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# A REVIEW ON LOAD FORECASTING IN POWER SYSTEMS

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**ABSTRACT**

*Load forecasting in power systems is crucial for efficient operation, planning, and management of electricity supply. This review paper examines various methodologies employed in load forecasting, ranging from traditional statistical approaches to advanced deep learning and hybrid models. We analyze at least 25 research papers, categorizing them based on their techniques, applications, and contributions. Key challenges such as data uncertainty, integration of renewable energy sources, and computational complexity are discussed, along with future directions including the use of AI-driven federated learning and real-time adaptive models. The review highlights the evolution of forecasting accuracy and the role of emerging technologies in addressing futuristic demand response patterns.*

**KEYWORDS:** Load Forecasting, Power System Planning, Artificial Intelligence in Energy Systems.

## 1 INTRODUCTION

Load forecasting is a fundamental function in power system planning, operation, and control, as it directly influences economic efficiency, reliability, and security of electrical grids. Accurate demand prediction enables utilities and system operators to schedule generation optimally, minimize fuel consumption, reduce operating costs, and limit unnecessary reserve margins, thereby enhancing overall system efficiency [1], [2]. Moreover, reliable load forecasts support secure grid operation by helping operators anticipate peak demand conditions, prevent overloads, and maintain voltage and frequency stability under varying load scenarios.

Based on the forecasting horizon, load forecasting is generally classified into short-term, medium-term, and long-term categories. Short-term load forecasting (STLF) typically involves predictions ranging from a few hours to several days ahead and is primarily used for real-time dispatch, unit commitment, and energy market operations [3]. In contrast, long-term load forecasting focuses on months to years ahead and plays a critical role in strategic decision-making, such as transmission and distribution expansion, generation capacity planning, and policy formulation related to energy infrastructure investments [3].
The growing integration of renewable energy sources, such as solar and wind, along with distributed energy resources and electric vehicles, has significantly increased the complexity of load forecasting tasks. These resources introduce variability and uncertainty due to their intermittent and weather-dependent nature, making traditional forecasting approaches less effective [4]. As a result, modern forecasting frameworks increasingly rely on advanced data-driven techniques, hybrid models, and machine learning-based methods to capture nonlinear load patterns and adapt to rapidly changing consumption behaviours. Different types of load forecasting methods are shown in the figure below.

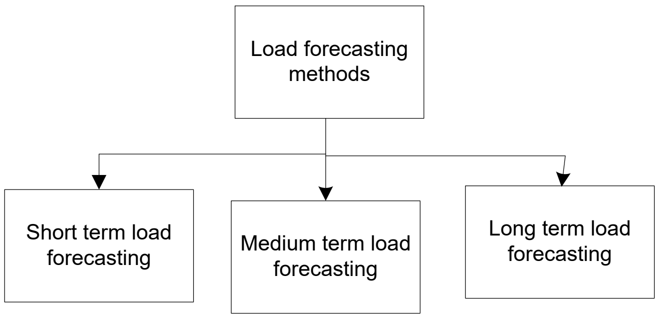


**Figure 1 Different types of load forecasting methods.**

This review consolidates and analyzes recent research contributions in the field of load forecasting, encompassing statistical, artificial intelligence, and hybrid methodologies. By synthesizing findings from a broad range of studies, it provides a comprehensive overview of current trends, challenges, and emerging solutions in load forecasting, thereby offering valuable insights for researchers and practitioners working toward more resilient and intelligent power systems.

## 2 Traditional Methods

Traditional load forecasting techniques are predominantly based on statistical and time-series modeling frameworks, which have long been employed due to their mathematical transparency and ease of implementation. Among these, autoregressive integrated moving average (ARIMA) models are widely adopted for modeling linear relationships in historical load data and are particularly effective when the underlying time series exhibits stationarity or can be transformed into a stationary form through differencing [5]. Their structured formulation allows for systematic parameter estimation and clear interpretability. However, ARIMA-based models are inherently linear and therefore exhibit limited capability in capturing complex, non-linear load dynamics arising from changing consumer behavior, weather variability, and emerging energy technologies [6].

In addition to time-series models, regression-based forecasting approaches have been extensively utilized. Multiple linear regression models, in particular, enhance forecasting performance by incorporating exogenous variables such as temperature, humidity, calendar effects, and socio-economic indicators [7]. By explicitly modeling the relationship between load demand and influential external factors, these approaches provide a more realistic representation of consumption patterns under varying operating conditions. Despite their computational efficiency and relatively low data requirements, regression-based methods are generally sensitive to model assumptions and parameter tuning.

