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Short-Term Photovoltaic Power Prediction Based on Deep Learning

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Abstract. In order to cope with the surge in global demand for clean energy and the challenges under the goals of "carbon peaking" and "carbon neutrality", this paper discusses the short-term prediction of photovoltaic (PV) power based on deep learning. This paper first summarizes the theoretical basis of deep learning and its application in PV power prediction, then expounds the key steps such as data preprocessing, data augmentation, and feature construction, and introduces the specific applications of deep learning models such as convolutional neural network, recurrent neural network and its variants long short-term memory network and gated recurrent unit in PV power prediction. Finally, this paper summarizes the progress of the current technology and looks forward to the future development direction of photovoltaic power prediction including multi-factor fusion prediction and optimization of deep learning models.

Keywords: deep learning, photovoltaic power prediction, data processing, feature construction, neural network.

1. Introduction

With the urgent need for global carbon emission reduction and clean energy utilization, solar energy is an important part of renewable energy [1], which is receiving increasingly attention. Photovoltaic (PV) power generation uses solar energy and directly convert it into electrical energy. It has the characteristics of zero emission and no pollution. It is an effective way to alleviate the energy crisis and reduce environmental pollution.

Driven by the goals of "carbon peaking" and "carbon neutrality" [2], the proportion of PV grid-connected has risen. Precise short-term forecasting of PV power is crucial for maintaining a balanced grid supply and demand, resource optimization, and energy efficiency improvement. In the short term, the PV system is affected by complex influence of multiple factors such as light, temperature, panel characteristics and the angle between the panel and sunlight. The output power exhibits significant variability and instability. Therefore, short-term PV power forecasting is becoming more and more essential.

Traditional PV power prediction mostly uses physical models, statistical approaches, or a fusion of both, but it is difficult to capture complex nonlinear relationships due to historical data and physical rules, and the accuracy is limited and the generalization ability is poor. The deep learning method can automatically mine the correlation between PV power and environmental factors by constructing a deep neural network, which has excellent feature extraction ability and nonlinear modeling ability, and has significant advantages in the field of PV power prediction. This paper focuses on the short-term PV power prediction based on deep learning, aiming to improve the accuracy of short-term PV power prediction through deep learning methods.

2. Fundamentals of deep learning and prediction

2.1. Theoretical Basis of Deep Learning

Backpropagation algorithm is the basis for deep learning to train neural networks [3]. The training process unfolds as follows: initially, input data is propagated forward through the neural network layer by layer via forward propagation to generate an output. Subsequently, a loss function is computed to quantify the discrepancy between the output and the actual value. Utilizing the chain rule, the gradient of the loss function is calculated for each weight and bias, layer by layer. Ultimately, the network's weights and biases are adjusted based on these gradients, with the objective of minimizing the loss function and refining the model [4]. This process is iteratively carried out until the training results are satisfactory.

2.2. Overview of short-term PV power forecasting techniques

2.2.1. Basic principles and methods of short-term PV power forecasting

Traditional methods usually include physical methods, statistical methods. The physical approach combines satellite imagery with numerical weather prediction (NWP) models [5]. Real-time information such as cloud cover, thickness and motion on the surface is captured by satellites, and ground observations and comprehensive meteorological data are integrated with NWP models [6] to enable detailed simulations of atmospheric conditions to predict future meteorological changes. The statistical method is to find out the statistical law between PV power generation power and environmental factors through the analysis of historical data, and establish a prediction model accordingly. Such methods include time series analysis [7], machine learning algorithms (such as artificial neural networks, random forest) [8].

2.2.2. Factors influencing short-term PV power generation

Short-term PV power forecasts are affected by multiple factors, including solar radiation, temperature, atmospheric pressure, wind velocity, and wind direction [9]. Solar irradiance directly affects the efficiency of converting light energy into electrical energy; Temperature changes affect the working efficiency of PV panels. The change of air pressure may indirectly affect the propagation of light and the temperature of PV panels. Wind speed and direction affect the heat dissipation performance and dust accumulation on the surface of PV panels. Some studies have pointed out that dust will make the light volt average power generation efficiency rate reduced by 17% [10]. In addition, clouds occlude [11], PV panels orientation, inclination, spacing and other factors also play a role.

