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A Comprehensive Review of Intelligent Electrical Load Forecasting Techniques for Modern Smart Power Systems

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Abstract:
Electrical load forecasting plays a crucial role in ensuring the reliable, secure, and economical operation of modern power systems. Accurate prediction of electricity demand enables effective generation scheduling, unit commitment, economic dispatch, demand-side management, renewable energy integration, and smart grid operation. This review presents a comprehensive analysis of recent advancements in electrical load forecasting techniques, covering conventional statistical methods, artificial intelligence, machine learning, deep learning, and hybrid forecasting frameworks. Traditional approaches, including regression analysis, time-series models, and autoregressive techniques, are discussed alongside their limitations in modeling complex nonlinear load patterns. The review further examines intelligent forecasting methods such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forest, Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), Convolutional Neural Networks (CNN), Transformer architectures, reinforcement learning, and optimization-based hybrid models. Recent developments involving large language models, meta-learning, transfer learning, Bayesian optimization, and explainable artificial intelligence are also highlighted. A comparative evaluation of existing studies demonstrates that hybrid deep learning and optimization-based models generally provide superior forecasting accuracy, robustness, and adaptability under dynamic operating conditions. Despite these advances, several challenges remain, including computational complexity, dependence on large-scale high-quality datasets, model interpretability, parameter optimization, and the uncertainty introduced by renewable energy integration. The review identifies current research gaps and emphasizes the need for intelligent, scalable, and computationally efficient forecasting frameworks capable of handling diverse operating environments.

Keywords: Electrical Load Forecasting, Smart Grid, Machine Learning, Deep Learning, Hybrid Forecasting Models, Artificial Intelligence.

I. INTRODUCTION

Electrical load forecasting has become one of the most critical research areas in modern power systems because of the rapid growth in electricity demand, urbanization, industrial expansion, and the increasing integration of renewable energy resources into electrical grids. The transition from conventional power systems to smart grids has significantly increased the complexity of electricity generation, transmission, distribution, and consumption. Modern power systems are

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characterized by highly dynamic and nonlinear load patterns influenced by weather conditions, seasonal variations, consumer behavior, economic activities, holidays, and the widespread adoption of distributed energy resources. Consequently, accurate forecasting of electrical load has emerged as an essential requirement for ensuring the reliable, secure, and economical operation of power systems. Electrical load forecasting refers to the process of estimating future electricity demand over different forecasting horizons, including very short-term, short-term, medium-term, and long-term periods. These forecasting horizons support different operational and planning objectives [1]. Very short-term and short-term forecasting assist in real-time system monitoring, generation scheduling, economic dispatch, reserve allocation, and demand response management. Medium-term forecasting supports maintenance scheduling, fuel planning, and resource allocation, whereas long-term forecasting provides valuable information for infrastructure expansion, transmission planning, policy formulation, and investment decisions. Accurate forecasting enables utilities to balance electricity generation with consumer demand while minimizing operational costs, reducing energy losses, improving system reliability, and enhancing overall grid stability. Figure 1 illustrates the process of predicting future electricity demand using historical data and influencing factors [2].

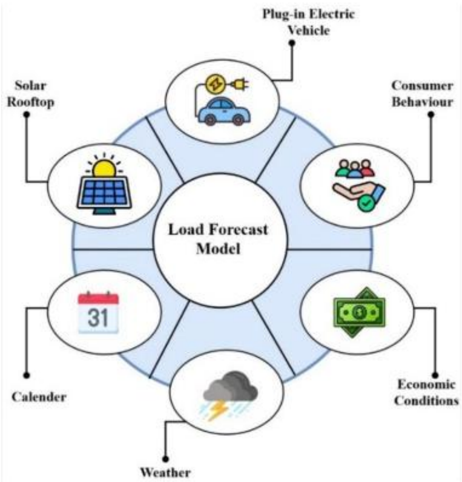

Figure 1: Load Forecasting [2]

Traditional load forecasting approaches, including statistical regression models, autoregressive methods, moving average techniques, exponential smoothing, and time-series analysis, have been widely applied for several decades because of their simplicity and ease of implementation. However, these methods generally assume linear relationships among variables and often fail to model the complex nonlinear behavior of modern electricity consumption. The increasing penetration of renewable energy sources such as solar and wind power, together with electric vehicles, smart meters, energy storage systems, and distributed generation, has introduced significant uncertainty and variability into electrical load patterns. These developments have reduced the effectiveness of conventional forecasting models and accelerated the adoption of intelligent forecasting techniques [3].

