Research Status and Difficulties of Ultra-short-term Prediction of Photovoltaic Power

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Abstract. As photovoltaic power generation capacity continues to increase, the impact of its random and volatility power generation characteristics on the power system cannot be ignored. Studying the ultra-short-term prediction model of photovoltaic power generation can provide strong support for safe and stable operation of power grids and power grid dispatching. In this paper, the research status and difficulties of photovoltaic power ultra-short-term prediction are comprehensively discussed. Firstly, various factors affecting photovoltaic power generation are introduced. Then, the application and technical difficulties of ground-based cloud map and numerical weather prediction in prediction model are summarized. The status quo of power ultra-short-term prediction research, and finally put forward the need for perfect direction of ultra-short-term prediction of photovoltaic power.

1. Introduction

With the increase in energy demand and environmental awareness, renewable energy such as photovoltaic power generation has been vigorously developed [1, 3]. In 2015, President Xi Jinping proposed the energy revolution, the state has introduced relevant policies to encourage greater absorption of new energy sources [4, 5]. Academician Zhou Xiaoxin believes that it is necessary to vigorously develop power sources for non-fossil energy in electric power, and realize the transformation of power systems [6, 7]. Nowadays, photovoltaic power generation accounts for a larger proportion of the total power generation, and gradually shifts from the complementary role of peak-cutting to the main role of power generation.

However, photovoltaic power generation is affected by many factors, its power generation has the characteristics of randomness and volatility. It is a serious threat to safe and stable operation of the power grid [8]. If accurate prediction of ultra-short-term power of photovoltaic power generation can be realized, it will not only have economic significance for increase of PV consumption capacity, reduce system standby, but also help the power grid to get rid of the impact caused by the randomness of photovoltaic power generation [9, 10].

With the development of numerical weather prediction, ground-based cloud image and image processing technology, researchers have combined the above technology with statistical methods to predict ultra-short-term photovoltaic power, and achieved certain results [11, 14]. This paper will first briefly introduce the factors affecting photovoltaic power generation, the pretreatment process of foundation cloud map, and the difficulties in applying numerical weather prediction technology. Then
we will focus on the short-term prediction model of photovoltaic power in China and the problems that during the modeling process. Finally, the improvement direction is proposed.

2. Factors affecting photovoltaic power generation
There are many factors affecting photovoltaic power generation. The internal factors include the temperature of photovoltaic modules and the structural materials of photovoltaic panels that affect the radiation power conversion efficiency. The external factors include the geographical location of the photovoltaic power station, climate, weather type, atmospheric irradiance, aerosol particle concentration, cloud mass, wind speed and direction, ambient temperature, etc., are essentially affecting the radiation intensity received on photovoltaic panels [15, 19].

For the ultra-short-term prediction of photovoltaic power generation, the most important reason for the large fluctuation of its power curve is the variation of the radiation received on the photovoltaic panel. The extent to which the cloud blocks the sun is undoubtedly an important factor leading to changes in ground level radiance [20]. Therefore, the accurate prediction of the speed and direction of cloud movement is of great significance for the ultra-short-term prediction of photovoltaic power.

3. Ground-based cloud map
Initially, the researchers used a cross-correlation method based on satellite cloud maps to match the cloud clusters, and then linearly extrapolate the cloud movements [28]. Due to the relatively low spatial and temporal resolution of the satellite cloud image, it is impossible to determine the cloud condition in a small range and affect the accuracy of cloud motion estimation [19]. In recent years, with the successful development of ground-based remote sensing cloud instruments such as the Total Sky Imager (TSI), more and more scholars have used the ground-based cloud map to predict the short-term movement of clouds.

3.1. Ground-based cloud image preprocessing
The Total Sky Imager is a full color imaging product that monitors and collects cloud image information over the daytime PV power station [21]. The TSI structure is shown in Figure 1. The camera lens, the support arm and the shading tape cause a certain area of occlusion on the cloud image, the hemispherical mirror surface causes the cloud image to be distorted, and the sunlight overexposed to make the clear white pixel "white point" misidentified as a cloud. Therefore, it is necessary to perform restoration and distortion correction on the cloud image.

