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A Review of Power Prediction Methods Under the COVID-19 Pandemic

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Abstract: Load forecasting, Prediction Models, COVID-19, Time Series Analysis, Combined models, Electricity is the foundation of national construction, and accurate electricity load forecasting is an important guarantee for the normal operation of power systems. During the COVID-19 pandemic, the electricity demand of various countries has fluctuated significantly due to various factors, which has had a certain impact on national development. To assist the government in planning power supply rationally and formulating plans in advance based on electricity demand, it is necessary to accurately predict electricity demand. Therefore, this paper systematically analyzes and introduces the development history of electricity load forecasting technology, which helps to better cope with the impact of the COVID-19 pandemic on the power industry. This paper introduces the research status of electricity load forecasting technology, including time series methods, machine learning methods, deep learning methods, hybrid model methods, and analyzes the advantages and disadvantages of each forecasting method. Establishing a model through these methods can accurately and effectively predict electricity demand, providing technical guarantees and theoretical support for the stable development and long-term construction of the country. Finally, this paper summarizes the current problems in electricity forecasting and the trends of future improvement and development. Through reviewing and summarizing the article, it can provide researchers with ideas and technical routes to solve problems, and also help non-professionals interested in this issue to have a general understanding.

Keywords: Load Forecasting, Prediction Models, COVID-19, Time Series Analysis, Combined Models

1. Introduction

Electricity is the basic energy source of modern society and is crucial for maintaining the normal operation of production and life. With the continuous increase in electrification, the intensification of great power political games, and the deepening of low-carbon transformation, the global energy market has entered a period of turbulence and change, and the security of power supply has become crucial. Forecasting and studying electricity consumption can not only provide a deep understanding of the changing patterns of electricity supply and demand, help improve the flexibility of power systems, but also provide early warning and decision support for governments, enterprises, and individuals on future electricity consumption. It has important application value for optimizing power allocation, adjusting the proportion of power generation energy structure, and ensuring the continuous safety and reliability of power supply. Therefore, forecasting and managing electricity consumption has important practical and social significance. In recent years, the COVID-19 pandemic has ravaged the world, bringing severe impacts on the global economy and social life. Countries around the world have taken measures to limit the spread of the epidemic, including restricting personnel movements and strengthening health protection. These measures have brought unprecedented economic and social impacts. As one of the important energy consumption areas, electricity consumption has also been greatly affected during the epidemic period [1]. Especially in some countries and regions with severe epidemics, the fluctuations in electricity consumption are more significant, posing enormous challenges to power supply and energy management. Changes in electricity consumption not only affect the production of enterprises and the operation of the economy but also directly affect the operation of residents' lives and public facilities. This change has brought enormous challenges to power supply and energy management, requiring scientific research and forecasting [2]. This article will introduce electricity forecasting methods, summarize and analyze them, and explore the current research status of electricity forecasting issues under the COVID-19 pandemic to better understand the application scenarios and development trends of electricity forecasting technology.

2. Methods for Forecasting Electricity Demand

Electricity demand forecasting can be classified into spot forecasting, short-term forecasting, medium-term forecasting, and long-term forecasting based on the length of the forecast period. Spot forecasting typically covers a period of one day or one week, while short-term forecasting covers a period of 12 to 24 months. Medium-term forecasting typically covers a period of 4, 6, or 8 years, and long-term forecasting typically covers a period of 10 to 30 years, which serves as the basis for comprehensive planning of power construction.

Electricity forecasting can be broadly classified into qualitative forecasting and quantitative forecasting based on the method used. Qualitative forecasting is based on personal experience and knowledge to judge the future development trends and states of things. Qualitative forecasting generally relies on experience, including expert opinion methods, analogical methods, and subjective probability methods. Quantitative forecasting uses statistical data and certain models to predict the future development trends and states of the forecast objects. In addition to traditional classical forecasting techniques such as power elasticity coefficient forecasting, unit consumption method, and load density method, modern forecasting techniques mainly include time series methods, machine learning methods, deep learning methods, hybrid model methods, etc. In addition, scholars such as Hadri [3] have studied three main methods of electricity consumption forecasting (univariate, multivariate, and multistep) and applied them to evaluate the performance of electricity consumption prediction strategies for buildings.

