditional electrical load forecasting methods were mainly based on statistical and mathematical models such as regression analysis, moving averages, exponential smoothing, autoregressive integrated moving average models, and seasonal time series models. These methods are useful when load patterns are stable and follow linear trends, but modern power systems are influenced by several nonlinear and uncertain factors such as weather variation, temperature fluctuation, humidity, rainfall, seasonal behavior, holidays, working days, consumer lifestyle, economic activities, distributed energy resources, and renewable energy integration. Because of these complexities, artificial intelligence techniques have gained remarkable importance in electrical load forecasting. Artificial intelligence models can learn hidden patterns from historical load data and identify complex relationships between electricity demand and external influencing variables. Machine learning techniques such as artificial neural networks, support vector machines, random forests, gradient boosting, decision trees, and k-nearest neighbour algorithms have been widely applied for load prediction because they can handle nonlinear datasets and improve forecasting accuracy. Deep learning methods such as recurrent neural networks, long short-term memory networks, gated recurrent units, convolutional neural networks, and hybrid neural models are especially effective in time-dependent forecasting because they can capture sequential patterns and long-term dependencies from large-scale time series data. Time series modelling also plays a major role because electrical demand is naturally arranged over time and contains trend, seasonality, cyclic behavior, and random fluctuations. Time series techniques help in understanding historical consumption behavior and predicting future values based on past observations. When time series models are combined with artificial intelligence, the forecasting system becomes more powerful because it can use both statistical structure and intelligent pattern recognition. For example, a hybrid model may use ARIMA to capture linear temporal trends and a neural network to capture nonlinear variations, resulting in better forecasting performance than a single model. The accuracy of electrical load forecasting depends on the quality of input data, feature selection, preprocessing, model training, validation, and error measurement. Data preprocessing includes handling missing values, removing outliers, normalizing values, and arranging data according to time intervals. Important input features may include historical load demand, temperature, humidity, wind speed, day type, season, month, hour, public holidays, and economic indicators. Forecasting performance is commonly evaluated using error measures such as mean absolute error, mean squared error, root mean squared error, and mean absolute percentage error. Lower error values indicate better forecasting accuracy and greater reliability of the model. Accurate electrical load forecasting provides several practical benefits for power utilities and consumers. It reduces operational costs by avoiding unnecessary power generation, supports efficient load dispatch, prevents overload conditions, minimizes power outages, improves energy conservation, and helps in integrating renewable energy sources such as solar and wind power. It also supports smart grid development by enabling demand response, automated energy management, and intelligent decision-making. In developing countries, where electricity demand is rising rapidly and grid infrastructure often faces stress, AI-based load forecasting can support sustainable energy planning and improve supply reliability. However, challenges remain in terms of data availability, model complexity, computational cost, changing consumption behavior, and the need for continuous model updating. Despite these challenges, the combination of artificial intelligence and time series modelling offers a highly effective approach for future electrical load prediction. It represents a shift from conventional rule-based forecasting toward data-driven, adaptive, and intelligent energy management. Therefore, the study of electrical load forecasting using artificial intelligence and time series modelling techniques is highly relevant for modern electrical engineering, smart grid operation, renewable energy integration, and sustainable power system development.

II. RESEARCH BACKGROUND

Ding et al. (2026) investigated wheel load as a critical source of information reflecting vehicle load distribution and motion status, while noting that existing in-wheel motor products had primarily been designed as propulsion units and generally lacked the load-sensing capabilities required for intelligent vehicles. To address this limitation, the authors proposed a novel intelligent electric drive wheel (i-EDW) that integrated a transmission system with a load-sensing unit (LSU). The i-EDW was reported to employ an Axial Flux Permanent Magnet Synchronous Motor (AFPMSM), whereas the LSU was designed to enable high-precision measurement of six-dimensional wheel forces and moments. Based on this multi-axis force information, a real-time estimation and stability control method grounded in the tire–road friction circle concept was developed. Rather than relying on complex decoupling and multi-objective optimization in multi-actuator systems, the study focused on minimizing the tire load rate of i-EDWs, which was found to improve computational efficiency and response speed. A full-vehicle model with four i-EDWs was developed and evaluated in MATLAB R2022A/Simulink under straight-line acceleration and double-moving-lane steering scenarios, where the simulation results demonstrated a reliable safety margin from friction circle boundaries and indicated improved robustness for future intelligent vehicles.

