Evaluating combination models of solar irradiance on inclined surfaces and forecasting photovoltaic power generation

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Abstract: The traditional photovoltaic (PV) forecasting method depends on sufficient historical data (PV power station historical power generation data and numerical weather prediction meteorological data), which is not suitable for a newly built PV power plant. In order to calculate the PV array irradiance and to predict the PV power, a physical prediction approach based on solar irradiance on inclined surfaces is proposed. This method selects three decomposition models and four transposition models to be combined into 12 combination forecasting models. Furthermore, solar spectral response, incidence angle, and soiling factor are taken into account in the modified model. The results show that the methods combining the Liu–Jordan transposition model have higher forecasting accuracy under the different weather types. Among them, the Erbs + Liu–Jordan model predictions are the most accurate.

Nomenclature

- \( E_h \): horizontal solar radiation
- \( E_b \): direct radiation
- \( E_{h,d} \): horizontal diffuse radiation
- \( E_t \): PV array irradiance on inclined surfaces
- \( k_T \): clearness index
- \( DF \): diffuse fraction
- \( E_e \): extraterrestrial horizontal irradiance
- \( \Delta k_T \): a stability index
- \( Z_S \): solar zenith angle
- \( kT \): modified clearness index
- \( W \): atmospheric precipitable water
- \( T_d \): surface dew-point temperature
- \( \alpha \): solar elevation angle
- \( E_{i,b} \): direct normal component of PV array irradiance
- \( E_{i,d} \): sky diffuse component of PV array irradiance
- \( E_{i,g} \): reflected ground diffuse component of PV array irradiance
- \( \theta \): incidence angle between solar beam and surface
- \( \beta \): surface tilt angle from horizon
- \( AZ_S \): azimuth angle of sun
- \( AZ_T \): azimuth angle of PV array
- \( \rho \): ground albedo assumed
- \( A \): anisotropic index
- \( E_0 \): direct extraterrestrial normal irradiance
- \( R_b \): ratio between the direct irradiance on inclined plane and the direct irradiance on horizontal plane
- \( q \): elementary charge (\( q = 1.602 \times 10^{-19} \) C)
- \( k \): Boltzmann’s constant (\( k = 1.381 \times 10^{-23} \) J/K)
- \( n \): diode ideality factor
- \( T_a \): absolute temperature
- \( R_s \): cell series resistance
- \( R_p \): cell parallel resistance
- \( E_{ref} \): reference irradiance (\( E_{ref} = 1000 \) W/m²)
- \( T_{ref} \): reference temperature (\( T_{ref} = 25^\circ \)C)
- \( P_{ac} \): AC power output from inverter
- \( P_{ac0} \): maximum AC power rating for inverter at reference operating condition
- \( P_{dc} \): DC power input to inverter
- \( P_{dc0} \): DC power level at which the AC power rating is achieved at reference operating condition
- \( P_{dc} \): DC power required to start the inversion process
- \( V_{dc} \): DC voltage input
- \( V_{dc0} \): DC voltage level at which the AC power rating is achieved at reference operating condition
- \( C_0-C_4 \): empirical coefficient which can be obtained by further experiments
- \( AM_1 \): air mass
- \( P \): atmospheric pressure
- \( P_0 \): standard atmospheric pressure (\( P_0 = 101.325 \) kPa)
- \( R_d(\lambda) \): spectral response of reference cell
- \( R_f(\lambda) \): spectral response of photovoltaic device
- \( E_{ref}(\lambda) \): reference spectral irradiance
- \( E(\lambda) \): spectral irradiance
- \( \lambda_{1-4} \): integration interval, and the cell spectral response wavelength range
- \( I_{dc} \): measured short circuit current at a given angle of incidence adjusted to the reference temperature and absolute air mass
- \( E_{eff} \): effective irradiance
- \( SF \): soil factor
- \( P_{me} \): measured power output
- \( P_{pred} \): predicted power output
- \( C_{api} \): capacity of analysed PV plants

1 Introduction

The increased solar penetration rate has a serious impact on the power quality of the power grid. Therefore, highly accurate and reliable photovoltaic (PV) power prediction methods play a very important role in the day-ahead planning of power system operations [1]. According to the prediction principle, PV power prediction methods can be divided into physical methods and statistical methods. A physical method is based on the principle of the PV power system, which depends on the detailed information of the PV power plant. The efficiency and performance model of each component in the process of photoelectric transformation is also important. A statistical method is based on a large amount of historical data and predicts the relationship between the model input and output factors. The most common approaches are neural networks [2–4], support vector machines [5], Markov chains [6], and so on. These methods need to extract the inherent relationship...
from a lot of historical power generation data. The corresponding mapping relationship can be established without considering the complex physical process of photoelectric transformation. However, the power prediction of a new PV power plant has a big difficulty, because there is no large amount of historical data. In addition, due to power outages or due to poor maintenance of data collection, there may be an incomplete record of PV power output, resulting in incomplete samples and training failure. In general, physical methods of PV power forecasting are more effective.

