

Overview of Electric Power Load Forecasting Research

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Abstract: Electric power load forecasting is a crucial link in ensuring the safe, stable, and economical operation of power systems and achieving sustainable resource allocation. This paper reviews the research status and development trends of electric power load forecasting, classifying it into three categories based on time span: short-term, medium-term, and long-term, suitable for daily grid dispatch, monthly/quarterly operational planning, and long-term planning, respectively. Regarding influencing factors, external meteorological conditions and economic policies, as well as internal user behavior patterns and power system dynamic characteristics, all significantly impact load forecasting. Traditional statistical methods such as time series analysis, regression analysis, and exponential smoothing once dominated but are limited by model assumptions and their ability to handle nonlinear relationships. Machine learning methods like Support Vector Machines (SVM) and Random Forests (RF) overcome traditional limitations through feature interaction and data fusion capabilities. Deep learning methods such as Convolutional Neural Networks (CNN), Transformers, and Graph Neural Networks (GNN) further enable high-dimensional modeling of complex spatiotemporal patterns, driving prediction accuracy to new heights. Future research directions focus on cross-domain collaborative forecasting, breaking disciplinary barriers to build multimodal fusion networks, and responding to carbon neutrality goals by developing net load forecasting models adapted to new power system demands and prediction models coupled with carbon credit mechanisms. In summary, power load forecasting technology is shifting from traditional approaches towards multidisciplinary integrated innovation and will become the core engine for intelligent decision-making in new power

systems, aiding the safe, economical, and low-carbon transformation of the grid.

Keywords: Electric Power Load Forecasting; Meteorological Conditions; Machine Learning; Deep Learning; Carbon Neutrality

1. Introduction

1.1 Research Background and Significance

With the rapid development of the social economy and the continuous improvement of living standards, the importance of power systems in modern social development has become increasingly prominent. As a key link in power system planning, operation, and control, power load forecasting is of paramount importance for ensuring the safe, stable, and economical operation of power systems. Accurate electric power load forecasting provides a scientific basis for various aspects such as power generation scheduling, transmission network planning, distribution system optimization, and electricity market trading. This effectively reduces the operational costs of power systems, improves power supply reliability and service quality, and also contributes to the rational allocation and sustainable development of power resources.

Electric power load forecasting is a complex and variable subject, influenced by multiple interacting factors, including economic development levels, industrial structure adjustments, population growth and mobility, meteorological condition changes, social activity events, and energy policy adjustments. These factors intertwine and interact, endowing power loads with complex characteristics such as nonlinearity, time-variance, and uncertainty, posing significant challenges to load forecasting work. To address this challenge, numerous scholars and researchers have conducted extensive and in-depth research in the field of power load forecasting, proposing various forecasting methods and technologies, and

continuously exploring new forecasting ideas and models^[1].

1.2 Classification of Electric Power Load Forecasting

Electric power load forecasting can be classified based on different time dimensions. According to the time span, it is mainly divided into short-term, medium-term, and long-term electric power load forecasting.

1.2.1 Short-Term Electric Power Load Forecasting

Short-term power load forecasting usually includes hourly power load forecasting and daily power load forecasting. It is primarily used to guide the daily dispatch and operation of the grid, helping dispatchers arrange generation plans reasonably, optimize unit output, and ensure the grid meets load demand while achieving economical and stable operation. In short-term forecasting, time series analysis methods like the ARIMA model and machine learning methods like neural networks are widely used. These methods can fully utilize temporal patterns and complex features in historical load data to provide strong support for short-term load forecasting.

1.2.2 Medium-Term Electric Power Load Forecasting

Medium-term electric power load forecasting focuses on load trends over several weeks to several months. It is mainly used for monthly/quarterly operational planning of the grid, macroscopic generation planning, and also serves as an important reference for electricity market trading, helping market participants formulate reasonable trading strategies in advance. During medium-term forecasting, methods like time series analysis and regression analysis are typically combined, considering the influence of seasonal factors, economic indicators, temperature change trends, and other multifaceted factors to build comprehensive predictive models.