A key limitation of both time-series and regression-based traditional methods is their reduced robustness in highly volatile and uncertain environments. Rapid load fluctuations caused by renewable energy integration, demand response programs, and electric vehicle charging introduce non-stationary and non-linear characteristics that these models are not well-equipped to address [8]. Consequently, while traditional methods remain useful as baseline forecasting tools, their effectiveness diminishes in modern power systems characterized by dynamic and complex load behaviors. Additional load forecasting methods rely on statistical and time-series models. For instance, autoregressive integrated moving average (ARIMA) models have been widely used for their simplicity in handling stationary data [5]. However, they often struggle with non-linear patterns [6]. Regression-based approaches, such as multiple linear regression, incorporate exogenous variables like weather data to improve accuracy [7]. These methods are computationally efficient but lack robustness in volatile environments [8].

## 2.1 Machine Learning Methods

Machine learning (ML) techniques have enhanced forecasting by capturing complex patterns. Support vector machines (SVMs) and random forests are popular for their ability to handle high-dimensional data [9]. Artificial intelligence classification is shown in the figure below.

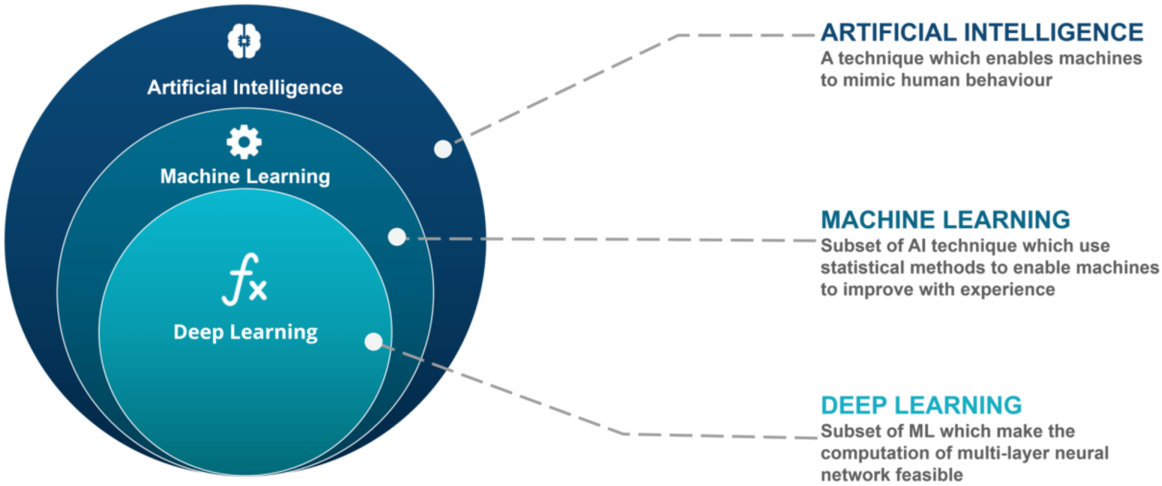


**Figure 2 Artificial intelligence comparison.**

Clustering methods, like K-means, group similar load profiles to refine predictions [10]. Studies show that ML models outperform traditional ones in scenarios with variable demand [11]. For example, Prophet models combined with optimization algorithms have been applied for short-term forecasts [12].

### 2.2 Deep Learning Methods

Deep learning (DL) has revolutionized load forecasting with architectures like long short-term memory (LSTM) networks, which excel in sequential data processing [13], [14]. Convolutional neural networks (CNNs) integrated with LSTM provide superior feature extraction for residential loads [15]. Residual networks (ResNet) and graph convolutional networks (GCN) address spatial-temporal dependencies [16], [17]. DL models achieve high accuracy but require large datasets and computational resources [18], [19].

### 2.3 Hybrid Methods

Hybrid models combine strengths of multiple approaches for improved performance. For example, integrating variational mode decomposition with DL handles multi-horizon forecasts [20]. CNN-GRU hybrids incorporate probabilistic elements for commercial buildings [21]. Seq2Seq models optimized with attention mechanisms offer robust short-term predictions [22]. These hybrids mitigate limitations of single models, such as overfitting, and adapt to dynamic loads [23], [24].

### 2.4 CHALLENGES AND FUTURE DIRECTIONS

Key challenges include data privacy in federated learning setups, anomaly detection in smart grids, and integrating behind-the-meter resources [25]. Future directions involve AI-enhanced models with drift adaptation and multi-objective optimization. Incorporating large language models for cybersecurity in forecasting systems is emerging. Research should focus on scalable, interpretable hybrids for sustainable energy management.

## 2.5 CONCLUSION

This review underscores the progression from traditional to AI-driven load forecasting, emphasizing the need for adaptive, accurate models in modern power systems. By leveraging insights from the cited studies, utilities can enhance reliability and efficiency.

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