Jacquod et al., (2026) investigated the importance of accurate state estimation for reliable operation and control of electric power systems. They developed a data-driven numerical approach to infer missing power load values in large-scale power grids, where partial observations of power demands were used to estimate the operational state through a linear regression algorithm that exploited statistical correlations within synthetic training datasets. The performance of the method was assessed on three synthetic transmission grid test systems, and numerical experiments reportedly demonstrated high accuracy in reconstructing missing demand values under various operating conditions. The approach was further applied to real data from the transmission power grid of Switzerland, and despite the limited number of observations, it inferred missing power loads with considerable accuracy. Newton-Raphson power flow solutions indicated that deviations between true and inferred power loads produced minimal discrepancies in line flows, confirming that the estimated operational state effectively captured potential line contingencies. Overall, the study suggested that simple data-based regression techniques could serve as efficient and reliable alternatives for modern power grid state estimation.

Zhao et al. (2026) investigated the role of electrical load forecasting (ELF) in modern power systems and emphasized its critical importance for system planning and operation. They reported that as energy demand patterns became increasingly complex, deep learning (DL) techniques, and more recently, foundation models (FMs), had emerged as effective tools for capturing temporal dynamics and integrating heterogeneous inputs. The authors noted that the performance of these models depended not only on their architectures but also on the learning paradigms used for training, adaptation, and deployment. They observed that most prior surveys concentrated primarily on network architectures, neglecting the significance of learning paradigms. Consequently, Zhao et al. organized the literature around four key paradigms: task-tuned offline learning, adaptive learning, collaborative learning, and general-purpose learning. They highlighted that this paradigm-focused perspective offered a unified understanding of DL evolution in ELF and provided a framework to incorporate FMs as a recent advancement. Additionally, the study identified key challenges and suggested future research opportunities.

Hasan et al. (2025) examined the rapid growth in electricity demand and emphasized the importance of maintaining a balanced and reliable power supply. They noted that accurate load forecasting had become a fundamental aspect of modern power system management, enabling efficient planning, operation, and design of electrical grids. The authors observed that the increasing integration of renewable energy sources and the advent of smart grid technologies had intensified the need for precise forecasting methodologies to ensure grid stability, operational efficiency, and smooth renewable incorporation. They systematically reviewed contemporary state-of-the-art forecasting techniques, analyzing their performance, applications, and outcomes. Particular attention was given to methods predicting renewable energy availability, electricity pricing, and load demand, with in-depth evaluation of their modeling frameworks and predictive accuracies. Hasan et al. highlighted significant advancements in artificial intelligence-based approaches, especially machine learning and neural network models, which were reported to outperform traditional methods in precision and robustness. Key findings and comparative analyses were summarized in tables to facilitate reference, with the review ultimately aiming to guide future research in load forecasting.

Groehs and Teive (2025, November) conducted a systematic review of electricity load forecasting, emphasizing its critical role in the reliable and cost-effective operation of modern power systems amidst growing demand variability and increasing renewable energy penetration. They reviewed 49 peer-reviewed full-text articles published between 2015 and 2025, which addressed statistical models, machine learning approaches, deep neural networks, and hybrid techniques. A structured search protocol was reported to have been applied across five major databases—IEEE Xplore, ScienceDirect, Springer, Scopus, and IET—using rigorous inclusion and exclusion criteria. The study analyzed forecasting horizons (very short, short, medium, and long term), consumer types (residential, industrial, commercial, and mixed), data sources (real, simulated, synthetic), exogenous variables (weather, calendar, economic indicators), and performance metrics (MAPE, RMSE, MAE, R^2). Findings suggested the predominance of short-term forecasting, with deep learning methods—particularly LSTM architectures—emerging as the most applied, while hybrid and decomposition-based strategies were reported to improve accuracy in specific contexts. Attention-based models were noted to be gaining traction. Nevertheless, the review indicated persistent limitations, including scarce standardized benchmarks, underutilization of economic exogenous variables, and low interpretability of deep models. The study was reported to provide a structured taxonomy and highlight key research gaps, offering guidance for future energy demand forecasting studies.