![Figure 1. TSI structure.](image-url)
3.1.1. *Ground-based cloud image repair.* As shown in Figure 2, ineffective area around the ground cloud map is first cut off. It can be seen that the ground-based cloud image taken by TSI is approximately elliptical. Therefore, the effective information of the cloud image is marked by the elliptic equation and the invalid area is black.

![Figure 2. Cloud map effective area marker.](image)

Since the camera lens and the support arm are fixed in the TSI, their projection positions on the cloud image are also fixed, that is, the slender strip in Fig. 2 and the black portion of the center of the cloud image. For the repair of such small areas, the symmetric mean interpolation method proposed in [22] can be used. It uses the neighboring pixel values on the left and right sides of the region to average the shadow reduction.

The light-shielding tape is a photosensitive element that blocks the incident light of the sun to protect the imaged portion of the system. The position on the cloud image is the widest black portion in Fig. 2, which continuously rotates as the position of the sun changes. Therefore, we can determine the position of the sash according to the position of the sun in the cloud. The position of the sun is determined by two physical quantities, the solar elevation angle and the azimuth angle, which can be obtained according to the method provided in [23]. The specific process is as follows, the solar height angle $H$ is calculated as:

$$H = \arcsin(\sin \varphi \sin \delta + \cos \varphi \cos \delta \cos \omega)$$

$$\delta = 23.45 \sin \left(360 \times \frac{284 + N}{365}\right)$$

$$\omega = 15(t - 12)$$

The formula for calculating the azimuth angle of the sun is:

$$\alpha = \arccos \left(\frac{\sin \delta - \sin H \sin \varphi}{\cos H \cos \varphi}\right)$$

Where: $\varphi$—the latitude of the photovoltaic power station; $\omega$—the solar time angle; $\delta$—the declination angle of the sun; $N$—the serial number of the year in the day of shooting; $t$—the true solar time of 24 hours, such as the sun at 12 noon, the time angle is 0; The $N$, $\omega$, and $t$ variables can all be obtained from the cloud file name.

The azimuth angle $\alpha$ is the angle between the axis of symmetry of the shading band and the south direction of the cloud image. Firstly, the center point of the cloud image and determine the position of the symmetry axis of the light-shielding belt, and then the width of the light-shielding belt can determine the area in the cloud image. At present, the ideal method for repairing occlusion regions is the mirror gradation interpolation algorithm proposed in [24]. This method makes full use of the symmetry of the
interpolation region and the texture features of the cloud map to ensure the continuity of connected pixels and reflect the sky. In addition, the literature [24] also considers that glare makes the cloud image overexposed, which may lead to the misidentification of the sky as a cloud. A series of processes, such as calculating the clear-air coefficient, setting the threshold, judging the existence of strong light, and identifying the glare region, modify the glare region to reduce the impact on the subsequent recognition of the cloud image.

3.1.2. Distortion correction of ground-based cloud image. TSI adopts camera CCD lens to shoot, and the object is reflected by spherical mirror, which inevitably causes optical distortion. It causes the size and shape of the cloud to be distorted and affects the subsequent cloud recognition process. Therefore, the cloud image needs to be corrected for distortion.

In [22], a distortion correction algorithm based on plane coordinate transformation is proposed. The calculation is relatively simple, but the formula involves the height of the cloud base. It is difficult to use accurate parameters to obtain this parameter. According to the transformation of zenith angle and azimuth coordinates, the literature [25] proposes a distortion-corrected coordinate transformation based on zenith angle coordinates, and uses bilinear interpolation to reconstruct the grayscale of the corrected image, which makes up for the lack of grayscale missing of some pixels. It can accurately and quickly complete the correction of cloud image distortion, laying the foundation for subsequent cloud group identification and extrapolation work.

3.2. Cloud recognition and feature extraction
Since the atmosphere and cloud particles scatter different degrees of visible light, in the foundation cloud map, the clear sky is blue and the cloud is white, and the cloud group is identified and extracted accordingly. The literature [26] uses the fixed threshold segmentation method of blue and red band ratio to distinguish the sky from the cloud. This method is simple, but it is only suitable for the weather conditions. When the weather quality is poor, the collected cloud image is worse, and the red and blue features are not obvious. Therefore, the literature [27] proposes an automatic detection method based on local threshold interpolation. The algorithm first normalizes the difference between the blue and red bands ratios R to increase the gray level difference between the sky and the cloud. The formula is as follows:

\[
R = \frac{b - r}{b + r}
\]

Where: \(b\) — the image blue channel luminance value; \(r\) — the red channel luminance value;

Then the cloud image is segmented, and the modified maximum inter-class variance adaptive threshold algorithm is used to calculate a local threshold for each sub-block. In order to avoid block effect generated by the block, the threshold matrix of each sub-block is finally interpolated by a bilinear interpolation algorithm. It has been proved by experiments that it is effective in cloud image recognition applications.