Recent advances in artificial intelligence, machine learning, and deep learning have transformed electrical load forecasting by enabling models to automatically learn complex relationships from large volumes of historical and real-time data. Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), Random Forests, Decision Trees, Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRUs), Convolutional Neural Networks (CNNs), Transformer architectures, reinforcement learning, transfer learning, and meta-learning have demonstrated remarkable improvements in forecasting accuracy compared with conventional statistical methods [4]. Furthermore, hybrid forecasting frameworks that integrate optimization algorithms with intelligent learning models have achieved superior predictive performance by combining the strengths of multiple forecasting techniques while overcoming their individual limitations. Recent research has also explored explainable artificial intelligence, Bayesian optimization, large language models, and adaptive learning frameworks to enhance forecasting reliability, interpretability, and computational efficiency.

Despite these significant advancements, several challenges remain unresolved. Many intelligent forecasting models require large, high-quality datasets, substantial computational resources, extensive parameter tuning, and effective feature engineering. Model interpretability, scalability, robustness under changing operating conditions, uncertainty associated with renewable energy integration, cybersecurity concerns, and real-time deployment continue to present important research challenges. Additionally, the absence of standardized benchmarking datasets and evaluation criteria makes fair comparison among forecasting models difficult.

The primary objective of this review is to provide a comprehensive and systematic analysis of recent developments in electrical load forecasting techniques for modern power systems. The review critically examines conventional statistical approaches, artificial intelligence methods, machine learning algorithms, deep learning architectures, optimization-based techniques, and hybrid forecasting frameworks. It compares their methodologies, forecasting performance, advantages, limitations, and practical applications while identifying current research trends and emerging technologies [5]. Furthermore, the review highlights existing research gaps and discusses future research opportunities aimed at developing more accurate, scalable, interpretable, and computationally efficient forecasting models suitable for next-generation smart grids. By consolidating recent advances into a unified framework, this review serves as a valuable reference for researchers, engineers, utility operators, and policymakers seeking to improve electrical load forecasting and support the continued evolution of intelligent and sustainable power systems.

II. FUNDAMENTALS OF ELECTRICAL LOAD FORECASTING

Electrical load forecasting is the process of estimating future electricity demand using historical consumption patterns and various influencing factors such as weather conditions, consumer behavior, economic activities, seasonal variations, and calendar information. It is one of the most fundamental functions in modern power system planning, operation, and management because electricity cannot be economically stored in large quantities and must be generated to closely match real-time demand. Accurate forecasting enables utilities and system operators to maintain the balance between electricity generation and consumption while ensuring system reliability, operational efficiency, and economic performance. With the rapid growth of smart grids, renewable energy integration, electric vehicles, distributed energy resources, and advanced metering infrastructure, electrical load forecasting has become increasingly complex. Traditional forecasting methods are gradually being replaced by intelligent data-driven approaches capable of modeling nonlinear relationships and adapting to continuously changing operating conditions [6].

Electrical load forecasting is generally classified according to the forecasting horizon, as different operational and planning activities require predictions over different time intervals. The four primary categories include Very Short-Term Load Forecasting (VSTLF), Short-Term Load Forecasting (STLF), Medium-Term Load Forecasting (MTLF), and Long-Term Load Forecasting (LTLF). Very Short-Term Load Forecasting typically predicts electricity demand from a few seconds or minutes up to one hour ahead. It plays a crucial role in real-time power system monitoring, automatic generation control, frequency regulation, voltage control, contingency analysis, and emergency power management. Since power system conditions change rapidly, VSTLF requires high-speed forecasting algorithms capable of processing streaming data from supervisory control and data acquisition (SCADA) systems, smart meters, and phasor measurement units.