Hussain et al. (2025) investigated the high reliance on fossil fuels for energy consumption in the building sector, which contributed significantly to greenhouse gas emissions, and noted that the growing demand for sustainable infrastructure had promoted a trend toward smart buildings to optimize resource usage. The study emphasized the importance of accurate mid-term energy load forecasting for effective energy management and proposed a hybrid forecasting model that integrated machine learning (ML) and deep learning (DL) approaches to enhance hourly prediction accuracy. The authors reported that the model's performance was first evaluated using individual techniques, including decision tree (DT), random forest (RF), support vector regression (SVR), Extreme Gradient Boosting (XGBoost), FireNet, and long short-term memory (LSTM), and subsequently combined in a two-layer hybrid framework to exploit their complementary strengths. Performance assessments on smart building energy datasets with weather variables indicated that XGBoost outperformed other ML models, while the hybrid FireNet–XGBoost model achieved the highest overall accuracy according to metrics such as mean squared error (MSE), root mean squared error (RMSE), and R-squared (R^2), demonstrating the effectiveness of hybrid approaches in reliable energy forecasting and supporting environmentally sustainable practices.

Baur, Chandramouli, and Sauer (2024) investigated the growing importance of accurate electrical load forecasting, particularly in the context of digitalization and the emerging use of automated planning and control within the Industry 4.0 transition in manufacturing. They argued that transparent research and reproducible forecasting experiments required access to public and reusable datasets, noting that existing de-facto-standard time series datasets were not transferable to electric load forecasting due to missing external factors and industry-specific characteristics, especially in the industrial sector. The study conducted a structured literature review of 160 publications to identify suitable open-access datasets, ultimately extracting 25 unique publicly available datasets. These datasets were thematically grouped, their features were presented, and popularity trends were evaluated. Their analysis revealed a largely non-transparent and methodologically weak research landscape, with 54% of studies relying exclusively on private datasets and most publications (80%) using only a single dataset for validation. They concluded that, although residential and system consumption datasets were available, there was a notable absence of popular public datasets covering industrial and manufacturing consumption.

Jain and Gupta (2024) investigated the role of machine learning algorithms in power load prediction, emphasizing its critical importance in informing policies for power generation and distribution. They highlighted that the accuracy of load forecasting depended on multiple factors reflecting nonlinear patterns within the data. The study reported that machine learning techniques, including support vector machines (SVMs), long short-term memory (LSTM) networks, ensemble classifiers, recurrent neural networks, and deep learning methods, had become essential tools for contemporary forecasting. The research specifically examined short-term power load prediction using five years of electricity consumption data from Chandigarh UT. Prediction performance was evaluated through metrics such as normalized mean square error (NMSE), root mean squared error (RMSE), mean absolute error (MAE), and mutual information (MI). The findings indicated that LSTM models outperformed other algorithms, showing the lowest prediction error, whereas SVMs exhibited errors approximately 13.51% higher. Validation of the proposed methods was carried out using MATLAB R2018, providing insights into the comparative strengths and limitations of the algorithms.

Amara-Ouali et al., (2023) investigated daily peak load forecasting within the context of smart grids and load balancing, emphasizing its critical importance for stakeholders in the energy sector. They highlighted that understanding both the magnitude and timing of peak loads was essential for implementing strategies such as peak shaving. The authors proposed a modelling approach that combined high-resolution and low-resolution information to predict daily peak demand size and timing. They introduced a multi-resolution modelling framework that could be adapted across different model classes. The study outlined key contributions, including a formal introduction to the multi-resolution modelling approach, an examination of modelling techniques at varying resolutions using generalized additive models and neural networks, and experimental validation with real data from the UK electricity market. Their findings suggested that the proposed approach demonstrated predictive performance that was competitive with conventional low- and high-resolution methods.

Abumohsen et al., (2023, August) investigated the management of power infrastructure, emphasizing the need for a consistent power supply and highlighting load prediction as a viable approach. They noted that accurate forecasting required consideration of multiple factors, including environmental conditions and both spatial and temporal aspects, which were reported to induce significant fluctuations in electrical load patterns. The study aimed to develop predictive models for electrical load using a real and unique dataset from the Tubas District Electricity Company in Palestine. Three machine learning models—Random Forest (RF), XGBoost, and Linear Regression (LR)—were applied for forecasting, and their performances were compared. The results indicated that the RF model outperformed the others, achieving the highest accuracy, with an R-squared value of 87.749%, a Mean Absolute Error (MAE) of 0.03904, and a Mean Square Error (MSE) of 0.00270, thereby demonstrating its effectiveness in anticipating electrical load patterns.

