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Review of photovoltaic power prediction based on artificial intelligence methods

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Abstract. With the continuous growth of global demand for renewable energy, photovoltaic power generation, as a clean and efficient form of energy, has received widespread attention. However, photovoltaic power is affected by various factors such as irradiance, temperature, resulting in significant fluctuations in its output power. Therefore, accurate prediction of photovoltaic power is of great significance for the stable operation of the power system. In recent years, the rapid development of artificial intelligence technology has provided new solutions for photovoltaic power prediction. This paper will review the photovoltaic power prediction based on artificial intelligence methods, introduce its basic principles, application status, and challenges, in order to provide useful insights in related fields.

Keywords: Artificial Intelligence, Photovoltaic, Power Prediction, Deep Learning.

1. Introduction

Currently, the increasing conflict between the growing global energy demand and the increasingly severe problem of global warming has received great attention from the international community. To achieve the goals of "carbon peak and carbon neutrality" and clean energy development, the proportion of non-fossil energy in total energy consumption is planned to reach approximately 25% by 2030. Photovoltaic power generation, as an important renewable energy source, is a key force in helping achieve the "dual carbon" goals. By the end of 2022, China's cumulative installed capacity of photovoltaic power generation reached 395 million kilowatts, ranking first in the world for consecutive years.

However, photovoltaic power generation, as an intermittent and fluctuating new energy source, its power generation efficiency is affected by various environmental factors such as irradiance, temperature, the tilt angle of photovoltaic panels. The changes of these factors make the output power of photovoltaic power generation highly uncertain, bringing challenges to power grid dispatching and power market operation. In order to improve the reliability and economy of photovoltaic power generation, accurate prediction of its power output becomes particularly important.

Traditional prediction methods [1] are usually based on physical model methods, time series modeling methods, grey system models, physical-statistical combined models, etc. However, they are often not accurate and convenient enough when dealing with complex and nonlinear relationships, and have high requirements for the professional knowledge level of modelers and large computational costs. In recent years, with the rapid development of artificial intelligence technology, especially the continuous emergence of machine learning and deep learning algorithms, it has provided new ideas and

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methods for photovoltaic power prediction. The prediction method based on artificial intelligence can automatically extract features and establish complex nonlinear models by learning a large amount of historical data, thereby achieving high-precision prediction of photovoltaic power; and the AI model has a strong adaptive ability to adapt to different working conditions and has relatively higher efficiency and accuracy than traditional methods. Therefore, this review will comprehensively sort out and summarize the research progress of photovoltaic power prediction based on artificial intelligence, including the principles, advantages and disadvantages in order to provide guidance and reference for future research and practical applications.

2. Overview of Photovoltaic Power Prediction Problem

The photovoltaic power prediction problem refers to estimating the power generation of a photovoltaic power station in the future period through a series of methods in the photovoltaic energy system. It includes multi-timescale predictions such as ultra-short-term (less than 4 hours), short-term (24-72 hours), and medium and long-term (one month to one year) [2]. This section will provide an overview of the photovoltaic prediction problem from two major aspects: traditional methods and artificial intelligence methods.

The traditional methods of photovoltaic power prediction are mainly based on physical models, statistical models, and combined models [3]: Physical models simulate the power generation process of photovoltaic systems through analytical or numerical methods based on the physical characteristics of photovoltaic components and the influence of environmental factors, including photovoltaic cell models, photoconversion Conversion efficiency models, etc. [3]. The physical model has a solid theoretical basis and can provide an in-depth understanding and precise description of the power generation process of the photovoltaic system. However, the complexity of the model and its dependence on precise parameters limit its wide applicability in practical applications and may be limited when dealing with nonlinear effects and environmental changes; Statistical models focus on analyzing the statistical characteristics of historical data and predicting photovoltaic power through probability theory and statistical methods. Commonly used models include time series, grey prediction, Markov chains, etc. [4], which can handle the complex dynamic characteristics of historical data and capture the statistical laws of photovoltaic power through mathematical methods. However, this model has limitations when dealing with nonlinear relationships and complex environmental influences; The combined method combines different prediction methods such as the physical method and the statistical method by using appropriate weights and combines photovoltaic power generation data and Numerical Weather Prediction (NWP) data to predict photovoltaic power generation, thereby maximizing the advantages of each method and achieving the goal of improving the prediction accuracy of photovoltaic power generation [3].

The artificial intelligence methods in photovoltaic power prediction mainly include machine learning and deep learning techniques to improve the prediction accuracy. Most used methods include: Support Vector Machine (SVM), Random Forest, Gradient Boosting Tree, and Neural Network, which are suitable for handling nonlinear relationships and multivariate data, Long Short-Term Memory Network (LSTM), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and Deep Belief Network (DBN), etc. Compared with traditional methods, artificial intelligence methods are better at handling complex nonlinear relationships and high-dimensional data, automatically extracting features and adapting to environmental changes.

3. Sections, subsections and subsubsections

In the modern energy system, photovoltaic power prediction models based on advanced artificial intelligence technologies, especially RNN and CNN, have become key tools to improve the prediction accuracy of the dynamic output of photovoltaic systems and the overall efficiency of the system. Next, we will analyze the application of RNN and CNN in the field of photovoltaic power prediction.

