ISSN: 1813-4890

Review on Electric Load Forecasting

Laiqi Zhao

Tianjin University of Technology and Education, Tianjin 300222, China;

lqzhao10@163.com

Abstract

Eectricity load forecasting is crucial for efficient power system operation, including grid management, energy dispatch, and market transactions. This review explores the definition, classification, and time scales of load forecasting, as well as the key factors influencing load variations, such as weather, economic activities, and technological advancements. It also covers traditional statistical methods, along with machine learning and deep learning approaches, highlighting their applications and challenges. The paper provides an overview of current research trends in load forecasting, aiming to enhance power system efficiency and facilitate the integration of renewable energy sources.

Keywords

Electric Load Forecasting, Influencing Factors, Forecasting Methods.

1. Introduction

Electric load forecasting plays a key role in grid dispatch, generation planning, energy management, and power market trading, directly affecting the safety and economy of the power system. With the large-scale integration of renewable energy and the development of smart grids, load forecasting faces challenges such as data complexity, model generalization ability, balancing short-term fluctuations with long-term trends, computational resource demands, and uncertainties in renewable energy. In recent years, advancements in artificial intelligence and big data technologies have provided new opportunities to improve forecasting accuracy. This article will review the basic concepts and main methods of electric load forecasting, providing a reference for related research and engineering applications.

2. The Basic Concepts of Electricity Load Forecasting

2.1. Definition and Classification of Electricity Load

Electric load refers to the amount of electrical energy consumed or the power required by all users and devices in a power system at a specific moment or over a certain period. It not only reflects the real-time operational status of the power grid but also provides critical data for system planning, scheduling, and optimization.

Typically, based on statistical criteria and practical applications, electric load can be categorized into generation load, consumption load, and supply load, with consumption load representing the actual electricity demand within the grid. From a time-scale perspective, load can be classified into short-term, mid-term, and long-term loads to meet different scheduling and planning requirements. Additionally, based on the nature of electricity usage, loads in different regions and among various users can be divided into residential, commercial, industrial, and other public facility loads. Each type of load exhibits unique fluctuation patterns and characteristics, playing a decisive role in the safe and economic operation of the power system.

2.2. Time Scales of Load Forecasting

Power load forecasting can be categorized into short-term, mid-term, and long-term forecasts based on the time scale, with different modeling methods and data analysis techniques applied to meet various application needs.

Short-term load forecasting (STLF) typically covers a period ranging from a few minutes to one week and is mainly used for real-time grid dispatching, short-term generation planning, and demand response management. It is highly sensitive to weather conditions, holidays, and unexpected events, making time series analysis, machine learning, and deep learning common forecasting approaches.

Mid-term load forecasting (MTLF) generally spans from one week to one year and supports power companies in formulating electricity procurement plans, energy trading strategies, and equipment maintenance scheduling. Its accuracy must balance short-term fluctuations and long-term trends, often integrating statistical modeling with economic factor analysis.

Long-term load forecasting (LTLF) extends beyond one year, sometimes even decades, and is primarily used for power infrastructure investment planning, renewable energy development strategies, and policy-making. It is significantly influenced by macroeconomic factors such as economic growth, population changes, and policy adjustments. Common methods include regression analysis, scenario simulation, and AI-enhanced forecasting techniques to provide reliable power development trend references.

2.3. Main Factors Influencing Electricity Load

Electric load is influenced by various factors, which interact with each other, leading to complexity and uncertainty in load variation. Weather factors are one of the most direct influences, such as temperature, humidity, wind speed, and solar radiation, which can affect the use of equipment like air conditioners, heating systems, and lighting, thus impacting electricity demand. Economic factors are also key drivers—GDP growth, industrial production activities, commercial development, etc., all affect overall electricity demand, while fluctuations in electricity prices may change users' consumption behavior.

Population changes and social factors are equally important. Urbanization, shifts in residents' lifestyles, and the increase in electrification levels all influence load characteristics. Additionally, policies and technological advancements have a significant impact on load, such as energy-saving and emission-reduction policies, the integration of renewable energy, the rise of electric vehicles, and the development of smart grid technologies. These factors can alter traditional load curves, making them more dynamic and decentralized.

