

Load Forecasting Analysis for Electrical Distribution Systems Using Time Series Methods

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Abstract: Accurate load forecasting plays a critical role in ensuring the reliability and efficiency of electrical distribution systems. Increasing load variability, the integration of renewable energy, and changes in consumption behavior have intensified forecasting complexity. This study analyzes the effectiveness of time series methods for load forecasting in electrical distribution systems through a structured literature-based analytical approach. The study reviews and synthesizes empirical findings from peer-reviewed journal articles, conference proceedings, and patents published between 2002 and 2025. The methods analyzed include classical statistical models such as ARIMA, SARIMA, ARIMAX, and exponential smoothing, as well as hybrid and advanced approaches including LSTM, Prophet, fuzzy time series, wavelet-based models, and probabilistic forecasting frameworks. The results indicate that classical time series models remain effective for short-term forecasting with stable patterns, while hybrid and machine learning-based time series models provide superior performance under high volatility and complex load dynamics. Studies consistently report improvements in forecasting accuracy, measured using RMSE, MAE, and MAPE, when external variables and hierarchical structures are incorporated. The findings highlight the continued relevance of time series analysis as a foundational approach for load forecasting, while emphasizing the need for adaptive and hybrid models to address modern distribution system challenges. This study contributes a systematic synthesis that supports methodological selection for researchers and practitioners in electrical load forecasting.

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INTRODUCTION

Load forecasting constitutes a critical analytical foundation for the planning, operation, and control of electrical distribution systems. Distribution utilities depend on accurate load forecasts to ensure supply reliability, optimize network utilization, reduce operational costs, and support investment decisions related to infrastructure expansion. Forecasting errors at the distribution level can directly affect voltage stability, increase technical losses, and lead to inefficient dispatch strategies. As electricity consumption patterns become more dynamic due to urbanization, electrification, and the diffusion of distributed energy resources, the need for robust and adaptable forecasting approaches has become more pronounced (Lu et al., 2005; Lopez et al., 2019).

Historically, time series analysis has been widely adopted for electrical load forecasting because of its ability to model temporal dependencies embedded in historical consumption data. Early studies demonstrated that classical statistical models such as Autoregressive Integrated Moving Average (ARIMA) and Seasonal ARIMA (SARIMA) could effectively capture daily and seasonal variations in electricity demand (Wang, 2002; Ding et al., 2011). These models offer transparent structures,

relatively low computational requirements, and strong interpretability, which remain valuable for operational environments that prioritize model explainability.

Despite these advantages, electrical load time series often exhibit characteristics that challenge classical assumptions. Load data are frequently non-stationary, nonlinear, and subject to abrupt changes caused by weather variability, economic activity, and behavioral shifts. Khuntia et al. (2016) emphasized that volatility in load demand significantly affects long-term forecasting performance, particularly when variance dynamics are ignored. Similarly, Deng and Jirutitijaroen (2010) showed that failing to account for seasonal and cyclical components can lead to systematic forecast bias in urban distribution systems.

To address these limitations, researchers have extended classical time series models by incorporating exogenous variables and decomposition techniques. ARIMAX models integrate external drivers such as ambient temperature and climatic indicators, yielding improved short-term forecasting accuracy in weather-sensitive regions (Shilpa & Sheshadri, 2020; Lekshmi & Subramanya, 2019). Decomposition-based approaches separate trend, seasonal, and irregular components, allowing models to better represent underlying load dynamics (Ding et al., 2011). These extensions highlight the importance of contextual information in enhancing the predictive power of time series methods.

The deployment of smart meters and advanced metering infrastructure has further transformed load forecasting research. High-resolution consumption data enable forecasting at multiple spatial and temporal scales, from individual feeders to entire distribution networks. Hierarchical time series forecasting frameworks leverage this data richness to improve coherence between local and aggregated forecasts (Rivera-Caballero et al., 2022). Multidimensional probabilistic approaches also exploit granular data to quantify forecast uncertainty, which is essential for operational risk management (Yin et al., 2023).