3. Data processing and feature construction

3.1. Data Preprocessing

Short-term PV power forecasts are affected by environmental fluctuations, changes in the performance of PV power plant equipment, and human interference, and the original data often contains outliers and missing values. To enhance prediction accuracy and reliability, data preprocessing is necessary., with a focus on data cleaning, including outlier handling and data interpolation.

3.1.1. Outlier Handling

Outliers are data points that are significantly different from other data in the dataset. The outliers in the PV power data are mainly caused by two aspects: first, abnormal clouds and radiation intensity caused by sudden weather changes or extreme conditions. The second is inaccurate or lost data caused by aging equipment, communication failures or human error.

The most commonly used outlier detection methods are the quartile method [12], cluster analysis [13], isolated forest law [14]. While many studies have focused on the field of outlier detection, only a few have integrated outlier detection with regression models, for instance, reference [15] proposes an innovative weighted Gaussian process regression method that reduces the weight of data with a higher potential for outliers, thereby mitigating their adverse effects on prediction results.

3.1.2. Data Interpolation

When dealing with missing data and anomalies, we often interpolate from both spatial and temporal dimensions. In the spatial dimension, reference [16] utilizes spatial interpolation to obtain horizontal radiation intensity, and then employs neural networks to reconstruct radiation data for PV arrays, thus accurately estimating historical power generation. In the time dimension, if the data presents time series characteristics, linear interpolation, polynomial interpolation, or hermite interpolation [17], based on the temporal trend and periodicity of the data to fill in the gaps. The method selection should consider the characteristics of the data and the application scenario to ensure that the interpolation results are accurate and reasonable.

3.2. Data Augmentation

In practical applications, data scarcity, imbalance, and noise are often encountered, so data augmentation technology has become the core strategy to improve the generalization ability and prediction accuracy of the model. The main technologies include transfer learning and generative adversarial networks.

Transfer learning technology transfers knowledge from the source domain to the target domain, which is suitable for data scarcity scenarios. In PV power forecasting, it uses similar PV data across regions or climatic conditions to accelerate model training and effectively make up for the lack of data in the target domain. Reference [18] uses historical solar irradiance data to optimize and pre-train Long Short-Term Memory (LSTM) networks, then fine-tunes the deep model with PV output data to predict PV output more accurately.

Generate adversarial networks (GAN) is a data augmentation method based on deep learning, which consists of a generator and a discriminator. In PV power forecasting, it can generate PV power time series data that is highly similar to the real data, alleviate data scarcity, and enhance the model's generalizability. In the reference [19], a weather classification model based on generative adversarial network and convolutional neural network was proposed to reclassify weather types.

3.3. Feature Construction

3.3.1. Automatic feature extraction in deep learning

The deep learning model has powerful automatic feature extraction capabilities. For time series data, such as power generation, solar radiation intensity, temperature, Recurrent Neural Networks (RNN) and its variants (LSTM, Gated Recurrent Unit (GRU)), through their multi-layer structure and nonlinear activation functions, can automatically learning and extracting high-level features from raw data that are essential for prediction [20]. These features capture the time dependencies in the data. The dynamic variation and nonlinear relationship significantly improve the accuracy and robustness of the prediction. Automatic feature extraction greatly simplifies the complexity of feature engineering and enhances the generalization ability of the model.

3.3.2. Feature Selection

Despite deep learning's potent automatic feature extraction abilities, in certain scenarios, careful feature selection can further enhance model predictive performance. This involves eliminating irrelevant and noisy features, and selecting a subset of features that most significantly influence the prediction task. For PV power forecasting, it's crucial to focus on key factors like solar irradiation, temperature, humidity, and historical power output, aiming to identify the features with the greatest impact on predictions. This approach can improve model performance and generalization, while reducing computational complexity and the risk of overfitting.

4. Short-term PV power generation prediction based on deep learning

In short-term prediction of PV power generation, deep learning has become a cutting-edge and effective prediction method due to its strong nonlinear mapping ability and self-learning ability. This section will detail several deep learning models commonly used in short-term PV power prediction, including convolutional neural networks (CNN), recurrent neural networks (RNN) and their variants, long short-term memory networks (LSTM) and gated recurrent units (GRU).