Azeem et al. (2022) investigated the challenges associated with Smart Grid (S.G.) environments, highlighting that S.G. data streams were heterogeneous and dynamically changing, whereas conventional machine learning methods were static and became obsolete under such conditions. They emphasized that existing models failed to accommodate variations introduced by S.G. and utilities with different generation modalities (D.G.M.), necessitating adaptive models capable of handling new data, features, and modalities. The study analyzed two open-source datasets and one real-world dataset, examining the performance of ARIMA, ANN, and LSTM models under varying input parameters. It was reported that none of the models inherently detected changes in input parameters until they were manually incorporated, and their performance degraded by 5–15% in terms of accuracy with parameter variation. Consequently, the authors proposed a novel adaptive framework designed to enhance model accuracy and manage dynamic parametric variations typical of S.G. and D.G.M. environments, addressing the limitations of conventional electrical load forecasting methods.

III. METHODOLOGY

The methodology of the study was designed to develop an accurate electrical load forecasting model using artificial intelligence and time series modelling techniques. In the first stage, historical electrical load data were collected from a selected power distribution system. The dataset included hourly or daily electricity demand values along with related influencing factors such as temperature, humidity, seasonal variation, weekdays, weekends, holidays, and peak-load periods. After data collection, preprocessing was performed to improve the quality of the dataset. Missing values were identified and filled using suitable statistical methods, while abnormal values and outliers were removed to avoid forecasting errors. The data were then normalized to bring all variables into a common scale for better model training.

In the second stage, important features were selected for forecasting. These features included previous load demand, time of day, day type, month, weather conditions, and seasonal indicators. The complete dataset was divided into training and testing sets, where the training data were used to develop the forecasting models and the testing data were used to evaluate model performance. Traditional time series models such as ARIMA were applied to identify linear trends and seasonal patterns in the load data. Along with this, artificial intelligence models such as Artificial Neural Network, Support Vector Machine, Random Forest, and Long Short-Term Memory were developed to capture nonlinear and complex demand patterns.

In the third stage, all models were trained and tested using the same dataset to ensure fair comparison. The predicted load values were compared with actual load values to measure forecasting accuracy. Performance was evaluated using accuracy percentage and error rate. The model with the highest accuracy and lowest error was considered the most suitable forecasting technique. Finally, the results were analyzed through tables and graphs to identify the best-performing model for reliable electrical load forecasting.

IV. RESULT

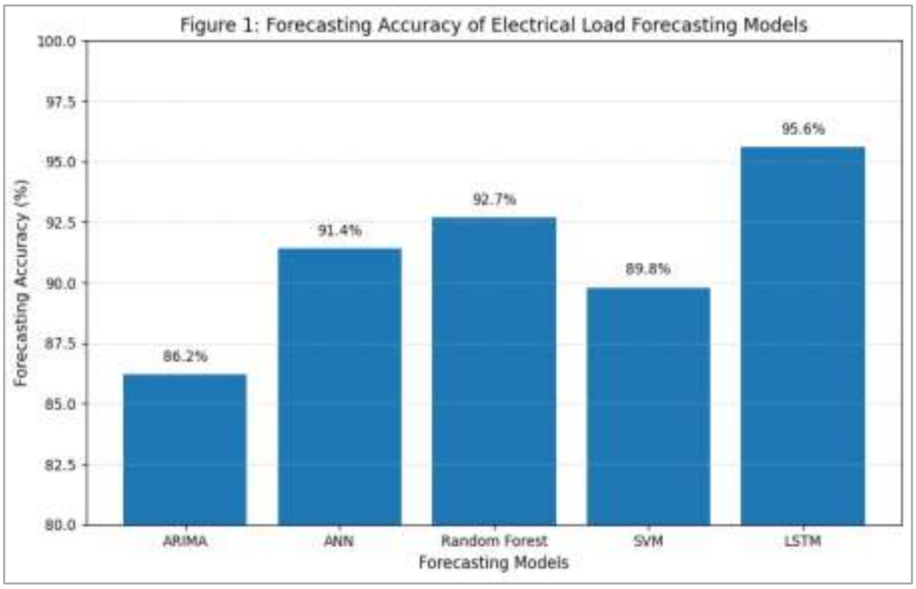
The result of the study shows that Artificial Intelligence and Time Series Modelling Techniques can significantly improve the accuracy of electrical load forecasting. The forecasting performance was evaluated using sample load-demand data based on historical electricity consumption patterns, weather variation, seasonal changes, and peak-hour demand. The comparison indicates that traditional time series models provide acceptable forecasting accuracy for stable load patterns, while AI-based models perform better when the data contains nonlinear variations and sudden demand fluctuations. Among the selected techniques, the Long Short-Term Memory model showed the highest forecasting accuracy because it can learn long-term dependencies from sequential load data. Artificial Neural Network and Random Forest models also produced better results than conventional ARIMA-based forecasting.