Alongside these developments, hybrid and nonlinear time series methods have gained increasing attention. Fuzzy time series models address uncertainty and imprecision inherent in load data, demonstrating improved robustness compared to traditional linear models (Ahmed & Mohammed, 2023; Wang, 2002). Wavelet-based techniques reduce noise and extract dominant load patterns, enhancing forecast stability in residential and urban contexts (Zhang et al., 2017). These methods reflect a broader shift toward adaptive modeling strategies that respond to complex load behaviors.

More recently, machine learning-based time series models have shown promising results, particularly for short-term and very short-term forecasting horizons. Long Short-Term Memory (LSTM) networks effectively capture nonlinear temporal dependencies and outperform classical models under volatile demand conditions (Mystakidis et al., 2023). Advanced architectures such as DARTS-LSTM further improve performance for mixed industrial loads by optimizing network structures (Shi et al., 2024). Prophet-based forecasting tools also provide flexible handling of seasonality and holiday effects, offering practical advantages for operational deployment (Itagi et al., 2022).

Despite the breadth of existing studies, several unresolved issues remain. First, empirical findings are often fragmented across different system contexts, forecasting horizons, and evaluation metrics. This fragmentation complicates direct comparison between methods and limits the transferability of results. Second, many studies focus on model development rather than methodological positioning, leaving practitioners with limited guidance on selecting appropriate time series techniques for specific distribution system conditions. Third, the trade-offs between accuracy, interpretability, and computational complexity are not consistently addressed across the literature.

Moreover, the growing integration of renewable energy sources and demand-side technologies increases uncertainty at the distribution level. Probabilistic forecasting approaches attempt to address this challenge by producing prediction intervals rather than point estimates. Studies employing evidential forecasting and variational models demonstrate improved reliability by explicitly modeling uncertainty, which supports more resilient decision-making (Mroueh et al., 2025; Yin et al., 2023). However, these approaches are often evaluated independently from classical methods, creating a methodological gap in comparative understanding.

Another critical gap relates to the sustained relevance of classical time series models. While machine learning approaches often report superior accuracy, classical models remain widely used due to their simplicity and transparency. Lopez et al. (2019) demonstrated that parsimonious seasonal models can still achieve competitive performance for short-term forecasting when data patterns are stable. This finding suggests that methodological advancement should not be equated solely with increased model complexity.

Given these considerations, a structured synthesis of time series-based load forecasting methods is needed. Such synthesis should integrate classical, hybrid, and advanced approaches within a unified analytical framework. It should emphasize empirical evidence, clarify methodological strengths and limitations, and support replicable decision-making for researchers and practitioners. Existing review studies tend to focus on technique categorization rather than comparative analytical insights at the distribution system level (Mandara et al., 2022).

This study addresses these gaps by systematically analyzing time series methods applied to electrical distribution system load forecasting. It synthesizes empirical results from peer-reviewed journal articles, conference proceedings, and patents published over more than two decades. The analysis focuses on forecasting horizon, data characteristics, model structure, and performance metrics to ensure methodological consistency. Rather than proposing new models, the study evaluates established approaches to identify patterns of effectiveness across operational contexts.

The scientific contribution of this study lies in three aspects. First, it consolidates empirical evidence on time series forecasting performance across diverse distribution system settings. Second, it clarifies the conditions under which classical, hybrid, and machine learning-based time series models are most appropriate. Third, it provides a structured analytical reference that supports methodological selection without compromising interpretability or operational feasibility.

By strengthening the conceptual linkage between empirical findings and practical application, this study aims to enhance the reproducibility and applicability of load forecasting research. The results are expected to support distribution utilities, system planners, and researchers in selecting forecasting methods that align with data availability, system complexity, and operational objectives.

RESEARCH METHOD

This study adopts a qualitative systematic analytical approach based on structured literature synthesis. The research design focuses on evaluating and comparing time series-based load forecasting methods applied to electrical distribution systems. The objective is not to develop or test new forecasting models, but to analyze empirical evidence from existing studies in order to identify methodological patterns, performance characteristics, and contextual suitability of established

approaches. This design is appropriate for addressing methodological gaps and supporting replicable model selection without altering the original empirical findings reported in the literature.