Short-Term Load Forecasting generally covers forecasting horizons ranging from one hour to one week. It is the most widely used forecasting category in practical power system operation because it directly supports daily generation scheduling, unit commitment, economic dispatch, reserve allocation, demand response programs, electricity market operations, and renewable energy management. STLF models commonly utilize historical load records, weather variables, holidays, weekdays, seasonal trends, and consumer behavior to estimate future electricity demand [7]. The increasing deployment of artificial intelligence and deep learning techniques has significantly improved the accuracy of short-term forecasting by capturing complex temporal dependencies and nonlinear load variations.

Medium-Term Load Forecasting predicts electricity demand over periods extending from one week to approximately one year. These forecasts primarily assist utility companies in maintenance scheduling, fuel procurement, budget planning, tariff design, resource allocation, and infrastructure management. Medium-term forecasting considers long-term weather trends, economic indicators, industrial production, demographic changes, and seasonal consumption behavior. Unlike short-term forecasting, medium-term forecasting emphasizes planning rather than real-time operational control and often combines statistical analysis with machine learning techniques to improve prediction accuracy.

Long-Term Load Forecasting estimates electricity demand for periods exceeding one year and supports strategic planning activities within power systems. These forecasts are essential for generation capacity expansion, transmission and distribution network development, investment planning, policy formulation, renewable energy integration, and long-term energy security. Long-term forecasting incorporates macroeconomic indicators, population growth, industrialization, urbanization, government policies, technological advancements, climate change, and future energy consumption patterns. Because of the long forecasting horizon, uncertainty is considerably higher, making advanced forecasting methodologies and scenario-based analysis increasingly important [8].

The accuracy of electrical load forecasting is strongly influenced by numerous technical, environmental, economic, and social factors. Weather conditions remain among the most influential variables affecting electricity demand. Temperature, humidity, wind speed, solar radiation, rainfall, and cloud cover directly impact heating, ventilation, and air-conditioning (HVAC) systems, thereby influencing residential, commercial, and industrial electricity consumption. Seasonal variations also produce significant fluctuations in electricity demand due to changing heating and cooling requirements.

Consumer behavior represents another major determinant of electrical load patterns. Daily routines, working hours, weekends, holidays, occupancy levels, appliance usage, industrial production schedules, and commercial activities all contribute to variations in electricity demand. Demographic characteristics, including population growth, urban expansion, and lifestyle changes, further influence long-term electricity consumption trends. Economic conditions such as gross domestic product (GDP), industrial development, employment rates, electricity prices, and income levels also affect electricity demand by altering industrial output and consumer purchasing behavior. Furthermore, the increasing penetration of renewable energy resources, distributed generation, electric vehicles, battery energy storage systems [9], and smart home technologies has introduced greater uncertainty and variability into modern load profiles, making accurate forecasting increasingly challenging.

Evaluating forecasting performance is essential for comparing different forecasting models and selecting the most appropriate technique for practical implementation. Various statistical error metrics are commonly employed to quantify forecasting accuracy. Mean Absolute Error (MAE) measures the average absolute difference between predicted and actual load values and provides a simple measure of forecasting error. Mean Squared Error (MSE) calculates the average squared prediction error, assigning greater penalties to larger forecasting deviations. Root Mean Squared Error (RMSE) is widely used because it expresses prediction errors in the same units as the original data while emphasizing larger deviations. Mean Absolute Percentage Error (MAPE) represents forecasting error as a percentage of actual values, making comparisons across different datasets more convenient. Other widely adopted evaluation metrics include Symmetric Mean Absolute Percentage Error (SMAPE), Mean Bias Error (MBE), Coefficient of Determination (R^2), Explained Variance Score (EVS), and Forecast Skill Score. In addition to statistical accuracy measures, computational efficiency, training time, memory requirements, model scalability, robustness against noisy data, interpretability, and adaptability to changing operating conditions are increasingly considered when evaluating modern forecasting models [10].

