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Application of AI Algorithms in Power System Load Forecasting Under the New Situation

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Abstract. AI algorithms can analyze historical data, weather patterns, and other relevant factors to predict electricity demand. Accurate load forecasting helps in efficient power generation, resource allocation, and grid stability. They are utilized by energy providers, grid operators, and system planners for short-term load forecasting, medium-term capacity planning, and long-term demand projections. These algorithms support decision-making in power generation, resource allocation, load balancing, demand response, and grid stability management. This article provides a detailed explanation of the principles, steps, applicable conditions, and application scenarios of the most promising AI intelligent algorithms, and provide valuable literature research results.

Keywords: AI algorithms, predict electricity demand, resource allocation

1. Introduction

Load forecasting plays a crucial role in efficient power generation and resource allocation. It allows utility companies and grid operators to anticipate and plan for fluctuations in electricity demand, ensuring that the right amount of power is generated and supplied to meet consumer needs. This helps avoid over-generation or under-generation of electricity, optimizing the utilization of generation assets and reducing waste.

State Grid Corporation of China (SGCC), which is responsible for China's power grid infrastructure, has been involved in load forecasting research. SGCC has been leveraging advanced AI technologies, including big data analytics and machine learning, to improve load forecasting accuracy and efficiency. In addition, Chinese universities and research institutes, such as Tsinghua University and Chinese Academy of Sciences, have conducted research on AI load forecasting algorithms. These studies often involve large-scale data analysis, feature selection, and the application of machine learning models to predict electricity load patterns.

Not limited to China, many countries around the world are actively involved in this field.

- Several research institutions and universities in the United States including the Electric Power Research Institute (EPRI) and Carnegie Mellon University, have

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been exploring machine learning models, time series analysis, and data mining approaches to enhance load forecasting accuracy.

- Various European Union countries within the European Union, such as Germany, France, and the United Kingdom, have been investing in AI load forecasting research. European researchers have been exploring machine learning algorithms, ensemble methods, and hybrid models to improve load forecasting precision and accommodate the increasing penetration of renewable energy sources.
- Japanese utility companies and research institutions have been investigating AI-based load forecasting algorithms to optimize power generation and demand response strategies. They have been focusing on deep learning models, hybrid forecasting approaches, and real-time data analysis.
- Australian researchers have been developing machine learning and data-driven models to predict electricity load patterns accurately. They have been exploring techniques such as support vector regression, artificial neural networks, and decision trees.

2. The Role of Load Forecasting in Power Systems

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2.1. Generation Strategy Development

Load forecasting plays a crucial role in efficient power generation by providing insights into the expected electricity demand. It helps power generators optimize their operations and ensure a reliable and cost-effective power supply.

- Generation Planning: By accurately predicting future load patterns, power generators can determine the optimal mix of power generation sources, including thermal, hydro, nuclear, and renewable energy. This helps in avoiding over-generation or under-generation, optimizing the utilization of generation assets, and minimizing operational costs.
- Economic Dispatch: By considering the forecasted demand and the characteristics of different generation units, AI algorithms can optimize the allocation of generation output among available units. This ensures that the most cost-effective and efficient units are dispatched, reducing overall production costs and maximizing the utilization of resources.
- Renewable Integration: Load forecasting is particularly important for integrating intermittent renewable energy sources, such as solar and wind power, into the grid. Accurate load forecasts enable power generators to anticipate periods of high renewable energy generation and plan for the necessary backup or balancing resources to maintain grid stability. This facilitates the efficient integration of renewable energy and reduces the reliance on conventional power plants.

2.2. Power Grid Energy Distribution

Load forecasting plays a significant role in efficient electricity distribution by helping grid operators manage and optimize the distribution network.

- Grid Planning and Expansion: By accurately predicting load growth, operators can identify areas that require infrastructure upgrades or new substations to accommodate increased demand. This proactive planning ensures that the distribution network is capable of efficiently serving the anticipated load, minimizing congestion and voltage fluctuations.
- Load Management and Balancing: Load forecasting enables grid operators to effectively manage and balance the electricity load across the distribution network. By accurately predicting load patterns, operators can allocate resources and adjust the distribution network's configuration to ensure balanced load distribution.
- Distribution Network Optimization: With accurate load forecasts, operators can optimize the routing of electricity flows, switch between feeders, and balance the load across transformers and substations. This optimization minimizes losses, reduces energy wastage, and improves the voltage profile and power quality throughout the distribution network.
- Grid Stability: Accurate load forecasts enable grid operators to anticipate peak demand periods and take necessary actions, such as load shedding or demand response programs, to avoid grid instability.
- Grid Resilience: Load forecasting aids in maintaining grid resilience by anticipating and planning for contingencies. Accurate load forecasts help grid operators identify potential overload conditions or voltage stability issues in advance.