3. Electricity Forecasting Method Based on Time Series Analysis

Time series analysis method can predict future electricity demand based on historical data. Common time series analysis methods include ARIMA, SARIMA, VAR, etc.

ARIMA can establish a model that describes the characteristics of the data by performing transformations such as autoregression, moving average, and differencing on the time series data, and use this model to predict future data changes. Angelaccio used trend fitting and ARIMA model based on historical data in Italy to predict electricity consumption, in order to explore the importance of electricity consumption prediction in the field of energy monitoring [4].

ARIMA is mainly used to process non-seasonal time series data, while SARIMA is more suitable for time series data with obvious seasonal changes. SARIMA is more complex than ARIMA. SARIMA needs to consider the influence of seasonal factors [5], so seasonal differencing needs to be introduced into the model, and seasonal terms need to be added. In the ARIMA model, the parameters that need to be set are p, d, and q, which represent the order of autoregression, the order of differencing, and the order of moving average, respectively. In the SARIMA model, in addition to these three parameters, additional seasonal parameters P, D, and Q need to be set. These parameters can be determined by the autocorrelation and partial autocorrelation graphs of the sample data.

The vector autoregressive model (VAR) is a non-structural equation model used to estimate the dynamic relationships between multiple variables. The VAR model constructs a model by treating each endogenous variable in the system as a function of the lagged values of all endogenous variables in the system, thus realizing the extension of the univariate autoregressive model to a "vector" autoregressive model composed of multiple time series variables. Ohtsuka et al. used the VAR model to predict electricity in Japan and compared it with the ARMA model. The results showed that the VAR model performed better [6].

Therefore, the advantage of the time series analysis method is that it can predict future trends based on historical data, and it has low requirements for data and is suitable for short-term forecasting. However, it also has disadvantages. For example, the prediction results may deviate due to the impact of unexpected events such as epidemics.

4. Electricity Forecasting Method Based on Machine Learning

Machine learning is a method that learns a model by training a large amount of data and uses the model for prediction. In the context of the COVID-19 pandemic, machine learning methods have been widely used in the field of electricity forecasting. Common machine learning algorithms include linear regression, support vector regression, XGBoost, etc. Many scholars have used these methods to solve many practical problems. For example, Huang et al. [7] demonstrated benchmark test results from three different machine learning algorithms (i.e., SVR, XGBoost, and LSTM) in this year, which were trained using a 1-year dataset with sub-hourly (30-minute) time granularity to identify the top-performing predictor. Gulati et al. [8] used conventional machine learning algorithms and artificial neural networks to analyze the impact on electricity consumption in Haryana, India, and conducted a one-week electricity load forecast to help the power authority understand the consumption situation in advance and limit power production as required. Abulibdeh et al. [9] used machine learning techniques and empirical big data to study the relationship between electricity consumption in buildings and the daily number of infected cases. Based on the electricity consumption trend from 2010 to 2019, three forms of machine learning models, namely support vector machines (SVM), extreme gradient boosting (XGBoost), and random forests (RF), were used to compare the actual and simulated electricity consumption (normal situation without the pandemic) in 2020 and 2021, and then compare the differences between the actual electricity consumption during the pandemic and the simulated electricity consumption under the pandemic situation to determine the impact of the pandemic on the power generation sector. Ku et al. [10] investigated changes in hourly residential electricity patterns in Arizona due to COVID policies. They used personal hourly electricity consumption data from 6,309 consumers and a machine learning framework to estimate how COVID policies and subsequent remote work practices have changed electricity consumption patterns.

4.1. Linear Regression

Linear regression assumes a linear relationship between input features and output and attempts to fit the best linear function for prediction. Although the linear regression model is simple, it can still provide useful prediction results in some cases and can be compared with other more complex models. The linear regression model is denoted as:

$$y = \sum_{i=1}^{n} w_i x_i + b = w^T x + b \tag{1}$$

where y is the prediction function, w is the model parameter, x is the input feature, b is the bias term, and the loss function is a measure of how well the model predicts once, i.e., the error between the true value y and the predicted value $\hat{y}$. The loss function of linear regression is generally taken as:

$$L = \frac{1}{2}(y - \hat{y})^2 \tag{2}$$

To find the model parameters w, we need to train the linear regression model. We use gradient descent to train the model, where α is the learning rate, $x_i^{(j)}$ is the i-th feature of the j-th sample, and the formula is as follows:

$$w_{i+1} = w_i + \alpha[\sum_{i=1}^{m}(y^{(j)} - \sum_{i=1}^{n} w_i x_i^{(j)} - b) * x_i^{(j)}] \tag{3}$$