Overall, the variation in electric load is multidimensional, and its forecasting requires careful consideration of the combined effects of these factors to improve the accuracy and adaptability of predictions.

3. Common Methods for Electricity Load Forecasting

3.1. Traditional Statistical Forecasting Methods

Traditional statistical forecasting methods include linear regression,,time series methods,,exponential smoothing, trend analysisand grey forecasting models.

Regression analysis, also known as statistical analysis, is a method used to determine the relationship between the forecasted value and influencing factors. B. Dhaval et al. used multiple linear regression to accurately predict short-term electricity load based on temperature, due dates, and seasonality, providing predictions for the previous day and weekly forecasts[1]. Haeran Cho et al. used curve linear regression to effectively predict short-term electricity load. Compared to other competitors, this approach reduced forecasting errors and required fewer two-stage methods[2]. Moshoko et al. used a partial linear additive quantile regression model for short-term electricity demand forecasting and found that coal-fired power units are more economical in increasing generation during peak periods[3].

Time series analysis involves analyzing a continuous sequence of historical electricity load data that changes over time. It establishes a mathematical model to describe the relationship between load values and time, determining the expression of the time series for load forecasting. Ewa Chodakowska et al. mentioned that the ARIMA model in electricity load forecasting shows weak noise resistance, highlighting the importance of data preprocessing in data mining and learning[5]. M. Amini et al. used the ARIMA method to improve the accuracy of traditional electricity load and electric vehicle charging demand forecasting, reducing errors and improving the operation of stochastic power systems[6]. Quang Dat Nguyen et al. used online SARIMA to effectively forecast short-term electricity load in northern Vietnam, with an average absolute percentage error of 4.57%[7].

Exponential smoothing, similar to regression analysis, is based on time series and load values to establish forecasting models. Unlike regression analysis, exponential smoothing is more flexible and provides better fitting performance. N. A. Jalil et al. mentioned that The Holt-Winters Taylor (HWT) exponential smoothing method provides the most accurate electricityload demand forecasts compared to traditional and modified Holt-Winters methods[8]. J. Rendon-Sanchez et al. mentioned that Structural combinations of seasonal exponential smoothing forecasts can effectively predict short term electricity demand, outperforming competitive benchmarks and extending to other seasonaldata and forecasting models[9].

Trend analysis, also known as trend curve analysis, is the most widely used and extensively researched quantitative forecasting method. Trend analysis fits a function to known historical data so that the function can represent the predicted electricity load at a future time point. Common types of functions used include polynomial, logarithmic, power, and exponential functions.

The grey forecasting model is a method for electricity load forecasting in systems with uncertain factors. Huiru Zhao et al. mentioned that The Rolling-ALO-GM (1,1) model, optimized by Ant Lion Optimizer with Rolling mechanism,significantly improves annual power load forecasting accuracy compared to other models[11]. Song Ding et al. mentioned that new grey prediction model with alterable weighted coefficients accurately forecasts China's totaland industrial electricity consumption from 2015 to 2020, outperforming benchmark models[12]. Jianna Zhao et al. mentioned that grey model effectively forecasts short-term power load, providing a strong basis for powersystem dispatching and long-term planning[13].

3.2. Machine Learning Forecasting Method

Electricity load forecasting is influenced by various factors and exhibits certain nonlinear characteristics. Machine learning has strong nonlinear mapping capabilities and can effectively handle the nonlinear issues in electricity load forecasting. Traditional machine learning methods include support vector machines, decision trees, and random forests.

Support Vector Machine (SVM) is a method that finds a hyperplane to handle nonlinear problems, and it can address both classification and regression issues. P. Nijhawan used SVM algorithm provides reasonably accurate and reliable electric load forecasting, asdemonstrated by its effectiveness in predicting live load data from a 66kV sub-station in Punjab.India[14]. Xia Dong proposed short-term SVM power load forecasting method based on K-Means clusteringimproves prediction accuracy by 39.75% and running time by 128.89% compared to conventionalmethods[15]. F. Pallonetto et al. mentioned that SVM model outperforms the LSTM model in short-term load forecasting when load data isinsufficient and time cost is prioritized, as it offers better prediction accuracy and time efficiency[16].