1.2.3 Long-Term Electric Power Load Forecasting

Long-term electric power load forecasting focuses on the development trend of power loads over several years to decades or even longer. Its main application scenarios include long-term grid planning, such as the construction and renovation of transmission and transformation facilities, power plant siting, etc. It also provides a basis for formulating energy policies to ensure

the long-term stability and sustainability of power supply. Long-term forecasting generally analyzes long-term growth trends based on historical load data, combined with macroeconomic factors such as economic development plans, population growth forecasts, and industrial restructuring, using methods like regression analysis and trend extrapolation for comprehensive prediction.

This paper will review existing research achievements in electric power load forecasting from the perspectives of influencing factors, types of forecasting methods, and future research directions, and provide some outlook and predictions for future research.

2. Influencing Factors of Electric Power Load Forecasting

2.1 External Factors

2.1.1 Meteorological Conditions

Meteorological conditions are the core driver of short-term load fluctuations. Temperature, as the dominant factor^[2], exhibits a nonlinear relationship with electricity demand – extreme high or low temperatures trigger surges in cooling/heating loads, forming seasonal peak loads. Meanwhile, parameters like humidity, wind speed, and sunshine indirectly affect electricity usage behavior (e.g., increased air conditioning energy consumption in high humidity) by altering perceived temperature. Disastrous weather events (e.g., typhoons, blizzards) can cause cliff-like load drops or emergency power usage surges, requiring targeted modeling. Meteorological modeling often couples numerical weather prediction data and introduces HDD/CDD indices to quantify cumulative temperature effects. (Heating Degree Days / Cooling Degree Days)

2.1.2 Economic Policies

Economic and policy factors dominate long-term load trends and structural changes. Macroeconomic fluctuations (e.g., GDP growth rate, industrial prosperity) directly determine the scale of industrial and commercial electricity consumption. Electricity price reforms reshape daily load curve patterns by changing user preferences through time-of-use pricing strategies. Industrial policies (e.g., production restrictions on energy-intensive enterprises) or sudden public events (e.g., pandemic lockdowns) can disrupt historical load patterns, causing short-term drastic changes or long-term

transformations in regional energy consumption models^[3]. Economic policy factors rely on dynamic dummy variables (policy effective flags, holiday variables) or external feature vectors (e.g., electricity price volatility, PMI index) for quantitative characterization.

2.2 Internal Factors

2.2.1 User Behavior Patterns

User behavior patterns shape the micro-level fluctuations of the load. Residential electricity consumption exhibits a typical dual-peak characteristic (morning and evening peaks), deeply influenced by lifestyle habits (e.g., commuting times, household appliance usage patterns) and the proliferation of new energy-consuming devices (e.g., concentrated charging of electric vehicles, smart home device cycling). Industrial and commercial loads are strongly correlated with production cycles – shift systems in manufacturing create stable daytime load plateaus, while business operating hours and promotions cause pulse-like fluctuations in nighttime loads. User response behaviors to price signals (e.g., participation in demand response programs) further increase the complexity of the load curve.

2.2.2 Power System Dynamic Characteristics

Power system dynamic characteristics define the physical boundaries of load evolution. Grid topology (e.g., regional interconnection strength) influences the spatial distribution of load and transmission losses. Equipment operating status (e.g., transformer aging, line capacity limits) may indirectly alter measurable load values through supply capacity constraints. System security control strategies (e.g., under-frequency load shedding, voltage regulation) actively shed part of the load under extreme operating conditions, causing deviations between measured data and actual demand.

3. Types of Electric Power Load Forecasting Methods

3.1 Traditional Statistical Methods

Traditional statistical methods build mathematical models based on the statistical patterns of historical load data. They are characterized by theoretical rigor and strong interpretability and dominated early load forecasting.

3.1.1 Time Series Analysis

Short-term power load forecasting usually

includes hourly power load forecasting and daily power load forecasting. Short-term power load forecasting commonly employs the time series model method. Time series models forecast by mining temporal dependencies in load data. The classic Autoregressive Integrated Moving Average (ARIMA) model uses differencing to handle non-stationary series, combining Autoregressive (AR) and Moving Average (MA) terms to capture short-term correlations. Its extension, Seasonal ARIMA (SARIMA), further introduces seasonal differencing to effectively depict daily/weekly/annual cyclical fluctuations in load. These methods rely on stationarity assumptions and have limited adaptability to abrupt load changes (e.g., holiday peaks), often requiring combined outlier correction strategies. Literature^[4] proposes an enhanced time series analysis method based on wavelet transform for power load forecasting, using lifting wavelet transform to extract key features from user power load data, avoiding interference from randomness and volatility in electricity consumption data.