Linear regression analysis has been applied to predict residential energy consumption [11]. In this study, simple and multiple linear regression analyses and quadratic regression analysis were performed on hourly and daily data from a research institute. Linear regression analysis showed good results compared to other methods, with reasonable accuracy and relatively simple implementation. Among the most commonly used STLF methods, linear regression (LR) [12], autoregressive integrated moving average (ARIMA), and artificial neural networks (ANN) are the best-performing methods in atypical consumption behavior and should be adopted during atypical consumption behavior in residential areas.

4.2. XGBoost

XGBoost is an ensemble learning model based on gradient boosting trees. It iteratively trains a series of weak classifiers and combines them to form a strong classifier. XGBoost has good capabilities in handling complex relationships and non-linear relationships between features and can provide more accurate prediction results. The prediction function is:

$$\hat{y}_i = \emptyset(x_i) = \sum_{k=1}^{K} f_k(x_i) \tag{4}$$

Where $\hat{y}_i$ is the predicted value of the sample by the model, $\emptyset(x_i)$ is the prediction function based on input features x_i, K is the number of base learners, and $f_k(x_i)$ is the predicted value of the k-th base learner (decision tree) for the sample x_i. The objective function is formulated as follows:

$$\mathrm{Obj}(\Theta) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{5}$$

where Obj(Θ) is the objective function, which represents the sum of the loss function and regularization term of the model, $l(y_i, \hat{y}_i)$ is the loss function used to measure the difference between the predicted value $\hat{y}_i$ and the true value y_i, and the subsequent terms are regularization terms used to control the complexity of the model and prevent overfitting. Θ is the set of model parameters, including the structure and weights of the base learners. Ribeiro et al.'s XGBoost model proposed in 2022 [13] outperforms other models in both very short-term load forecasting (VSTLF) and short-term load forecasting (STLF).

4.3. Support Vector Machines

Support Vector Machines (SVM) is a binary classification machine learning algorithm that can be used to solve various nonlinear problems such as classification, regression, and outlier detection. SVM attempts to find a hyperplane to separate the dataset into two categories and maximize the margin between the two categories. In two-dimensional space, you can imagine a linear SVM as a line that separates two categories. Above the line belongs to one category, and below the line belongs to another category. The goal of SVM is to find the optimal separating line that maximizes the margin between the two categories. This margin is called the "geometric margin," and it is an important concept in SVM. SVM can handle nonlinear problems because it introduces kernel functions. Kernel functions map input data to higher-dimensional spaces, allowing data to be linearly separated in that space.

In summary, the advantage of machine learning methods is their ability to handle nonlinear relationships, strong adaptability, and applicability for medium and long-term predictions. However, they have high requirements for data quality and quantity, requiring large amounts of data for training.

5. Electricity Forecasting Method Based on Deep Learning

Deep learning is a branch of machine learning that simulates the human brain's learning method by establishing multi-layer neural networks. In the context of the COVID-19 pandemic, deep learning methods have also been applied in the field of electricity forecasting. Common deep learning algorithms include Convolutional Neural Networks (CNN), Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), etc. Tudose et al. [14] aimed to use a model based on Convolutional Neural Networks (CNN) to integrate current aspects of the global COVID-19 pandemic in addressing STLF problems, in addition to traditional factors (weather, holidays, etc.) in 2021. Saha et al. [15] studied short-term power load forecasting through deep learning algorithms to mitigate the impact of the COVID-19 pandemic on power demand. LSTM is a recurrent neural network model whose special structure allows it to remember and process long-term sequential dependencies. By introducing gating units into the network, LSTM can selectively ignore or remember past information and apply it to current predictions. This allows LSTM to better capture long-term trends and patterns when processing time series data. The LSTM model contains multiple gating units that control the flow and storage of information through gating mechanisms, effectively capturing long-term memory and avoiding the problem of vanishing gradients. The basic formulas of the LSTM model are as follows:

Input Gate:

$$i_t = \sigma(W_{xi} \cdot x_t + W_{hi} \cdot h_{t-1} + b_i) \tag{6}$$

Forget Gate:

$$f_t = \sigma(W_{xf} \cdot x_t + W_{hf} \cdot h_{t-1} + b_f) \tag{7}$$

Output Gate:

$$o_t = \sigma(W_{xo} \cdot x_t + W_{ho} \cdot h_{t-1} + b_o) \tag{8}$$

Candidate memory cell:

$$\tilde{C}_t = \tanh(W_{xc} \cdot x_t + W_{hc} \cdot h_{t-1} + b_c) \tag{9}$$

Memory cell:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \tag{10}$$

Hidden state:

$$h_t = o_t \cdot \tanh(C_t) \tag{11}$$

x_t represents the input sequence at time step,h_t represents the hidden state at time step t, which is also the output.i_t is the output of the input gate, controlling the input of new information.f_t is the output of the forget gate, controlling the forgetting of old information.o_t is the output of the output gate, controlling the output of the hidden state.$\tilde{C}_t$ is the output of the candidate memory cell, representing the candidate value of new information. C_t is the output of the memory cell, representing the memory state at time step t. σ is the sigmoid function used to transform the input of the gate units into values between 0 and 1. W represents the weight matrix, and b is the bias vector. In specific applications, Kong et al. [16] proposed a Long Short-Term Memory (LSTM) recurrent neural network framework to address the challenging problem of highly volatile and uncertain electricity load forecasting for individual energy users. Liu et al. made a contribution by innovatively proposing a mobile optimized load forecasting method based on multi-task learning and LSTM networks [17] to mitigate the impact of COVID-19 on short-term load forecasting.

Therefore, deep learning methods can handle nonlinear relationships, have strong adaptability, can be used for medium and long-term predictions, and have high prediction accuracy. However, due to high requirements for data quality and quantity, a large amount of data is required for training, and the model's training time and computational cost are also high.

6. Electricity Forecasting Method Based on Hybrid Models

A hybrid model is a method that combines the advantages of two or more different models. In the context of the COVID-19 pandemic, hybrid models have also been widely used in the field of electricity forecasting. Common hybrid models include those based on ARIMA and neural networks, SVM and neural networks, and LSTM and XGBoost. To improve the accuracy of power load forecasting, Li et al. [18] proposed a combined forecasting model based on LSTM and XGBoost in 2019. Fan et al. [19] proposed a hybrid model that includes STL, Long Short-Term Memory Neural Network (LSTM), and XGBoost to improve the accuracy and robustness of predictions. Alhussein et al. [20] proposed a deep learning framework based on a combination of Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) in 2020. Wang et al. [21] designed a research framework that compared the scenario without the pandemic with the actual energy consumption in 2020 (under the COVID-19 situation). The difference between the two was considered as the loss value of the power industry affected by the pandemic. They combined models to establish a combined model, providing more convincing results for the study and further analyzing the correlation between the decline of the power industry and the severity of the pandemic. Therefore, it can be seen that combined models can combine the advantages of different models, improve prediction accuracy and stability. However, the construction and adjustment of the model are more complex, and it is necessary to consider the parameter and weight configuration issues between different models to obtain the optimal accuracy.

7. Conclusion

Electricity is the foundation of national development. This study systematically summarizes the current technical methods used in electricity forecasting, introduces the principles of time series analysis, machine learning, deep learning, and hybrid models. Each method has its unique advantages and can play its role in accurately predicting electricity demand in corresponding situations, thus helping decision-makers plan and deploy electricity in advance according to plans. However, each method also has its limitations, and their scope of application and conditions of use are limited. If the chosen method is inappropriate, it is likely to result in large errors between the predicted results and the actual situation. In the context of the COVID-19 pandemic, the choice of electricity forecasting methods needs to be comprehensively considered based on specific circumstances. This is because the COVID-19 pandemic will lead to changes in human activity times, peak electricity usage, electricity prices, policies, etc., which will cause problems with the original forecasting methods. In current electricity research, combined models often have better accuracy because they combine the advantages of single models and can compensate for their limitations. Therefore, we should fully utilize combined models and use them as a research direction to obtain the best results. In practical applications, we need to choose appropriate forecasting methods based on the characteristics of electricity demand, the type and quality of data, and other factors to better cope with the impact of the pandemic on the power industry.

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