4.1. Convolutional Neural Networks

CNN is a feedforward neural network that is good at automatically extracting spatially hierarchical features from images or transformed time series data. It consists of a series of key layers [21]. The input layer receives the data, the convolutional layer sliding convolutional kernel extracts local features, the activation layer applies the nonlinear activation function to introduce nonlinear factors, the pooling layer down samples to streamline the data and extract the key features, and finally the fully connected layer outputs the comprehensive information and predicts.

In practice, CNN is often used as a means of mixing with other technologies. In the reference [22], the Variational Mode Decomposition (VMD) is integrated with CNN to decompose PV data into multiple frequency components using VMD and then construct them into a two-dimensional format. CNN is then applied to extract features from both the data and the residuals, and the meteorological data is fused to train the model, achieving accurate short-term PV power prediction. Reference [23] introduces a weather classification model that combines GAN with CNN. It first simplifies weather categories into 10 types, then uses GANs to generate additional training data to fill in gaps. After that, the CNN model is trained on this enhanced dataset to precisely capture the relationship between weather conditions and power generation.

4.2. Recurrent Neural Networks

RNN is a neural network designed to process sequential data, and its core lies in the circular connection between nodes in the hidden layer [24], which allows the network to "remember" and use information from previous moments to influence the output of the current moment. In PV power forecasting, RNNs are able to capture the continuous changes of meteorological factors such as light intensity, cloud thickness, and temperature over time, as well as their power output to PV power generation impact.

However, traditional RNN is prone to experience gradient vanishing when processing long sequences [25] problems, limiting its application. To this end, the researchers propose improved models such as LSTM and GRU.

4.2.1. Long short-term memory networks

LSTM introduces three control units: the forgetting gate, the input gate, and the output gate[26] and effectively solves the gradient problem of traditional RNN, realizing the selective retention and forgetting of important information in the sequence. This gating mechanism greatly enhances the ability of LSTM to capture long-term dependencies, so that it can more accurately simulate the dynamic changes of PV power generation over time in PV power forecasting.

Reference [27] presents a CNN-LSTM hybrid model, which uses CNN to capture features from PV data and LSTM to address long-term dependencies in time series data. This combination leverages the strengths of both networks, resulting in robust performance under diverse weather and seasonal scenarios. Alternatively, Reference [28] introduces a hybrid deep learning ensemble framework for forecasting short-term PV power generation, utilizing LSTM and an attention mechanism. The framework incorporates two LSTM networks to independently predict temperature and power, emphasizes crucial input features via the attention mechanism, and enhances prediction accuracy with flatten and fully connected layers. Across multiple time scales, the model has proven to surpass traditional forecasting methods.

4.2.2. Gated Recurrent Unit

GRU is a simplified version of LSTM that combines forgotten and input gates in LSTM into an updated gate [29] while maintaining the timing modeling capabilities of LSTM. And the nonlinear activation function in the output gate is removed. Variables are reduced [30], and computational efficiency are improved. This gives GRU an advantage in terms of training speed and model complexity. reference [31] proposes a hybrid short-term PV power interval forecasting method based on Sparrow Search Algorithm (SSA) – VMD - CNN - GRU. This method arranges entropy and clusters PV data through VMD, optimizes GRU parameters using SSA, and employs CNN-GRU to obtain quantile predictions. Ultimately, it combines these predictions into an interval, significantly enhancing forecasting accuracy.

5. Conclusion

This paper explores basic knowledge, factors influencing PV forecasting, data processing and feature construction methods, and introduces several deep learning models applied in short-term PV power forecasting. Amidst the surge in global demand for clean energy and the pursuit of the "dual carbon" targets, PV power generation has vast potential. However, PV power forecasting still requires further development in the following aspects:

1) Advancing multi-factor integrated forecasting: As meteorological prediction and sensing technology advance, it is crucial to take into account various factors like solar radiation, temperature, atmospheric pressure, wind conditions (speed and direction), and cloud cover in future PV power predictions. Creating a multi-source integration model will boost prediction precision and resilience, allowing it to adapt to the intricate and dynamic natural environments.

2) Enhance deep learning models for PV power forecasting: While deep learning offers notable benefits in this field, it encounters hurdles like high computational demands and vulnerability to overfitting. Moving forward, optimizing model architectures, such as through the application of attention mechanisms and employing lightweight designs, is vital to enhance both training efficiency and predictive capabilities. Furthermore, incorporating advanced techniques like transfer learning and GAN is crucial to address challenges posed by limited and imbalanced datasets.

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