3. Mainly used AI algorithms

3.1. Time Series Analysis

Time series analysis is a fundamental method used in electricity demand forecasting. Such as autoregressive integrated moving average (ARIMA) and seasonal decomposition of time series (STL), can analyze historical demand data to identify trends, seasonality, and other patterns. These algorithms capture the temporal dependencies and provide forecasts based on historical patterns.

3.1.1. Algorithm Steps

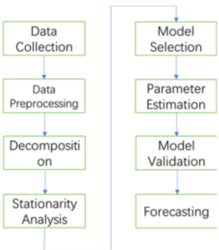

Figure 1. Steps of Time Series Analysis.

Here are the steps involved in using time series analysis for load forecasting. As shown in Figure 1.

- 1. Data Collection: The first step is to collect historical load data, typically in the form of time-stamped measurements of electricity consumption.
- 2. Data Preprocessing: Before applying time series analysis, data preprocessing is necessary to handle missing values, outliers, and ensure data consistency.
- 3. Decomposition: Time series data often exhibits various components such as trend, seasonality, and irregular fluctuations. Decomposition techniques like additive or multiplicative decomposition can be used to separate these components.
- 4. Stationarity Analysis: Stationarity refers to the statistical properties of a time series remaining constant over time. Time series analysis assumes that the data is stationary, meaning the mean, variance, and autocorrelation structure do not change with time. Stationarity analysis is performed to check the stationarity of the load data.
- 5. Model Selection: Based on the characteristics of the load data and the results of the decomposition and stationarity analysis, an appropriate time series model is selected. Common models include autoregressive integrated moving average (ARIMA), seasonal ARIMA (SARIMA), exponential smoothing models, and state space models. The choice of model depends on the specific characteristics of the load data, such as the presence of trend, seasonality, and other patterns.
- 6. Parameter Estimation: Once the model is selected, the parameters of the model need to be estimated. This involves using estimation techniques such as maximum likelihood estimation or least squares estimation to find the best-fit parameters that minimize the difference between the observed load data and the predicted values from the model.
- 7. Model Validation: After parameter estimation, the model needs to be validated to assess its performance. This is typically done by comparing the predicted load values with the actual load values for a validation period. Various error metrics, such as mean absolute percentage error (MAPE) or root mean squared error (RMSE), are used to evaluate the accuracy of the model.
- 8. Forecasting: Once the model is validated, it can be used for load forecasting. Future load values are predicted based on the estimated parameters and the most recent available data. The forecast horizon can vary depending on the specific requirements, ranging from short-term hourly forecasts to long-term monthly or yearly forecasts.

3.1.2. Applicable conditions

Time series analysis is well-suited for load forecasting when the following conditions are met:

- Sufficient Historical Data: Time series analysis requires a substantial amount of historical load data to capture meaningful patterns and trends. The availability of a reliable and extensive dataset is essential for accurate load forecasting.
- Stationarity: The load data should exhibit stationary behavior, meaning that the statistical properties of the data do not change over time. If the data is non-stationary, appropriate techniques like differencing or transformation should be applied to achieve stationarity.

- Patterns and Trends: Time series analysis assumes the presence of patterns and trends in the load data, such as seasonality and long-term trends. If the data is highly irregular without any discernible patterns, other forecasting techniques may be more suitable.
- Adequate Model Selection: The choice of an appropriate time series model is crucial for accurate load forecasting. The selected model should be able to capture the specific patterns and characteristics present in the load data, such as seasonality, trend, and any other relevant factors.

3.1.3. Typical Research Results

Reference [1] uses trend moving average method and exponential smoothing method to model time series of different types of loads in the region. Reference [2] proposed a time series analysis method suitable for adjusting the Spring Festival effect of electricity consumption, in order to estimate and eliminate the impact of the Spring Festival effect on electricity consumption. Reference [3] first used time series analysis to predict and model short-term loads, and secondly, based on the establishment of Kalman state equations and measurement equations through time series models, a prediction model was established using Kalman filtering algorithm. Reference [4-5] proposes a time series analysis method based on lifting wavelet for power load prediction. The time series method is used to obtain autocorrelation and partial correlation coefficients from the power load sequence denoised by lifting wavelet, establish corresponding mathematical models, and predict future electricity consumption.

3.2. Artificial Neural Network

Neural Networks: Neural networks, particularly deep learning models like recurrent neural networks (RNNs) and long short-term memory (LSTM) networks, are highly effective in capturing temporal dependencies and patterns in electricity demand data. These models can learn complex relationships between historical demand, weather data, and other factors. They are capable of handling sequential data and can provide accurate predictions.

3.2.1. Algorithm Steps

Algorithm Steps of Artificial Neural Network are as shown in Figure 2.

