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Short-term PV power prediction considering the influence of aerosol

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Short-term PV power prediction considering the influence of aerosol

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Abstract. To improve the accuracy of photovoltaic power prediction under haze weather, a short-term PV power prediction method combining the PM2.5 forecast and SVR model is proposed. The WRF-CHEM air quality model is used to realize the simulation calculation of PM2.5 concentration, combined with the historical output data of PV power plants, and based on the SVR machine learning model to build a direct mapping relationship model between multiple meteorological elements and PV output. A forecast experiment was carried out for a certain area in North China, and the results showed that the proposed method can effectively improve the accuracy of PV power forecasting under haze weather conditions, thereby providing strong support for power grid dispatch and operation.

1. Introduction

In recent years, countries around the world have accelerated the development and utilization of renewable energy and energy transformation on a large scale. In the field of power grid regulation, to reduce the impact of the uncertainty of photovoltaic(PV) output on grid dispatching operation, PV power prediction technology has become an important supporting technology. PV output power is closely related to meteorological conditions. The power curve is relatively smooth in the headroom state, but the changes in aerosol particle concentration and other factors will cause the PV output power to attenuate to varying degrees. In practical applications, complex weather conditions such as haze have a greater impact on the power generation capacity of PV power stations, and also put forward higher requirements for PV power prediction. At present, most PV power forecasting algorithms rely on the radiation forecast products of numerical weather forecasting, but traditional numerical weather forecasting radiation forecasting products are difficult to feedback on the influence of aerosols, and their forecasting ability under haze conditions is limited.

To improve the accuracy of PV short-term power prediction in special weather forecasts, this paper proposes a PV power prediction method considering PM2.5 forecasts. The air quality model WRF-CHEM is used to simulate and forecast the aerosol concentration (PM2.5), combined with the classic machine learning method SVR to build a power forecast model, which improves the accuracy of PV ultra-short-term power prediction under haze conditions.

2. Related research

PV power output is highly sensitive to weather changes and will vary greatly depending on the type of weather. Many scholars have researched this subject.

Ming Ding et al. proposed a similar day selection algorithm, which selects the same weather type as the test day and recent historical records as one of the inputs, and uses an improved BP neural network to train and predict the 24h power generation of the next day. The MAPE of this method on sunny and rainy days is 10.06% and 18.89%[1].S. Leva et al. divided historical data into three weather types: sunny, cloudy, and cloudy according to the daily average illumination amplitude, and then based on the set threshold, and used adaptive feedforward neural network (AFFNN) to train each weather type separately[2].L. Alfredo Fernandez-Jimenez et al. used the sunny index to classify the weather types and forecast short-term PV power[3].

However, in the current research, no scholar has specifically researched the relationship between haze weather types and PV power output. Therefore, this paper adds aerosol particles represented by PM2.5 to the input parameters of the SVR model to predict PV power output.

3. Data

This paper analyzes and studies the operating data and weather monitoring data of PV power plants in a certain region of northern China from December 28, 2018 to February 26, 2019. Statistics show that due to the haze incidents, the area's air quality index (AQI) in January and February of 2019 had 5 days of severe pollution and 12 days of severe pollution, with severe pollution lasting up to 4 days. Due to the above influence, the uncertainty of PV power generation in this region has increased, and the difficulty of forecasting new energy power has increased significantly, which is not conducive to the safe and stable operation of the power grid.

In this paper, PM2.5 concentration is used to describe the impact of haze in the area, and the air quality model WRF-CHEM [4] is used to generate aerosol particle concentration data, which are mainly high-impact factors such as PM2.5 and PM10 for solar radiation attenuation [5]. Based on the traditional WRF model, WRF-CHEM realizes the simultaneous calculation of atmospheric physical process and chemical process through the online coupled chemical process module, so it is widely used in related scientific research and business fields. In this experiment, by coupling the Tsinghua MEIC man-made emission source list, the resolution is set to $0.25° \times 0.25°$, and the time resolution is 15 minutes.