3.1.2 Regression Analysis

Regression analysis focuses on quantifying the causal relationship between external factors and load. Multiple Linear Regression (MLR) achieves prediction by fitting linear relationships between covariates (e.g., meteorology, economy) and load. To enhance nonlinear fitting capability, piecewise regression (e.g., introducing temperature thresholds) or Generalized Additive Models (GAM) are widely adopted. Such methods require strict verification of multicollinearity among variables and have insufficient capacity to represent complex nonlinear relationships.

3.1.3 Exponential Smoothing Method

The exponential smoothing method combines historical data using exponentially weighted averaging to directly forecast future values of a time series.

Its formula is as follows:

$$x(t+1) = \sum_{i=0}^n \alpha(1-\alpha)^i x(t-i) \quad (1)$$

In the formula, $x(t+1)$ represents the predicted value; $x(t-i)$ represents the actual load value; α is the attenuation factor; n is the number of initial load values.

In the above formula, α is equal to $1/n$, and the value of α ranges between 0 and 1, reflecting the principle of "recent points matter more." Its core idea is that data from the more recent past has a stronger influence on the forecast than older data.

When α is larger, the weight coefficients decrease more rapidly from recent to older data, primarily to emphasize the importance of the latest data in the forecasting process.

3.2 Machine Learning Models

Machine learning methods adaptively learn complex nonlinear mappings between load and multi-source features through data-driven strategies, breaking the linear constraints of traditional statistical models and demonstrating significant advantages in the field of load forecasting.

3.2.1 Support Vector Machine (SVM)

Support Vector Machines (SVM) utilize kernel functions to map low-dimensional features into high-dimensional space to construct optimal separating hyperplanes. They exhibit strong noise resistance and robustness in small-sample scenarios, particularly suitable for modeling mixed features like continuous variables (temperature, humidity) and categorical variables (holidays). However, their computational efficiency decreases sharply with data scale, and they are sensitive to kernel function parameters requiring repeated tuning. Literature^[5] optimized the SVM parameter selection process using a chaotic electromagnetism-like algorithm, improving convergence efficiency and optimization capability, making it suitable for short-term power load forecasting.

3.2.2 Random Forest

Ensemble tree models have become mainstream tools for load forecasting. Random Forest (RF) builds multiple decision trees via Bootstrap sampling and integrates their outputs. It natively supports feature interactions and unstructured data processing (e.g., the "high temperature + weekday" combination effect), effectively reducing overfitting risks. Gradient Boosting Trees (GBDT/XGBoost/LightGBM) adopt an iterative residual fitting strategy, correcting prediction errors step-by-step. Their advantage lies in efficiently capturing temporal dependencies (e.g., lagged load features) and quantifying variable importance (e.g., identifying temperature sensitivity thresholds). LightGBM's histogram optimization algorithm further enhances computational efficiency for minute-level high-frequency forecasting.

3.2.3 Other Methods

Other methods include K-Nearest Neighbors (KNN), which performs weighted prediction

based on similar day patterns but is sensitive to local fluctuations and prone to interference from outliers; Gaussian Process Regression (GPR), which provides probabilistic prediction outputs to quantify uncertainty but suffers from high computational complexity. Overall, while machine learning methods possess capabilities for automatic feature interaction and multi-source heterogeneous data fusion, they still face common challenges such as weak model interpretability, dependence on high-quality labeled data, and the need for manual construction of temporal features (e.g., sliding window statistics). They often complement deep learning in short-term forecasting scenarios.

3.3 Deep Learning Models

Deep learning methods achieve high-dimensional modeling of complex spatiotemporal patterns in electric power loads through multi-level feature abstraction and end-to-end learning mechanisms, becoming cutting-edge technologies for high-precision forecasting.

3.3.1 Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNN), traditionally used for image processing, extract local temporal patterns (e.g., weekday morning peak shapes) in load forecasting using 1D convolution kernels, or process spatial load data (e.g., regional gridded consumption distribution) using 2D convolution. Their advantages lie in the shared weight mechanism reducing parameter count and the ability to capture long-period features using dilated convolutions to enlarge the receptive field.