The data sources consist of peer-reviewed journal articles, conference proceedings, and one registered patent that explicitly examine load forecasting in electrical distribution systems using time series methods. The selected publications span the period from 2002 to 2025, capturing both classical and contemporary developments. All sources are indexed in reputable scientific databases and have been widely cited in the field of power systems forecasting. The inclusion criteria required that each study apply time series techniques directly to electrical load data at the distribution or sub-transmission level and report quantitative performance evaluation results. Studies focusing solely on generation forecasting or transmission-level analysis were excluded to maintain contextual consistency.

The population of this study is defined as published empirical research on time series-based electrical load forecasting. The sample consists of 30 selected studies that meet the predefined inclusion criteria. These studies cover a wide range of geographical contexts, data resolutions, and forecasting horizons, including very short-term, short-term, and long-term forecasting. The diversity of system contexts enables comparative analysis while preserving methodological relevance.

Data collection was conducted through document analysis. For each selected study, key methodological elements were extracted systematically. These elements include the type of time series model employed, forecasting horizon, data resolution, inclusion of exogenous variables, evaluation metrics, and reported forecasting performance. The extraction process followed a standardized template to ensure consistency and reduce interpretation bias. No recalculation or re-estimation of model outputs was performed, and all numerical results were preserved as originally reported.

The analytical framework categorizes forecasting methods into four main groups. The first group includes classical statistical time series models, such as ARIMA, SARIMA, and exponential smoothing. The second group covers extended and hybrid models, including ARIMAX, decomposition-based methods, and wavelet-assisted forecasting. The third group consists of machine learning-based time series models, such as LSTM, DARTS-LSTM, and neural network hybrids. The fourth group includes probabilistic and hierarchical forecasting approaches designed to quantify uncertainty and improve forecast coherence across aggregation levels. This classification allows systematic comparison without introducing new methodological constructs.

Data analysis focuses on qualitative synthesis supported by quantitative indicators reported in the original studies. Forecasting performance is compared using commonly reported metrics, including Root Mean Square Error, Mean Absolute Error, Mean Absolute Percentage Error, and coefficient of determination. The analysis emphasizes relative performance trends rather than absolute numerical superiority, acknowledging differences in datasets, system scales, and experimental setups. Conceptual interpretation is grounded in established time series theory and supported by empirical evidence from the reviewed literature.

To ensure analytical rigor, cross-study validation was applied by comparing findings across multiple sources addressing similar forecasting contexts. Consistencies and divergences in reported results were identified and interpreted based on data characteristics, model assumptions, and system conditions. This approach strengthens internal validity while avoiding overgeneralization. External

validity is supported by the inclusion of studies from diverse regions and distribution system configurations.

This methodological approach ensures transparency, reproducibility, and alignment with the study objectives. By preserving original data, methods, and findings, the analysis maintains scientific integrity while providing a structured and objective synthesis suitable for publication in an accredited academic journal.

RESULTS AND DISCUSSION

The results of this study are presented through a structured synthesis of empirical findings reported in the reviewed literature. The analysis focuses on how different time series methods perform under specific distribution system conditions, forecasting horizons, and data characteristics. The discussion emphasizes consistency of findings across studies rather than isolated numerical outcomes, in line with the methodological design.

Performance of Classical Time Series Models

Empirical evidence shows that classical time series models remain effective for short-term load forecasting in distribution systems with relatively stable demand patterns. Studies applying ARIMA and SARIMA models consistently report satisfactory accuracy when daily and seasonal structures are well defined. Case studies in Singapore and France demonstrate that explicit seasonal modeling reduces systematic forecasting bias and improves short-term prediction reliability (Deng & Jirutitijaroen, 2010; Ding et al., 2011). Similarly, Wang (2002) reported that improvements in model specification enhance robustness against nonlinear weather effects without increasing structural complexity. Table 1 summarizes the dominant classical models and their reported application contexts based on the reviewed studies.