4. Materials and Methods

4.1. Data selection

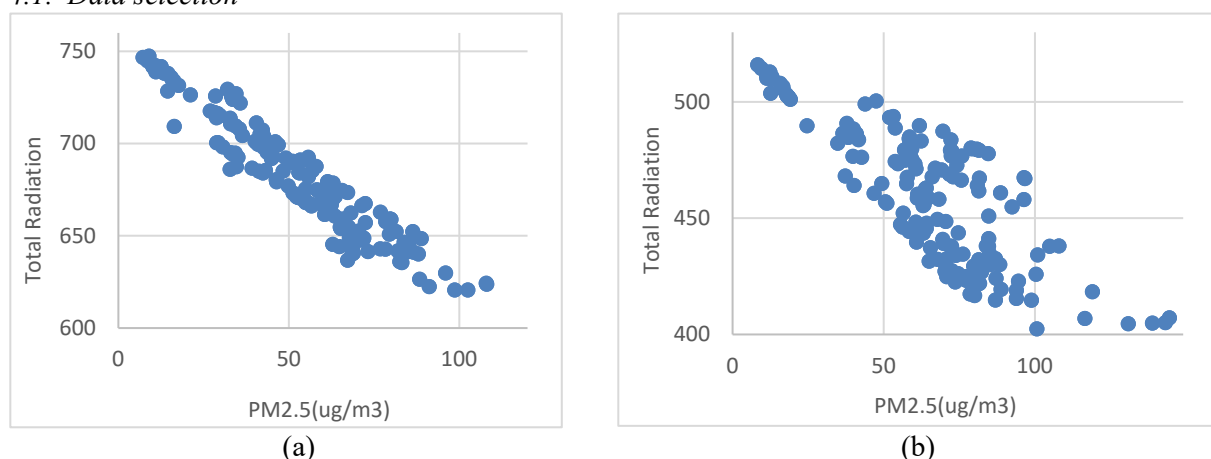(a)   (b)

Figure 1. Relationship between total irradiance and PM2.5.

Figure 1 reflects the relationship between the total irradiance and PM2.5 concentration of multiple PV power plants in a certain area at 12 o'clock(a) and 15 o'clock(b) daily. On the whole, PM2.5 concentration and total irradiance show obvious negative correlation characteristics, so this article considers adding PM2.5 as a new input factor based on the traditional SVR short-term prediction

model, training a new model, and performing Short-term PV power prediction under haze weather conditions.

4.2. SVR

Since the amount of data for haze weather is relatively small, the use of complex neural network models is not considered in the paper.

In recent years, SVM has been widely used in classification, modeling, and prediction due to its advantages in handling small sample nonlinear problems including power prediction issues [6][7]. SVR (Support Vector Regression) is an important application branch of SVM. It can be regarded as the application of SVM in the field of regression. Since the effect of SVR has been verified by many practical applications, this article adopts the classic SVR model and adds the above new input parameter PM2.5 concentration for power prediction. The model can be simply expressed as follows:

$$y = f(x) = \omega\phi(x) + b \tag{1}$$

Where ω and b are model parameters; x is numerical weather forecast data, including radiation and temperature; y is the power output.

In SVM, to prevent overfitting, the insensitive loss of ε is proposed, which can tolerate the maximum deviation between the predicted value and the true value. The optimization goals of the SVM model are as follows:

$$\min_{\omega,b} C \frac{1}{N} \sum_{i=1}^{N} L_\varepsilon(f(x_i), y_i) + \frac{1}{2}\|w\|^2 \tag{2}$$

$$L_\varepsilon(f(x) - y) = \begin{cases} |f(x) - y| - \varepsilon, & |f(x) - y| > \varepsilon \\ 0, & others \end{cases} \tag{3}$$

Where C is the regularization constant.

Equation (2) is a convex quadratic programming problem that can be solved efficiently by adding Lagrange multipliers, then w can be transformed into:

$$w = \sum_{i=1}^{n}(\hat{a}_i - a_i)\phi(x_i) \tag{4}$$

Where $\hat{a}_i, a_i$ are the Lagrange multipliers.

In summary, SVM can be expressed as:

$$f(x) = \sum_{i=1}^{n}(\hat{a}_i - a_i)\kappa(x, x_i) + b \tag{5}$$

Where $\kappa(x, x_i) = \phi(x)^T\phi(x_i)$ is the kernel function.

In the short-term power prediction of this paper, we exploit RBF (Radial Basis Function) to be kernel function, which is expressed as follows:

$$\kappa(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right) \tag{6}$$

Where σ is the width of the RBF kernel function.