3.3.2 Transformer

The attention mechanism and Transformer have revolutionized time series modeling paradigms. Self-attention layers dynamically assign importance weights to different historical time points (e.g., focusing on recent load or similar day patterns), solving the sequential computation bottleneck of RNN-based models. Positional encoding preserves temporal order information. Transformers excel in predicting long-term load trends (e.g., weekly forecasts), particularly suitable for fusing multi-source heterogeneous inputs (external features like weather data, economic indicators). Literature^[6] proposed a load forecasting model based on feature embedding and Transformer. First, load feature vectors are obtained by fusing load position,

trend, periodicity, time, and weather information. Then, the Transformer model mines the nonlinear temporal dependencies within the feature vectors. Finally, a fully connected layer predicts the power load. *(Note: Ref [6] cited in the Chinese text actually refers to an LSTM-based method in the references, but the description here matches a Transformer approach. I've translated the text as provided.)

3.3.3 Graph Neural Network (GNN)

Graph Neural Networks (GNN) model the spatial correlation of electric power loads. By abstracting grid topology (substation-feeder-user hierarchy) into graph data, they use Graph Convolutional Networks (GCN) or Graph Attention Networks (GAT) to aggregate neighbor node information, enabling collaborative forecasting of regional loads. Such methods are indispensable in scenarios with high penetration of distributed energy resources (e.g., where local PV output affects net load).

4. Future Research Directions

4.1 Cross-Domain Collaborative Forecasting

Innovation in cross-domain collaborative forecasting paradigms requires breaking down disciplinary barriers between meteorology, economics, and power systems. Building multimodal fusion networks (e.g., coupling spatiotemporal graph convolution with Transformers) to jointly deduce the cascading effects of extreme weather events, industrial chain fluctuations, and load evolution; further linking carbon flow tracing technologies to quantify load carbon emission intensity profiles, supporting low-carbon scheduling in high-energy-consumption parks and green electricity trading pricing.

4.2 New Forecasting Requirements under Carbon Neutrality Goals

New forecasting paradigms driven by carbon neutrality scenarios are rapidly emerging. For prosumer groups aggregated with "PV + storage + electric vehicles," net load bidirectional fluctuation forecasting models need development. Facing green electricity markets, predicting the flexible adjustment potential of loads and coupling carbon credit mechanisms to provide dynamic pricing support for

carbon-electricity coordinated trading.

Chapter 5 Conclusion

Electric power load forecasting technology has evolved from traditional statistical models towards innovative paradigms of multidisciplinary integration. Traditional methods (e.g., ARIMA) retain simplicity advantages in stable scenarios but struggle with the complexity of high renewable energy penetration. Machine learning (e.g., XGBoost) dominates short-term forecasting through feature interaction, while deep learning (LSTM, Transformer, GNN) achieves leaps in long-term accuracy via end-to-end spatiotemporal modeling. Load forecasting is evolving from an auxiliary tool into an intelligent decision engine for new power systems. Its development will profoundly empower the safe, economical, and low-carbon transformation of the power grid.

References

- [1] Kang Chongqing, Xia Qing, Zhang Boming. (2004) Review of Power System Load Forecasting Research and Discussion on Development Directions [J]. Automation of Electric Power Systems, (17): 1-11.
- [2] Liang Hongtao, Liu Hongju, Li Jing, et al. (2022) Review of Short-Term Load Forecasting Algorithms Based on Machine Learning [J]. Computer Systems & Applications, 31(10): 25-35.
- [3] Li Tao. Research on Medium and Long Term Power Load Forecasting for User Side in Electricity Market [D]. Chongqing University of Technology, 2022.
- [4] Zhang Fan, Zhang Feng, Zhang Shiwen. (2017) Power Load Forecasting Based on Lifting Wavelet Time Series Analysis Method [J]. Electrical Automation, 39(3): 72-76.
- [5] Wang Qian, Li Haoran, Wang Xinna, et al. (2019). Short-Term Load Forecasting Based on Support Vector Machine Optimized by Chaotic Electromagnetism-Like Algorithm [J]. Computing Technology and Automation, 38(4): 15-18.
- [6] Wang Yongzhi, Liu Bo, Li Yu. (2020). A Power Load Forecasting Method Based on LSTM Neural Network [J]. Research and Exploration in Laboratory, 39(5): 41-45.