III. CONVENTIONAL LOAD FORECASTING TECHNIQUES

Conventional load forecasting techniques have served as the foundation of electricity demand prediction for several decades. These methods estimate future electrical load using historical consumption data and mathematical relationships between load demand and influencing variables. Owing to their simplicity, ease of implementation, and low computational requirements, conventional forecasting approaches have been extensively adopted by utility companies for power system planning, generation scheduling, and operational management. Although these techniques perform satisfactorily under stable operating conditions, they often struggle to model the nonlinear, dynamic, and uncertain characteristics of modern power systems. The growing integration of renewable energy resources, electric vehicles, distributed generation, and smart grid technologies has further exposed the limitations of traditional forecasting models [11]. Nevertheless, conventional techniques remain valuable because they provide baseline forecasting performance and serve as the foundation for many advanced machine learning and hybrid forecasting models.

Among conventional approaches, statistical methods are the earliest and most widely used forecasting techniques. These methods establish mathematical relationships between historical electricity demand and various influencing factors by analyzing statistical properties of the available data. Statistical forecasting models are generally simple, computationally efficient, and require relatively small datasets for model development. Common statistical techniques include exponential smoothing, moving averages, autoregressive regression models, and probability-based forecasting approaches. These methods perform well when electricity demand follows consistent trends and seasonal patterns. Their transparent mathematical formulation also makes them easy to interpret and implement in practical applications [12]. However, statistical methods assume linear relationships among variables and therefore exhibit reduced forecasting accuracy when electricity demand is affected by complex nonlinear interactions involving weather conditions, consumer behavior, renewable energy generation, and economic activities.

Time-series forecasting models represent another important category of conventional forecasting techniques. These methods predict future electricity demand by analyzing sequential historical observations collected over time. Time-series models assume that future load patterns are strongly influenced by previous consumption values and recurring temporal characteristics such as daily, weekly, monthly, or seasonal cycles. The most widely applied time-series techniques include the Autoregressive (AR) model, Moving Average (MA) model, Autoregressive Moving Average (ARMA) model, Autoregressive Integrated Moving Average (ARIMA) model, and Seasonal Autoregressive Integrated Moving Average (SARIMA) model. The AR model predicts future load using previous load observations, whereas the MA model estimates future values based on past forecasting errors. ARIMA combines autoregressive and moving average components with differencing operations to model non-stationary time-series data effectively. SARIMA further extends ARIMA by incorporating seasonal variations, making it particularly suitable for electricity demand characterized by periodic consumption patterns [13]. These models have demonstrated satisfactory performance in short-term and medium-term forecasting under stable operating conditions. However, their forecasting capability declines when load behavior becomes highly nonlinear or when external variables such as weather, holidays, and consumer activities significantly influence electricity demand.

Another widely adopted conventional forecasting approach is regression-based modeling, which estimates future electricity demand by establishing mathematical relationships between load and multiple independent variables. Regression models identify correlations between electricity consumption and influencing factors such as temperature, humidity, time of day, calendar information, economic indicators, industrial activities, and population growth. Linear regression, multiple linear regression, nonlinear regression, and polynomial regression are among the most frequently used regression techniques in load forecasting. These models provide interpretable forecasting equations and allow analysts to quantify the contribution of each predictor variable to overall electricity demand. Regression-based methods are particularly useful when the relationships between dependent and independent variables are relatively stable and well understood. However, their forecasting performance strongly depends on accurate variable selection, high-quality datasets, and appropriate model assumptions [14]. They often fail to capture highly nonlinear relationships and complex temporal dependencies observed in modern smart grid environments.

Overall, conventional load forecasting techniques continue to play an important role in electrical power systems due to their simplicity, transparency, and computational efficiency. Although their predictive performance is generally lower than that of modern artificial intelligence and deep learning models, they remain valuable benchmark approaches and continue to support numerous practical forecasting applications while providing the theoretical foundation for the development of advanced intelligent forecasting frameworks.