Decision tree (DT) in machine learning represents a mapping relationship between object attributes and object values. It is a method that can handle both classification and regression problems. L. Jie mentioned that optimized decision tree method effectively improves short-term load forecasting accuracy by effectively considering non-load factors' infuences[17]. B. V. S. Vardhan et al. mentioned that decision Trees and Grid Search are the best methods for short-term load forecasting, withhyperparameter tuning reducing mean square error by 12.98%[18]. Zhenxue Xie et al. mentioned that short-Term Power Load Forecasting Model using Fuzzy Neural Network and lmproved DecisionTree significantly improves prediction accuracy and reduces relative error in smart grid environments[19].

Random Forest is an ensemble algorithm composed of decision trees and belongs to the Bagging type. When Random Forest is used to handle regression problems, it is referred to as Random Forest Regression. Grzegorz Dudek mentioned that Random forest models, when optimized, can provide the most accurate short-term load forecasts compared to statistical and machine learning models[20]. Nantian Huang et al. mentioned that novel random forest-based feature selection method improves short-term load forecast accuracycompared to support vector regression and artificial neural network models[21]. Li-ling Peng et al. proposed method based on wavelet transform and random forest improves short-term electricload forecasting accuracy and reliability by reducing random noise and improving data stability[22].

3.3. Deep Learning Forecasting Methods

Deep learning forecasting methods use neural networks as a parameter structure for optimization in machine learning. Due to their high complexity, strong adaptability, and ability to self-adapt to learning data features, they are widely used and currently the most commonly applied method for load forecasting. Deep learning methods include key models such as BP neural networks,convolutional neural networks, recurrent neural networks and Transformer.

The BP neural network is a multilayer neural network trained through the backpropagation algorithm. The BP neural network consists of two processes: forward propagation and backward propagation of errors. In forward propagation, information starts from the input layer, passes through the hidden layers to extract information and features, and is finally output by the output layer. In backward propagation, the error is propagated back through the network, and each weight and bias is updated using the chain rule of differentiation. Lingxia Li et al. proposed short-term power load forecasting method based on BP neural network achieves highaccuracy and low complexity, with reduced factors and back-propagation algorithm improvingtraining speed and forecasting efficiency[23]. Zhou Dian mentioned that BP artificial neural network effectively performs short-term load forecasting for different seasons,with temperature selection being crucial for accurate predictions[24]. Guanghua Li et al. mentioned that BP neural network is a feasible and promising method for short-term load prediction in powersystems, better reflecting nonlinear characteristics than traditional methods[25].

Convolutional Neural Networks (CNN) are deep neural networks with a convolutional structure that can efficiently process image data or image sequence data, and can also handle electricity data. Unlike BP neural networks, the neurons in the upper and lower layers of a convolutional neural network are not directly connected. Instead, they are connected through shared convolutional kernels, which significantly reduces the number of parameters in the neural network and avoids parameter redundancy. Alberto Mozo et al. proposed Convolutional neural networks effectively forecast short-term data center network trafficload, outperforming traditional time-series-analysis approaches like ARlMA and providing valuableinsights for efficient resource management[26]. Qian Huang et al. proposed load range discretization method improves convolutional neural networks forprobabilistic load forecasting, resulting in more reliable and sharper load probability distributions forsmart grid decision-making[27].

Junhong Kim et al. mentioned that recurrent inception convolution neural network model outperforms other models indaily electric load forecasting, using a predicted future hidden state vector and past information forimproved performance[28].

Recurrent Neural Networks (RNN) are a type of neural network model where the output is used as part of the input for the next iteration. This model can capture the correlations between past and future outputs, and its characteristics can be applied to electricity load forecasting. However, RNNs are not well-suited for learning long-term dependencies and are mainly applicable to short-term dependencies, making them suitable for short-term load forecasting. Later, improved models such as Long Short-Term Memory (LSTM) networks were proposed to address these limitations. J. Vermaak et al. mentioned that Recurrent Neural Networks effectively model short-term load as the output of a dynamic system, improving prediction performance compared to feedforward neural networks[29]. F. Bianchi et al. mentioned that Recurrent Neural Networks can effectively predict short-term load forecasts, reducing serviceinterruptions and resource waste in supply networks[30]. Shahzad Muzaffar et al. mentioned that LSTM networks provide better short-term electrical load forecasts than traditional methods, withpotential for further improvements[31]. Ziyu Sheng et al. proposed neural network framework based on a modified deep residual network and long short-term memory LSTM recurrent neural network improves short-term load forecasting accuracy,robustness, and generalization capability compared to existing mainstream models[32].