In this paper, through SVR model training, a short-term PV power prediction model under the comprehensive influence of meteorological elements such as PM2.5 particle concentration, irradiance and temperature is constructed. The forecast process is shown in the figure below.
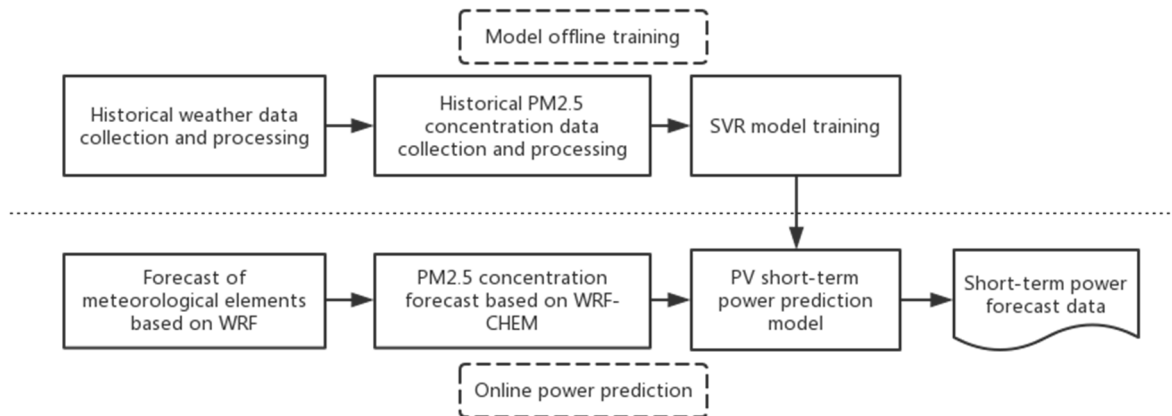
Figure 2. Model training and power prediction process

5. Results & Discussion

5.1. Evaluation indices

According to the existing evaluation indexes, this paper mainly uses the mean absolute error (MAE) and standard root mean square error (RMSE) as the evaluation indexes to measure the prediction accuracy of the model, which are specifically defined as follows:

$$e_{MAE} = \frac{1}{P_{rated}N}\sum_{i=1}^{N}|\hat{P}_i - P_i| \tag{7}$$

$$e_{RMSE} = \frac{1}{P_{rated}}\sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{P}_i - P_i)^2} \tag{8}$$

Where $\hat{P}_i$ and P_i are the ith foretasted and actual power values, N is the size of the testing dataset, and P_{rated} is the installed capacity.

5.2. Case analysis

For the experimental data, the data of a grid-connected PV power station in a certain area of North China from December 28, 2018 to February 22, 2019 was selected as the training set, and the forecast experiment was carried out for three days from February 23 to 25, 2019. The PM2.5 concentration curve of a PV power station on February 23-25 is shown in the figure below.
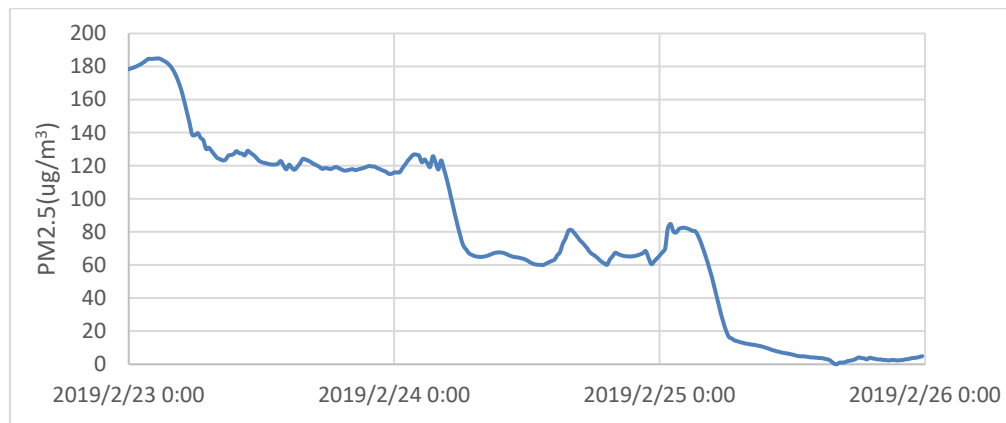