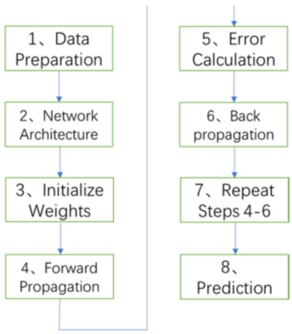

Figure 2. Algorithm Steps of Artificial Neural Network.

- 1. Data Preparation: Preprocess the input data by normalizing, scaling, or encoding categorical variables, if required.
- 2. Network Architecture: Define the architecture of the neural network, including the number of layers, the number of neurons in each layer, and the activation functions to be used.
- 3. Initialize Weights: Assign initial random weights to the connections between neurons in the network.
- 4. Forward Propagation: Pass the input data through the network from the input layer to the output layer, applying the activation functions and computing the output values.
- 5. Error Calculation: Compare the network's output with the desired output, calculate the error or loss function, which represents the discrepancy between the predicted and actual outputs.
- 6. Backpropagation: Propagate the error backward through the network, adjusting the weights of the connections to minimize the error. This is done by computing the gradients of the error with respect to the weights and updating the weights using an optimization algorithm, such as gradient descent.
- 7. Repeat Steps 4-6: Iterate the forward propagation, error calculation, and backpropagation steps for multiple epochs or until the network's performance reaches a satisfactory level.
- 8. Prediction: Once the network is trained, it can be used to make predictions on new, unseen data by passing the input through the network and obtaining the output.

3.2.2. Applicable Conditions

The artificial neural network (ANN) algorithm can be effectively applied to power system load forecasting under the following conditions:

- Sufficient Historical Data: To train the ANN for load forecasting, a significant amount of historical load data is required.
- Temporal Dependencies: Load forecasting in power systems often involves capturing temporal dependencies, such as hourly, daily, weekly, or seasonal patterns. ANN models can effectively learn and capture these dependencies if the historical data reflects them.
- Adequate Training: ANN models require an appropriate training process to optimize the network's weights and biases. Sufficient computational resources and time are necessary to train the network, especially for complex architectures or large datasets.

3.2.3. Typical Research Results

Reference [6] proposed a novel power load combination prediction model based on multiple models. This model uses the VMD singular spectrum analysis denoising method to optimize the raw data, and then optimizes the ELM neural network through the EOBL-CSSA algorithm to construct a composite prediction model. Reference [7] proposes a new power load forecasting model based on the Transformer model. This method effectively captures the long-term dependence characteristics of power loads through the encoder decoder structure, while the recurrent neural network can capture the short-term dependence of power loads. Reference [8] proposes an optimization method for sample processing. Reference [9-10] reduces the prediction error caused by irrelevant features by extracting decisive load features, and uses the most representative fish swarm clustering behavior and tail chasing behavior in artificial fish swarm algorithms to assist the BP neural network in jumping out of the local optimal solution.

3.3. Machine Learning

Machine learning algorithms, such as decision trees, random forests, and gradient boosting, can be applied to electricity demand prediction. They can handle large datasets, non-linear relationships, and interactions between variables.

3.3.1. Algorithm Steps

Algorithm Steps of machine learning are as shown in Figure 3.

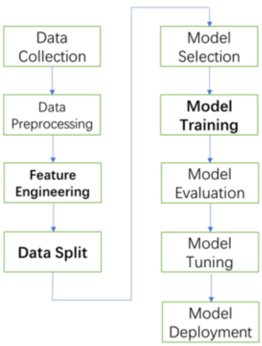

Figure 3. Algorithm Steps of Machine learning.

- 1. Data Collection: Collect historical load data along with relevant predictors or factors that can impact electricity demand.
- 2. Data Preprocessing: Clean and preprocess the data by handling missing values, outliers, and inconsistencies.
- 3. Feature Engineering: Extract meaningful features from the data that capture important characteristics and relationships.
- 4. Data Split: Divide the dataset into training, validation, and testing subsets. The training set is used to train the machine learning model, the validation set helps tune model hyperparameters, and the testing set is used to evaluate the model's performance.
- 5. Model Selection: Choose an appropriate machine learning algorithm or model for load forecasting. Commonly used algorithms include decision trees, random forests, gradient boosting, neural networks, and support vector machines. The choice depends on the characteristics of the data and the specific requirements of load forecasting.
- 6. Model Training: Train the selected machine learning model using the training data. The model learns the patterns and relationships between the load and the predictors by adjusting its internal parameters to minimize the prediction error.
- 7. Model Evaluation: Evaluate the performance of the trained model using the validation data. Various metrics, such as mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), and R-squared, can be

used to assess the model's accuracy and predictive power.