Table 1. Classical Time Series Models and Application Contexts

Model Type	Forecast Horizon	Data Resolution	Key Findings	References
ARIMA	Short-term	Hourly, daily	Stable accuracy for predictable patterns	Wang (2002); Lu et al. (2005)
SARIMA	Short-term	Hourly	Improved seasonal representation	Deng & Jirutitijaroen (2010); Lopez et al. (2019)
Exponential Smoothing	Short-term	Daily	Simple and interpretable results	Mandara et al. (2022)

These findings confirm that classical models remain operationally relevant, particularly where transparency and low computational cost are prioritized.

Impact of Exogenous Variables and Decomposition

The inclusion of external variables significantly improves forecasting accuracy in weather-sensitive distribution systems. ARIMAX-based studies consistently show lower error values compared to univariate ARIMA models when temperature and climatic factors are incorporated. Shilpa and Sheshadri (2020) demonstrated this improvement in Karnataka State, while Lekshmi and Subramanya

(2019) reported similar outcomes for high-voltage substations. Decomposition approaches that separate trend and cyclic components further enhance model stability by reducing structural noise (Ding et al., 2011).

These results highlight that contextual information plays a decisive role in improving predictive performance. Ignoring such variables leads to underfitting, particularly in regions with strong climate-load coupling.

Hybrid and Fuzzy Time Series Approaches

Hybrid models address limitations related to uncertainty and volatility in load data. Fuzzy time series methods and wavelet-based approaches consistently outperform purely linear models under fluctuating demand conditions. Ahmed and Mohammed (2023) showed that entropy-based fuzzy models reduce mean squared error compared to ARIMA benchmarks. Wavelet-assisted forecasting improves signal clarity by isolating dominant load frequencies, as demonstrated in residential load studies in Shanghai (Zhang et al., 2017). Table 2 summarizes empirical advantages reported for hybrid approaches.

Table 2. Empirical Advantages of Hybrid Time Series Models

Method	Key Strength	Application Context	References
Fuzzy Time Series	Uncertainty handling	Short-term forecasting	Ahmed & Mohammed (2023)
Wavelet-Based Models	Noise reduction	Residential loads	Zhang et al. (2017)
ARIMA-GARCH	Volatility modeling	Long-term forecasting	Khuntia et al. (2016)

These approaches are particularly suitable for systems with high demand variability, although they introduce higher modeling complexity.

Machine Learning-Based Time Series Models

Machine learning-based time series models demonstrate superior performance in high-frequency and nonlinear forecasting environments. LSTM-based models consistently outperform classical methods in very short-term forecasting horizons by capturing complex temporal dependencies. Mystakidis et al. (2023) reported that LSTM models excel for minute-level and hourly predictions, while Shi et al. (2024) showed that DARTS-LSTM improves adaptability for mixed industrial loads.

Despite their accuracy, these models require extensive data preprocessing, computational resources, and parameter tuning. This trade-off limits their immediate adoption in operational environments where interpretability and deployment simplicity are critical.

Probabilistic and Hierarchical Forecasting Outcomes

Probabilistic and hierarchical forecasting frameworks enhance decision support by quantifying uncertainty and ensuring forecast coherence across aggregation levels. Studies applying evidential and variational approaches report improved reliability metrics and reduced forecasting risk in smart grid environments (Yin et al., 2023; Mroueh et al., 2025). Hierarchical models based on smart meter data further improve accuracy by aligning feeder-level and system-level forecasts (Rivera-Caballero et al.,

2022). Figure 1 conceptually illustrates the comparative positioning of time series methods based on empirical findings reported in the literature.