Figure 3. PM2.5 concentration curve

Use the PV short-term power prediction model established in this paper to predict, and the results are shown in the following figure. Method 1 is a forecast model that does not introduce PM2.5 concentration as an input factor, and method 2 is a forecast model established in this paper.
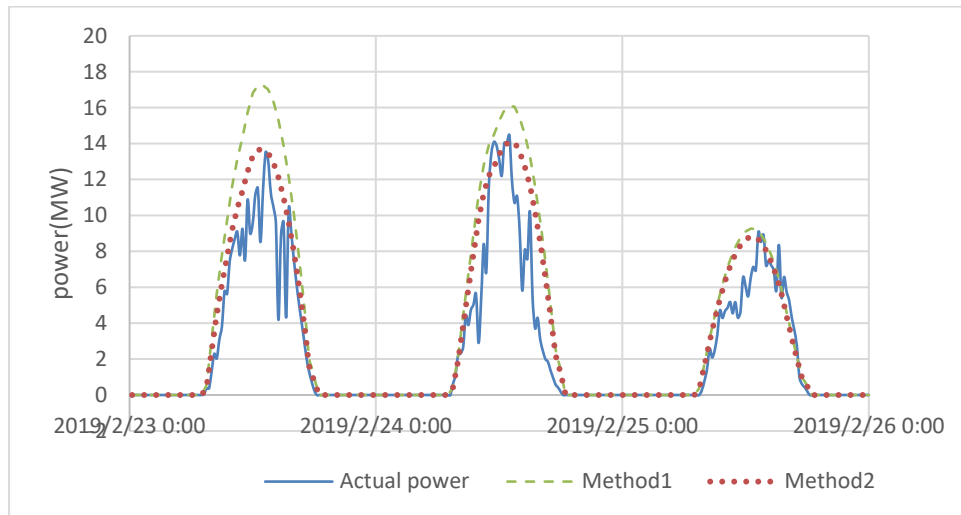

Figure 4. Comparison of PV power prediction

It can be seen from the figure that the method of introducing PM2.5 as an input factor in this article predicts power closer to the actual measurement. Moreover, the higher the PM2.5 concentration, the greater the prediction error regardless of the PM2.5 concentration, and the more obvious the accuracy advantage of the method proposed in this paper is in the prediction. The following table shows the comparison of the statistical results of forecast errors from February 23 to February 25, 2019.

Table 1. Comparison of PV power prediction error.

Date	Method1		Method2	
	MAE	RMSE	MAE	RMSE
2.23	0.0926	0.1595	0.0429	0.0837
2.24	0.0837	0.1492	0.0599	0.1126
2.25	0.0335	0.0618	0.0297	0.0549

According to Figure 3, Figure 4 and Table 1, the following analysis can be drawn. On the 23rd, where the smog was particularly severe, the PM2.5 concentration was introduced as an input factor for power prediction, MAE decreased by 0.0497, and RMSE decreased by 0.0758. On the 24th, where the smog was relatively severe, the MAE decreased by 0.0238 and the RMSE decreased by 0.0366. On the 25th, where the smog is relatively slight, the reduction in MAE and RMSE is not significant. The data shows that considering the concentration of aerosol particles can effectively improve the accuracy of forecasts under haze weather conditions.

6. Conclusion

Because of the large deviation of short-term PV power prediction under haze weather, this paper proposes a new aerosol concentration as an input parameter prediction model. Based on the WRF-CHEM model, the PM2.5 concentration forecast is realized, and the direct mapping relationship model between meteorological elements and photovoltaic output is constructed through the SVR model, and the power forecast result is calculated. Through experimental analysis, the conclusions are as follows:

1) The introduction of PM2.5 can effectively improve the accuracy of power prediction under haze and other weather conditions. At the same time, combined with the SVR model, it can better describe the nonlinear mapping relationship between total radiation, PM2.5 concentration and other

meteorological elements and PV output. The results of the case show that compared with the traditional input parameters, the model trained by adding PM2.5 as the input parameter can achieve better prediction results.

2) In this experiment, PM2.5 is selected for predictive analysis. Other aerosol particles such as PM10 and other particulate matter have not been considered. In-depth research will be conducted on this issue in the future.

Acknowledgments

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