- 8. Model Tuning: Fine-tune the model hyperparameters to optimize its performance. This step involves adjusting parameters like learning rate, regularization, depth of trees, number of hidden layers, and neurons to find the best configuration.
- 9. Model Deployment: Once the model is deemed satisfactory, it can be deployed to make load forecasts for future time periods. The selected predictors are input into the trained model to generate load predictions.

3.3.2. Applicable Conditions

The following are the applicable conditions of the algorithm

- 1. Nonlinear Relationships: Machine learning models excel at capturing nonlinear relationships between the load and predictors. If the relationship is highly nonlinear or complex, machine learning algorithms can effectively model such patterns.
- 2. Large and Complex Datasets: Machine learning algorithms can handle large and complex datasets with numerous predictors. They can automatically extract relevant information and learn intricate patterns from the data.
- 3. Dynamic Load Patterns: Machine learning models can adapt to changing load patterns and adjust their predictions accordingly. If the load exhibits time-varying or evolving characteristics, machine learning techniques can capture and accommodate such dynamics.
- 4. Abundance of Data: Machine learning algorithms typically require a substantial amount of historical data to learn accurate load patterns. The availability of a rich dataset with a long history can enhance the forecasting performance of machine learning models.
- 5. Computational Resources: Machine learning algorithms can be computationally intensive, particularly for complex models with large datasets. Adequate computational resources, such as processing power and memory, may be required to train and deploy machine learning models effectively.

3.3.3. Typical Research Results

According to the demand of the power system for the accuracy of short-term power load forecasting, the literature [11] uses the differential adaptive evolutionary algorithm to further improve the short-term power load forecasting based on the short-term memory algorithm, thus proposing a hybrid algorithm based on machine learning (SaDE-LSTM) for short-term power load forecasting. Reference [12] proposes a method of using time series analysis to predict the load changes of the power grid in the next 72 hours, enabling the power grid scheduling department to understand the short-term trend of user load changes and adopt corresponding scheduling strategies to ensure power quality. Reference [13] proposes an interpretable load forecasting framework based on Bayesian time-varying coefficients (BTVC) and CatBoost model. Literature [14-15] uses the deep random forest algorithm to make short-term prediction of user load by obtaining weather data and combining user load data of JH city. With the help of four evaluation indicators, by comparing the support vector regression algorithm, K nearest neighbour algorithm, Bayesian ridge regression algorithm, random forest algorithm and multiple depth neural network algorithms, it is found that the depth random forest algorithm has the best prediction effect, followed by the support vector regression algorithm, and the depth neural network algorithm performs generally on the data set.

3.4. Deep Learning

Deep learning is a type of machine learning, and machine learning is a necessary path to achieve artificial intelligence. The concept of deep learning originates from the research of artificial neural networks. The multilayer perceptron with multiple hidden layers is a deep learning structure. Deep learning combines low-level features to form more abstract high-level representations of attribute categories or features, in order to discover distributed feature representations of data.

3.4.1. Algorithm Steps

The algorithm steps of deep learning are very similar to machine learning, the only difference is that the parameter adjustment in machine learning is hyperparameter adjustment in deep learning algorithm. Hyperparameter adjustment is to fine tune the hyperparameter of the deep learning model to optimize its performance.

Hyperparameters include the number of layers, number of neurons in each layer, learning rate, batch size, and regularization techniques. Techniques like grid search or random search can be used to explore different hyperparameter combinations.

3.4.2. Applicable Conditions

The applicable conditions for deep learning are very similar to machine learning and will not be further elaborated.

Deep learning techniques, with their ability to capture complex patterns and temporal dependencies, have shown promising results in load forecasting. However, it is important to carefully preprocess the data, select appropriate architectures, tune hyperparameters, and continually update and evaluate the models to ensure accurate and reliable load forecasting in practical applications.

3.4.3. Typical Research Results

Reference [16] proposes a novel integrated deep algorithm for multi-step prediction of gas loads. Reference [17-18] proposes a multi-objective coordinated scheduling optimization method for microgrids based on Pearson correlation coefficient meta learning (PCC-ML) source load prediction. Reference [19] proposed a power load interval forecasting method based on deep learning quantile regression.

4. Summary

In summary, load forecasting plays a crucial role in efficient electricity distribution by supporting grid planning, load management, network optimization, outage management, grid stability, and grid resilience. Accurate load forecasts empower grid operators to make informed decisions, optimize resource allocation, enhance system reliability, and ensure efficient delivery of electricity to consumers. By aligning generation and transmission with the anticipated load, load forecasting contributes to a reliable, efficient, and resilient power supply system.

AI algorithms have the capability to predict electricity demand accurately by analyzing historical data, weather patterns, and other relevant factors. Different artificial intelligence algorithms vary in terms of applicability, algorithm models, calculation steps, and complexity. In practical applications, selecting appropriate artificial intelligence algorithms based on needs is crucial for accurate load forecasting.

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