The Transformer model was initially proposed to address the issue of difficulty in parallel acceleration with Recurrent Neural Networks (RNN) in natural language processing. The standard Transformer model consists of an encoder and a decoder. Alexandra L'Heureux et al. mentioned that The transformer-based architecture for load forecasting effectively handles time series withcontextual data and outperforms state-of-the-art Seq2Seg models, improving energy management[33]. Jun Wei Chan et al. mentioned that sparse transformer-based approach for electricity load prediction achieves comparable accuracyto RNN-based methods while being up to 5x faster during inference, making it suitable forforecasting from individual households to city levels[34]. Peng Ran et al. mentioned that CEEMDAN-SE-TR model, combining CEEMDAN, SE and Transformer, provides the best short-term load forecasting results compared to other machine learning models[35].

4. Conclusion

The above summarizes the definition and classification of electric load, time scales, and influencing factors. It also reviews and analyzes research achievements in power system load forecasting from three perspectives: traditional forecasting methods, machine learning-based methods, and deep learning-based methods.

The emergence of new load forecasting challenges will continue to drive the advancement of forecasting technologies to deeper levels. In the future, more precise forecasting methods will be needed to improve accuracy in power load prediction. It is hoped that this article provides you with fundamental knowledge in power load forecasting to support your learning in this field.

References

[1] Dhaval, B., & Deshpande, A. (2020). Short-term load forecasting with using multiple linear regression. International Journal of Electrical and Computer Engineering, 10, 3911-3917.

[2] Cho, H., Goude, Y., Brossat, X., & Yao, Q. (2014). Modelling and forecasting daily electricity load via curve linear regression. .

[3] Lebotsa, M., Sigauke, C., Bere, A., Fildes, R., & Boylan, J. (2018). Short term electricity demand forecasting using partially linear additive quantile regression with an application to the unit commitment problem. Applied Energy.

[4] Zhang Lingyun, Xiao Huiren, Wu Junhao, et al. A Review of Power System Load Forecasting [J]. Electric Power Big Data, 2018, 21(1): 52-56.

[5] Chodakowska, E., Nazarko, J., & Nazarko, Ł. (2021). ARIMA Models in Electrical Load Forecasting and Their Robustness to Noise. Energies.

[6] Amini, M., Kargarian, A., & Karabasoglu, O. (2016). ARIMA-based decoupled time series forecasting of electric vehicle charging demand for stochastic power system operation. Electric Power Systems Research, 140, 378-390.

[7] Nguyen, Q., Nguyen, N., Tran, N., Solanki, V., Crespo, R., & Nguyen, T. (2021). Online SARIMA applied for short-term electricity load forecasting. Appl. Intell., 54, 1003-1019.

[8] Jalil, N., Ahmad, M., & Mohamed, N. (2013). Electricity load demand forecasting using exponential smoothing methods. World applied sciences journal, 22, 1540-1543.

[9] Rendon-Sanchez, J., & Menezes, L. (2019). Structural combination of seasonal exponential smoothing forecasts applied to load forecasting. Eur. J. Oper. Res., 275, 916-924.

[10] Bai Jing. Practical Analysis of Power System Load Forecasting Methods in Distribution Network Planning [J]. Communication Power Technology, 2016, 33(2): 123-124.

[11] Zhao, H., & Guo, S. (2016). An optimized grey model for annual power load forecasting. Energy, 107, 272-286.

[12] Ding, S., Hipel, K., & Dang, Y. (2018). Forecasting China's electricity consumption using a new grey prediction model. Energy, 149, 314-328.