The cloud group can be classified and the feature quantity of solar radiation such as cloud image brightness and cloud amount can be extracted, which lays a foundation for subsequent photovoltaic power prediction. In [22], the fixed threshold method of normalized red-blue difference ratio is used to divide the cloud into thin clouds and opaque clouds. Different radiation prediction models are established based on cloud types, which improves the prediction accuracy. In [30], the brightness and cloud amount of the processed cloud image were calculated, and the two were used as the input of the RBF neural network prediction model, which significantly improved the ultra-short-term prediction accuracy of photovoltaic power.
3.3. Cloud extrapolation

At present, relevant scholars use the maximum connected domain to mark the cloud group according to a series of adjacent captured images, extract the centroid position, and then find the best matching region in the adjacent two clouds through some matching method. The average motion vector of the same cloud group is obtained by using a series of cloud maps to replace the short-term moving speed and direction of the cloud group, and the extrapolation work of the cloud group is completed. The commonly used matching method is the cross-correlation method proposed in [28]. By calculating the correlation coefficient of clouds in two adjacent clouds, the method finds the cloud with the largest correlation coefficient for matching. The experimental results show that the prediction effect is better for clouds with relatively stable movement.

In addition, with the development of numerical weather prediction technology (NWP), some scholars use the NWP model, that is, the model cloud map to predict the cloud trajectory. For example, in [29], the information such as wind speed, wind direction and cloud amount output by NWP is combined with the projection of the cloud cluster on the horizontal plane to predict the position of the cloud cluster to determine whether it blocks the power station. Studies have shown that this method is feasible under certain working conditions.

However, the above methods are based on the hypothesis of cloud group linear motion, which is only applicable to the case where the cloud group does not change much. In fact, the shape and size of the cloud are constantly changing, and its generation and movement are highly random. In the future research, nonlinear motion should be taken into account, which is the key to determining the accuracy of cloud short-term prediction. It is also a difficult point for follow-up research.

4. Numerical weather forecast

Numerical weather prediction (NWP) is a method of parameterizing physical processes, describing them by mathematical expressions, and solving the atmospheric state by high-speed computer. It can quantitatively and objectively reflect weather conditions and has been widely applied to weather forecasting [31]. More and more scholars use the irradiance, cloud amount, wind speed and direction, temperature and other information provided by numerical weather prediction as the input of the PV prediction machine learning model, and achieved good results in the experimental examples [32, 33]. In order to apply NWP to a small area, it is necessary to use downscaling methods and assimilate a large amount of information. These are the difficult and hot issues of current research [34].

5. Current status of photovoltaic prediction research

5.1. Photovoltaic prediction method

Currently, there are physical methods, statistical methods and hybrid methods for short-term prediction methods of photovoltaic power generation. The physical method uses physical equations to describe the relationship between photovoltaic output and meteorological data. The statistical method uses neural network and other models to analyze historical data and find out its relationship with PV power. The hybrid method is to use the above two methods that combined with a certain weight, or the model with the smallest error is used for prediction. Literature [33] first established a PV prediction model based on physical methods, and then used statistical methods to process the historical data of the power station to modify the physical method model.