IV. ARTIFICIAL INTELLIGENCE AND DEEP LEARNING-BASED LOAD FORECASTING

Artificial intelligence (AI) and deep learning have revolutionized electrical load forecasting by enabling predictive models to learn complex nonlinear relationships directly from historical electricity consumption data and multiple influencing variables. Unlike conventional statistical approaches that rely on predefined mathematical assumptions, AI-based forecasting models automatically identify hidden patterns, temporal dependencies, and nonlinear interactions among weather conditions, seasonal variations, calendar information, consumer behavior, economic activities, and renewable energy generation. The rapid deployment of smart grids, advanced metering infrastructure, Internet of Things (IoT) devices, and distributed energy resources has generated massive volumes of real-time data, making AI-driven forecasting techniques increasingly effective for modern power systems. Recent studies demonstrate that intelligent forecasting models consistently outperform traditional forecasting methods in terms of prediction accuracy, robustness, adaptability, and scalability, particularly under dynamic operating conditions [15].

Among AI techniques, Artificial Neural Networks (ANNs) were the earliest intelligent models applied to electrical load forecasting. ANNs are inspired by the biological structure of the human brain and consist of interconnected neurons organized into input, hidden, and output layers. During training, the network automatically adjusts connection weights to minimize forecasting errors while learning nonlinear relationships between input variables and electricity demand. ANN models have been successfully applied to short-term, medium-term, and long-term load forecasting because of their capability to model highly complex consumption patterns. However, ANN performance depends heavily on network architecture, training data quality, and parameter optimization, and the models may suffer from overfitting and slow convergence when handling large datasets.

Support Vector Machines (SVMs) have also been widely adopted for electrical load forecasting due to their strong generalization capability and effectiveness with limited training samples. SVM-based forecasting constructs an optimal decision boundary by maximizing the separation margin between data points in a high-dimensional feature space. Through kernel functions, SVM models successfully capture nonlinear relationships between electricity demand and influencing variables. Their robustness against overfitting makes them suitable [16] for forecasting problems involving noisy datasets. Nevertheless, forecasting performance is sensitive to kernel selection and hyperparameter optimization, while computational complexity increases considerably for very large datasets.

Another important category includes Random Forest (RF) and ensemble learning techniques. Random Forest combines multiple decision trees constructed from randomly selected subsets of training data and predictor variables. Final forecasting results are obtained by aggregating predictions from individual trees, thereby improving model stability and reducing variance. Ensemble learning further enhances forecasting performance by integrating multiple machine learning models using techniques such as bagging, boosting, and stacking. These approaches generally provide higher forecasting accuracy, greater robustness, and improved resistance to overfitting compared with individual learning algorithms. However, ensemble models often require increased computational resources and may sacrifice model interpretability because of their complex structures. Deep learning has significantly advanced electrical load forecasting through recurrent neural network architectures, including Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Gated Recurrent Units (GRUs). These models are specifically designed to process sequential time-series data by preserving historical information across multiple time steps. Conventional RNNs effectively capture temporal dependencies but frequently experience vanishing and exploding gradient problems during long sequence training. LSTM networks overcome these limitations using memory cells and gating mechanisms that selectively retain or discard historical information, enabling accurate modeling of long-term temporal relationships. GRUs provide a simplified alternative to LSTM by reducing computational complexity while maintaining comparable forecasting performance. Consequently, LSTM and GRU models have become the dominant deep learning architectures for short-term electrical load forecasting in modern smart grids [17].

More recently, Convolutional Neural Networks (CNNs) and Transformer-based models have demonstrated remarkable success in load forecasting applications. CNNs automatically extract meaningful spatial and local temporal features from multivariate electricity consumption data through convolution and pooling operations, making them highly effective when combined with recurrent architectures such as CNN-LSTM hybrids. Transformer models employ self-attention mechanisms that capture long-range dependencies without relying on sequential processing, enabling efficient parallel computation and improved forecasting accuracy for large-scale datasets. Their ability to model complex temporal relationships has led to widespread adoption in advanced forecasting frameworks.