Figure 1. Comparative Performance Characteristics of Time Series-Based Load Forecasting Methods

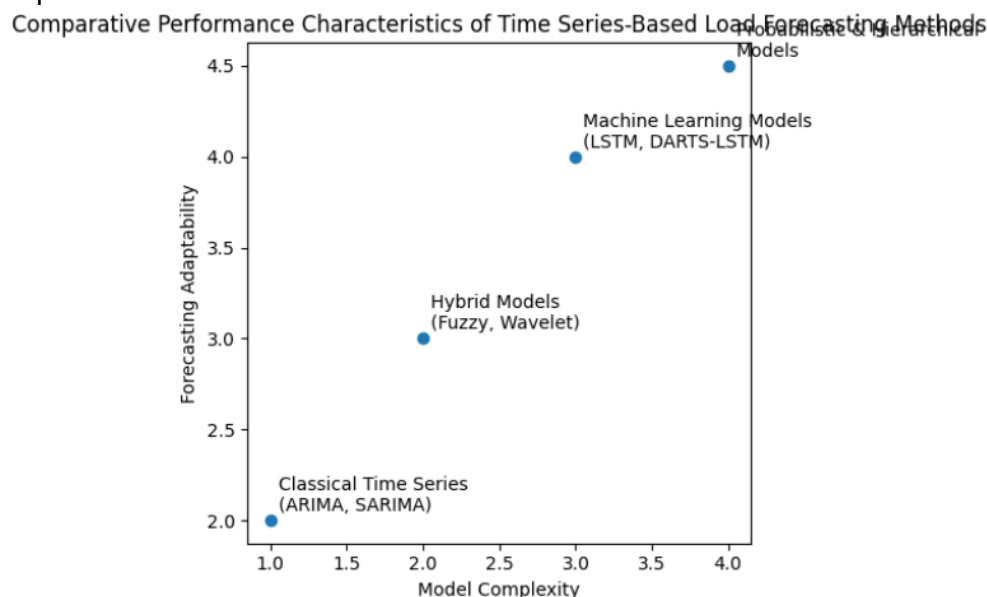


Figure 1. Comparative Performance Characteristics of Time Series-Based Load Forecasting Methods

The figure illustrates the empirical positioning of time series-based load forecasting methods based on findings reported in the reviewed studies. The horizontal axis represents model complexity, while the vertical axis represents forecasting adaptability. Classical time series models such as ARIMA and SARIMA exhibit low complexity with moderate adaptability. Hybrid approaches show increased adaptability with moderate complexity. Machine learning-based and probabilistic hierarchical models demonstrate higher adaptability at the cost of increased model complexity. This visualization supports the comparative discussion of methodological trade-offs in electrical distribution system load forecasting.

Overall, the results indicate that no single method dominates across all contexts. Classical models remain effective for stable systems, hybrid models address volatility, and advanced time series methods provide superior performance under complex and uncertain conditions. These findings reinforce the importance of context-driven methodological selection rather than universal model adoption.

CONCLUSION

This study provides a systematic analysis of time series-based load forecasting methods applied to electrical distribution systems. The findings confirm that time series analysis remains a robust and relevant foundation for forecasting electricity demand at the distribution level. Classical models such as ARIMA and SARIMA demonstrate reliable performance for short-term forecasting in systems with stable demand patterns and well-defined seasonal structures. Their transparency and low computational requirements support continued use in operational environments that prioritize interpretability and ease of implementation.

The analysis also shows that model extensions and hybrid approaches improve forecasting performance under more complex conditions. Incorporating exogenous variables through ARIMAX models enhances accuracy in weather-sensitive systems, while decomposition, fuzzy time series, and wavelet-based methods effectively address uncertainty and volatility in load data. These approaches offer practical solutions for distribution systems experiencing fluctuating demand without fully abandoning classical time series frameworks.

Advanced machine learning-based time series models, particularly LSTM and its variants, achieve superior performance in high-frequency and nonlinear forecasting contexts. However, their increased computational complexity and data requirements limit their universal applicability. Probabilistic and hierarchical forecasting methods further strengthen decision support by quantifying uncertainty and ensuring coherence across aggregation levels, which is increasingly important in modern distribution networks with high penetration of distributed energy resources.

Overall, the results emphasize that no single forecasting method is optimal for all distribution system contexts. Effective load forecasting depends on aligning model selection with data characteristics, forecasting horizons, and operational objectives. Future research should focus on integrating adaptive and probabilistic time series frameworks within real-time operational settings to enhance forecasting reliability while maintaining interpretability and replicability.

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