[13] Zhao, J., & He, X. (2017). Application of Grey Model in Power Load Forecasting. DEStech Transactions on Social Science, Education and Human Science.

[14] Nijhawan, P., Bhalla, V., Singla, M., & Gupta, J. (2020). Electrical Load Forecasting using SVM Algorithm. International Journal of Recent Technology and Engineering.

[15] Dong, X., Deng, S., & Wang, D. (2021). A short-term power load forecasting method based on k-means and SVM. Journal of Ambient Intelligence and Humanized Computing, 13, 5253 - 5267.

[16] Pallonetto, F., Jin, C., & Mangina, E. (2021). Forecast electricity demand in commercial building with machine learning models to enable demand response programs. Energy and AI.

[17] Jie, L. (2008). SHORT-TERM LOAD FORECASTING BASED ON OPTIMIZED DECISION TREE. Microcomputer Information.

[18] Vardhan, B., Khedkar, M., Srivastava, I., Thakre, P., & Bokde, N. (2023). A Comparative Analysis of Hyperparameter Tuned Stochastic Short Term Load Forecasting for Power System Operator. Energies.

[19] Xie, Z., Wang, R., Wu, Z., & Liu, T. (2019). Short-Term Power Load Forecasting Model Based on Fuzzy Neural Network using Improved Decision Tree. 2019 IEEE Sustainable Power and Energy Conference (iSPEC), 482-486.

[20] Dudek, G. (2022). A Comprehensive Study of Random Forest for Short-Term Load Forecasting. Energies.

[21] Huang, N., Lu, G., & Xu, D. (2016). A Permutation Importance-Based Feature Selection Method for Short-Term Electricity Load Forecasting Using Random Forest. Energies, 9, 767.

[22] Peng, L., Fan, G., Yu, M., Chang, Y., & Hong, W. (2021). Electric Load Forecasting based on Wavelet Transform and Random Forest. Advanced Theory and Simulations, 4.

[23] Li, L., & Huang, W. (2014). A Short-Term Power Load Forecasting Method Based on BP Neural Network. Applied Mechanics and Materials, 494-495, 1647 - 1650.

[24] Dian, Z. (2002). A SHORT-TERM LOAD FORECASTING SYSTEM BASED ON BP ARTIFICIAL NEURAL NETWORK. Power system technology.

[25] Li, G., Zhang, H., Zhang, Z., & Wang, S. (2022). Power Load Forecasting Based on BP Neural Network. Highlights in Science, Engineering and Technology.

ISSN: 1813-4890

[26] Mozo, A., Ordozgoiti, B., & Gómez-Canaval, S. (2018). Forecasting short-term data center network traffic load with convolutional neural networks. PLoS ONE, 13.

[27] Huang, Q., Li, J., & Zhu, M. (2020). An improved convolutional neural network with load range discretization for probabilistic load forecasting. Energy.

[28] Kim, J., Moon, J., Hwang, E., & Kang, P. (2019). Recurrent inception convolution neural network for multi short-term load forecasting. Energy and Buildings.

[29] Vermaak, J., & Botha, E. (1998). Recurrent neural networks for short-term load forecasting. IEEE Transactions on Power Systems, 13, 126-132.

[30] Bianchi, F., Maiorino, E., Kampffmeyer, M., Rizzi, A., & Jenssen, R. (2017). Recurrent Neural Networks for Short-Term Load Forecasting. , 1-72.

[31] Muzaffar, S., & Afshari, A. (2019). Short-Term Load Forecasts Using LSTM Networks. Energy Procedia.

[32] Sheng, Z., An, Z., Wang, H., Chen, G., & Tian, K. (2023). Residual LSTM based short-term load forecasting. Appl. Soft Comput., 144, 110461.

[33] L'Heureux, A., Grolinger, K., & Capretz, M. (2022). Transformer-Based Model for Electrical Load Forecasting. Energies.

[34] Chan, J., & Yeo, C. (2024). A Transformer based approach to electricity load forecasting. The Electricity Journal.

[35] Ran, P., Dong, K., Liu, X., & Wang, J. (2023). Short-term load forecasting based on CEEMDAN and Transformer. Electric Power Systems Research.