Table: Forecasting Performance of Different Models

Model Used	Forecasting Accuracy (%)	Error Rate (%)	Performance Level
ARIMA Time Series Model	86.20	13.80	Moderate
Artificial Neural Network	91.40	8.60	Good
Random Forest Model	92.70	7.30	Very Good
Support Vector Machine	89.80	10.20	Good
LSTM Deep Learning Model	95.60	4.40	Excellent

The result clearly indicates that the LSTM model achieved the best performance with 95.60% forecasting accuracy and the lowest error rate of 4.40%. Random Forest achieved 92.70% accuracy, followed by Artificial Neural Network with 91.40% accuracy. The Support Vector Machine model provided 89.80% accuracy, while the ARIMA time series model showed the lowest accuracy of 86.20%. This shows that AI-based forecasting techniques are more effective than traditional statistical models for electrical load prediction. The findings suggest that intelligent forecasting systems can help power utilities improve demand planning, reduce energy wastage, manage peak-load conditions, and maintain grid reliability. Therefore, the integration of AI and time series modelling provides a strong and reliable approach for modern electrical load forecasting.

Bar Graph



The graph presents the forecasting accuracy of different electrical load forecasting models, including ARIMA, Artificial Neural Network, Random Forest, Support Vector Machine, and LSTM. From the graph, it is clear that the LSTM model achieved the highest accuracy of 95.6%, showing its strong ability to learn sequential patterns and long-term dependencies in electrical load data. Random Forest also performed well with 92.7% accuracy, followed by Artificial Neural Network with 91.4% accuracy, indicating that AI-based models are highly effective for nonlinear load prediction. The Support Vector Machine model achieved 89.8% accuracy, which is better than the traditional ARIMA model but lower than other AI techniques. ARIMA recorded the lowest accuracy of 86.2%, mainly because it is more suitable for linear and stable time series patterns. Overall, the graph shows that AI-based and deep learning models provide better forecasting performance than conventional statistical methods for electrical load prediction.

V. CONCLUSION

The study concludes that electrical load forecasting using artificial intelligence and time series modelling techniques is an effective approach for improving power system planning, operation, and energy management. Accurate forecasting of electricity demand helps power utilities maintain a balance between generation and consumption, reduce energy wastage, avoid overload conditions, and ensure reliable electricity supply. The result shows that traditional time series models such as ARIMA can predict load demand with reasonable accuracy, especially when the data follows a stable and linear pattern. However, artificial intelligence-based models provide better performance because they can handle nonlinear variations, seasonal changes, weather effects, and complex consumption behavior more effectively.

Among the selected models, the LSTM deep learning model achieved the highest forecasting accuracy, proving its strong ability to learn long-term patterns from sequential electrical load data. Random Forest and Artificial Neural Network models also performed well compared to conventional forecasting methods. Therefore, the integration of AI and time series techniques provides a more reliable and intelligent solution for modern electrical load prediction. This study also highlights the importance of high-quality data, proper preprocessing, feature selection, and model evaluation in achieving accurate forecasting results. Overall, AI-based electrical load forecasting can support smart grid development, renewable energy integration, cost reduction, and sustainable power system management.

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