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3.1. Recurrent Neural Network

The RNN is an improved multi-layer perceptron network, including the input layer, hidden layer, and output layer, with connections from the input to the hidden layer at the next time step in the hidden layer [5]. The Long Short-Term Memory (LSTM) is a deep neural network based on RNN [6], which can efficiently handle complex time series. As a core model in a deep learning architecture, its uniqueness lies in its ability to efficiently handle the time series characteristics of photovoltaic power through memory units and gating mechanisms (including input gates, output gates, and forget gates) [7]. In the field of photovoltaic power prediction, the significant advantages of LSTM are as follows: First, since photovoltaic power is affected by various environmental factors, including weather conditions, seasonal changes, and geographical locations. LSTM is good at capturing and analyzing long-term dependencies, and its memory units can store the long-term effects of these factors on photovoltaic power, significantly improving the prediction accuracy by learning these complex time series relationships; Second, LSTM has the ability to automatically adjust the information in its memory units and can adapt to dynamic changes in environmental conditions. This adaptive learning ability ensures that the prediction model can maintain a high degree of robustness and adaptability under various complex environmental conditions, such as sudden weather changes or seasonal alternations. In addition, the flexibility of LSTM enables it to handle nonlinear relationships and high-dimensional data, thereby showing excellent performance in photovoltaic power prediction [8].

The Gated Recurrent Units (GRUs) are good at efficient computing and resource optimization. As an efficient variant of LSTM, by simplifying its gating structure (merging the input gate and forget gate into the update gate) [9], it effectively reduces the computational complexity while retaining the ability to handle long-term dependency information. In the field of photovoltaic power prediction, GRUs can achieve comparable prediction effects to LSTM at a lower computational cost, especially suitable for scenarios with limited computing resources, such as edge computing environments [10]. The efficient computing characteristics of GRUs make it possible to deploy models on real-time predictions and resource-limited devices, further expanding the application scope of photovoltaic power prediction technology.

3.2. Convolutional Neural Network

The original design of the CNN is for image recognition, but its excellent feature extraction ability shows significant advantages when dealing with time series data with spatial structure (such as photovoltaic power prediction) [11]. The specific applications are as follows: First, CNNs can deeply analyze solar radiation images. For example, when analyzing satellite cloud images, CNNs can automatically identify and extract key features such as cloud distribution and atmospheric transparency, which are crucial for accurately predicting solar radiation intensity. Through its convolutional layer, CNNs can extract features from the input data, optimize the size, shape, and number of convolutional kernels, and identify patterns in the image, while the pooling layer can replace local features with all adjacent output features, reduce the spatial complexity of the data, prevent overfitting, and extract the most informative features, providing an accurate solar radiation prediction basis for photovoltaic power prediction [12]. The image analysis ability of CNNs can also be extended to other types of image data, such as topographic maps or meteorological radar images, providing multi-source information support for photovoltaic power prediction, thereby accurately predicting the power generation of photovoltaic power stations and facilitating the stable operation of power dispatching [13]; Secondly, combining CNNs with time series analysis models such as LSTM or GRUs can construct Convolutional Recurrent Neural Networks (CRNNs) [14] to handle both spatial and temporal information simultaneously. This combination can effectively handle multi-scale data, from local cloud changes to global weather patterns, extract features from the input data, and utilize the spatiotemporal dependence of the input data, thereby providing a more comprehensive perspective for photovoltaic power prediction [15]. CRNNs can not only handle high-resolution image data but also integrate historical photovoltaic power data and real-time meteorological data to achieve accurate prediction of photovoltaic power. In addition, CRNNs can also automatically learn the complex relationship between the output of photovoltaic systems and environmental factors through deep learning technology, maintaining high prediction accuracy and stability even under rapidly changing environmental conditions or poor data quality.

3.3. Ensemble Learning

In addition, through ensemble learning strategies, such as model fusion (including averaging, weighted averaging, or voting mechanisms), the stability and accuracy of the prediction can be further enhanced. By combining the outputs of multiple prediction models, the bias and variance of a single model can be reduced, thereby providing more robust prediction results [16]. This photovoltaic power prediction model combining deep learning, CNN, and ensemble learning not only provides more accurate and reliable decision support for the operation management of photovoltaic systems but also significantly improves its overall operation efficiency and economic value, promoting the efficient utilization of renewable energy and the development of smart grids.

4. Summary and Outlook

In conclusion, the application of artificial intelligence technology in photovoltaic power prediction provides strong technical support for solving the dynamic output prediction of photovoltaic systems under complex environments. These technologies can not only improve the prediction accuracy but also enhance the robustness and adaptability of the system, which is of great significance for promoting the wide application of photovoltaic energy and the efficient operation of smart grids. With the continuous advancement of technology and the expansion of application scenarios, the photovoltaic power prediction model based on artificial intelligence will continue to play a key role in the field of renewable energy and promote the intelligent and sustainable development of the energy system.

In the future, the development trend in the field of photovoltaic power prediction will pay more attention to the interpretability, real-time performance, and intelligence of the model. Interpretability models will help industry experts understand the logic behind the predictions and improve the transparency of decision-making; Real-time prediction models will be able to respond quickly to environmental changes and provide support for the immediate scheduling and control of photovoltaic systems; Intelligent prediction models will combine advanced technologies such as the Internet of Things, big data, and cloud computing to achieve comprehensive intelligent management of photovoltaic systems. These trends will drive the continuous advancement of photovoltaic power prediction technology and lay a solid foundation for building a clean, efficient, and intelligent energy system.

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