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The latest advancement in intelligent forecasting involves the application of Large Language Models (LLMs). Although originally developed for natural language processing, LLMs have recently been adapted for electrical load forecasting by integrating numerical time-series data with contextual information such as weather forecasts, calendar events, and external influencing factors. Their powerful representation learning capability enables improved feature extraction, reasoning, and multi-source information fusion, resulting in enhanced forecasting accuracy under complex operating conditions. Despite their promising performance, [18] LLM-based forecasting frameworks require extensive computational resources, large-scale training datasets, and substantial memory, making practical deployment challenging. Nevertheless, AI and deep learning techniques continue to define the state of the art in electrical load forecasting and are expected to play a central role in the development of intelligent, adaptive, and highly reliable smart power systems.

V. HYBRID AND OPTIMIZATION-BASED FORECASTING APPROACHES

Hybrid and optimization-based forecasting approaches have emerged as advanced solutions for addressing the limitations of conventional statistical methods and individual artificial intelligence models in electrical load forecasting. Modern electricity demand is influenced by highly nonlinear relationships, renewable energy integration, weather uncertainty, and dynamic consumer behavior, making accurate prediction increasingly challenging. Hybrid forecasting models combine the strengths of multiple machine learning and deep learning techniques, while optimization algorithms enhance parameter selection, feature extraction, and model convergence. Consequently, these approaches have demonstrated superior forecasting accuracy, robustness, and adaptability in smart grid environments. Among hybrid techniques, CNN–LSTM models have gained significant attention because they integrate the feature extraction capability of Convolutional Neural Networks (CNNs) with the temporal learning ability of Long Short-Term Memory (LSTM) networks. CNN automatically extracts spatial and local temporal features from historical load data, whereas LSTM effectively captures long-term sequential dependencies. This combination improves forecasting accuracy while reducing information loss, making CNN–LSTM architectures highly suitable for short-term electrical load forecasting under complex operating conditions.

Another emerging hybrid architecture is the Transformer–LSTM model, which combines the global attention mechanism of Transformer networks with the sequential memory capability of LSTM. The Transformer efficiently captures long-range dependencies through self-attention, while LSTM preserves temporal information across time steps. This integrated architecture effectively models both local and global load variations, resulting in improved forecasting performance for large-scale and multivariate electricity demand datasets. Reinforcement learning-based forecasting models have also shown considerable potential in adaptive load prediction. Unlike conventional supervised learning methods, reinforcement learning continuously learns optimal forecasting strategies through interactions with the operating environment. Adaptive frameworks, such as Deep Reinforcement Learning (DRL), dynamically update forecasting policies to accommodate changing electricity consumption patterns, renewable energy fluctuations, and uncertain grid conditions, thereby enhancing forecasting robustness [19]. Recent research has further introduced meta-learning and transfer learning techniques to improve forecasting performance under limited training data conditions. Meta-learning enables forecasting models to rapidly adapt to new environments by utilizing prior learning experiences, whereas transfer learning transfers knowledge from source domains to target applications, reducing training requirements and improving prediction accuracy for data-scarce regions. These approaches have become increasingly valuable for building-level and regional load forecasting applications.

Optimization algorithms play a critical role in enhancing hybrid forecasting frameworks by automatically determining optimal model parameters and feature subsets. Bayesian Optimization efficiently identifies the best hyperparameter combinations while minimizing computational cost. Nature-inspired optimization techniques such as Grey Wolf Optimization (GWO) and Greylag Goose Optimization (GGO) improve forecasting accuracy by optimizing network weights, feature selection, and learning parameters, thereby reducing prediction errors and accelerating convergence. Another important advancement is Explainable Artificial Intelligence (XAI)-based forecasting, which improves the transparency and interpretability of intelligent forecasting models. Explainability techniques enable users to understand the contribution of influential variables and decision-making processes, thereby increasing trust in AI-driven forecasting systems. Overall, hybrid architectures combined with optimization and explainable AI have significantly advanced electrical load forecasting and represent promising directions for developing accurate, adaptive, scalable, and reliable forecasting frameworks for next-generation smart power systems [20].