According to the prediction time scale, it can be divided into short-term prediction and ultra-short-term prediction. Ultra-short-term forecasts are within four hours and require minute-level accuracy. Therefore, some researchers propose a model of photovoltaic power based on the foundation cloud map. Literature [37] realizes the prediction of cloud movement by processing the time series of cloud maps, and then combines the trajectory of the sun to judge the occlusion of the cloud, predict the change of irradiance. Finally, the power projection is based on the radiant power conversion relationship obtained from historical data statistics. In [22], the ground-based cloud map restoration and distortion correction are firstly performed to carry out cloud group classification and motion prediction. Then, the historical
radiation data is used to obtain the total radiation attenuation rate when different cloud types block the solar state, and the radiation model under clear sky conditions is established. Literature [30] extracted the image brightness and cloud characteristics reflecting the change of radiance, plus the extra-atmospheric radiation and atmospheric mass as the input of the RBF neural network prediction model to obtain the ground radiation prediction model. Together with the battery module temperature model as the input of the photoelectric conversion model to obtain the prediction of the photovoltaic power. Literature [29] proposed that NWP combined with ground-based cloud image for power prediction. The pattern cloud map is used for correction within one hour and four hours. The above models are all based on linear extrapolation of cloud clusters and under clear-air conditions. When the cloud changes greatly or there are aerosols in the sky, the prediction accuracy of the model is greatly reduced.

In addition, in [35], a three-layer BP neural network prediction model was trained and simulated using historical power generation data and weather data in the PV monitoring system database. In [36], the RBF neural network was used to fuzzily identify NWP. Three sub-models were established for different weather classifications, and an online prediction system was designed to improve the accuracy of power generation prediction. Literature [34] carried out the practical application of the short-term power prediction main station research of distributed power source, realizing the access and visual management of photovoltaic operation information and real-time weather data.

5.2. Data processing

Photovoltaic power ultra-short-term prediction models involve statistics on historical data, so sufficient and accurate data support is needed. Since photovoltaic power is related to the season, it takes at least one year of complete data to be modeled seasonally. After obtaining the sample data, it is necessary to clear the unit power generation abnormal data such as the fault and the limit state to ensure the accuracy of the prediction model.

Based on the machine learning method such as neural network, the data needs to be normalized to reduce the difference of numerical range of different physical quantities and improve the prediction accuracy [38]. At the same time, when using the neural network training model, the ratio of training data to verification data is better in 2-4. If it is too small, the training is not enough. If it is too large, it is over-fitting [33].

5.3. Evaluation standard

There are many literatures on the research of photovoltaic power generation, and various photovoltaic power generation prediction models have achieved certain results, but the evaluation criteria are not uniform. In [29], the root mean square error (RMSE), the mean absolute error (MAE), and the correlation coefficient $\rho$ are used as the evaluation indicators, and the measurement method is power. The literature [32] uses the mean absolute percentage error MAPE to evaluate the measurement method. Literature [33] uses the RMSE and MAE formulas for error calculation according to international practice. Due to the large difference in capacity of different power plants, it is more reasonable to use percentage as a metric. The relevant evaluation criteria are calculated as follows [39]:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left( \frac{P_{Mi} - P_{Pi}}{Cap_i} \right)^2}$$

$$MAE = \frac{1}{N} \sum_{i=1}^{N} \left( \frac{|P_{Mi} - P_{Pi}|}{Cap_i} \right)$$

$$\rho = \frac{Cov(P_{Mi}, P_{Pi})}{\sqrt{Var(P_{Mi}) Var(P_{Pi})}}$$

(4)
Where: PMi — the actual average power of the i period; PPi — the predicted power of the i period; Cap — the rated installed capacity of the station. Different prediction models use different accuracy indicators, it is difficult to compare the accuracy of photovoltaic power generation prediction, and a unified evaluation standard must be established.

6. Conclusion
Through the above literature analysis, China has made some progress in the research of ultra-short-term prediction of photovoltaic power generation, mainly by using ground-based cloud map, NWP technology combined with artificial neural network and other machine learning methods to model, and designed the corresponding forecasting system. But still in the exploratory stage, it is not perfect. In the light of the problems in the research process, this paper puts forward the following suggestions:

1) Strengthen the processing of input data, including the extraction process of the cloud group feature quantity by the foundation cloud map, and deeply excavate the physical quantity that affects the photovoltaic power generation, and continuously improve the model accuracy;
2) The sample data should be sufficient and correct to model different seasons and different weather types;
3) establish a nonlinear model for cloud movement prediction to adapt to rapid changes of cloud clusters;
4) To classify the weather types in more detail, and to incorporate the increasingly serious effects of haze on solar radiation into the PV power prediction model;
5) Unify the model prediction accuracy standards to compare different models and determine the optimal research method;
6) Really apply the prediction model to the power grid to develop a scheduling plan, so that it has real research value and significance.

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