Table 1: Comparative Analysis, Research Gaps, And Challenges

Ref.	Method / Technique Used	Key Results	Limitations
[7]	Hybrid DNN–SVR Framework	Produced accurate national-scale hourly load forecasts.	Careful parameter optimization is required.
[8]	Meta-Learning Framework	Improved forecasting adaptability under regional distribution shifts.	Needs multiple source domains and high training complexity.
[9]	Hybrid VMD–LSTM–Transformer with Bayesian Optimization	Reduced forecasting errors through signal decomposition and optimized learning.	Long optimization time and computational overhead.
[10]	Structured Narrative Review	Reviewed AI applications, architectures, and modernization of electrical systems.	No experimental comparison or validation.
[11]	Transfer Learning with Temporal Fusion Transformer	Improved building load forecasting under limited data conditions.	Depends on similarity between source and target datasets.

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[12]	Comparative Review of Load Forecasting Methods	Compared conventional, ML, and AI forecasting techniques and research trends.	No benchmarking or practical implementation.
[13]	Greylag Goose Optimization with Time-Series Analysis	Improved smart city load forecasting accuracy through optimization.	Requires extensive parameter tuning.
[14]	Machine Learning-Based Algorithms	Achieved reliable industrial short-term load forecasting.	Validated using only one industrial facility.
[15]	Large Language Models with Weighted External Factor Optimization	Improved forecasting by incorporating weather and external variables.	High computational requirements and large training datasets.
[16]	Optimized LSTM-based RNN	Reduced forecasting error for smart grid applications.	Performance decreases with noisy or incomplete data.
[17]	CNN–LSTM Hybrid (Review & Simulation)	CNN–LSTM models consistently outperformed standalone CNN and LSTM models.	High computational complexity and hardware requirements.
[18]	Review of Time-Series and Hybrid Models	Concluded hybrid forecasting models provide superior predictive performance.	Review-oriented without implementation.
[19]	Comprehensive Review of AI and Optimization Techniques	Identified intelligent forecasting and optimization strategies for power systems.	Limited quantitative comparison among studies.
[20]	Comparative Evaluation of Machine Learning Algorithms	Ensemble ML methods achieved better forecasting accuracy than conventional algorithms.	Results depend on dataset quality and feature engineering.
[21]	Time-Series and Machine Learning Models	Machine learning methods outperformed traditional time-series forecasting techniques.	Sensitive to data quality and feature selection.
[22]	PredXGBR (XGBoost Regression)	Achieved lower forecasting errors and better generalization than traditional regression.	Requires careful hyperparameter tuning.

[23]	Comprehensive Review of DER Load Forecasting	Reviewed forecasting models, challenges, and emerging technologies for distributed energy resources.	Data privacy and lack of benchmark datasets remain major issues.
[24]	Time-Series and Deep Learning Models	Deep learning outperformed conventional time-series models for city-scale forecasting.	Increased computational complexity and large data requirements.
[25]	Review of Machine Learning and Deep Learning Methods	Deep learning methods achieved higher forecasting accuracy across multiple forecasting horizons.	Limited interpretability, high computational cost, and dependence on data availability.

VI. CONCLUSION AND FUTURE SCOPE

In this review, recent advancements in electrical load forecasting techniques have been comprehensively analyzed, covering conventional statistical methods, time-series models, artificial intelligence, deep learning, hybrid frameworks, and optimization-based approaches. The review highlights that intelligent forecasting models, particularly LSTM, CNN, Transformer, reinforcement learning, and hybrid optimization techniques, consistently achieve higher prediction accuracy and greater adaptability than traditional methods. Furthermore, emerging approaches such as transfer learning, meta-learning, explainable artificial intelligence, and large language models have demonstrated significant potential for improving forecasting performance in modern smart grids. Despite these advances, challenges related to data quality, computational complexity, model interpretability, scalability, uncertainty arising from renewable energy integration, and real-time implementation remain unresolved. Future research should focus on developing lightweight, explainable, and energy-efficient forecasting frameworks capable of handling heterogeneous data sources and dynamic operating conditions. Integrating federated learning, edge computing, digital twins, advanced optimization algorithms, and trustworthy AI with smart grid technologies is expected to enhance forecasting accuracy, reliability, and decision-making, thereby supporting the development of resilient, sustainable, and intelligent next-generation power systems.

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