In the literature [7], a PV power physical prediction model is established based on a four-parameter battery model, five-parameter battery model and seven-parameter battery model. The results show that the prediction accuracy of the four- or five-parameter models is higher. Tossa et al. [8] compared the effects of different parameters in battery models and two battery temperature models on the accuracy of the PV power prediction. The results show that the complex battery parameter model has no obvious prediction advantage. Based on the measured data of the 120 W monocrystalline silicon PV module in the southern part of Turkey, Celik and Acikgoz [9] compared the calculation accuracy of the four-parameter and five-parameter cell models. The study shows that the five-parameter model has higher accuracy than the four-parameter model, especially around solar noon.

However, the main factor determining PV power is the PV array irradiance on inclined surfaces. Therefore, the key to ensuring the accuracy of prediction is by analysing the influence of different combination models and accurately selecting a combination model to calculate the PV array irradiance. The PV array irradiance calculation involves two steps: (i) The horizontal solar radiation ($E_b$) is decomposed into direct radiation ($E_{b,d}$) and horizontal diffuse radiation ($E_{b,d}$) by the direct dispersion model. (ii) The combination model transposes $E_b$ and $E_{b,d}$ into PV array irradiance on inclined surfaces ($E_s$). The Typical decomposition models include Erbs, Dirint and Reindl2, and the transposition models include Liu–Jordan, Hay–Davies and Reindl. These typical model creators provide a theoretical basis for subsequent combined models. Therefore, researchers focus on evaluating combinations of decomposition and transposition models. Ineichen [10] compared and validated the Erbs, Dirint, DirlIndex, and Skartveit decomposition models, and the performance of the modified DirlInt model was slightly improved. Loutzenhiser et al. [11] investigated seven transposition models in four building energy simulations and found that the Muneeer and Perez models have a good agreement with the measured PV array irradiance. Padovan and Col [12] measured the global and diffuse horizontal irradiance and the PV array irradiance of different surface tilt angles and orientations. After that, he discussed the combined models of three decomposition models and four transposition models (one isotropic and three anisotropic). Lave et al. [13] measured global horizontal irradiance and coincident measured PV array irradiance from 12 meteorological stations within the USA. Then, the combination of three decomposition models and four transposition models were evaluated. The results suggest that the Erbs and Dirint decomposition models showed the best performance, and the model combined with the Hay–Davies transposition model had the smallest mean bias difference. In order to evaluate the influence of different combined models on PV forecasting, Pelland et al. [14] explored 12 combination models by combining each of the decomposition models and transposition models. The results show that different combination models have little effect on the accuracy of PV power forecasting.

Accordingly, this paper studies the traditional PV power physical model and analyses in detail three decomposition models and four transposition models. Decomposition models and transposition models are, respectively, composed of 12 kinds of combination models. After evaluating its application in PV power forecasting, the most suitable combination model is selected. Finally, solar spectral response, incidence angle, and soiling factor are introduced to establish the modified physical forecasting model. After measuring a PV power plant under different weather types in East China, the prediction accuracy and validity of the 12 kinds of forecasting models are compared.

2 Traditional PV power forecasting model

The traditional PV power forecasting model considered detailed geographical location information of the PV power plant and the mathematical model of the solar-to-electric energy conversion process of the energy conversion device. There are three main types of input data: (i) numerical weather prediction data, such as solar irradiance, ambient temperature, wind speed and the atmospheric pressure; (ii) PV array installation parameters, such as surface tilt angle from horizon and azimuth angle of PV array; and (iii) PV modules and inverter technical parameters. The prediction model mainly includes the combination model of slope radiation and the mathematical model of the PV system. Based on the above data, $E_{b,d}$ and $E_b$ are calculated by using the combination model, and they enter into the PV cell mathematical model and the inverter mathematical model. Then, the PV power generation can be predicted. The structure diagram of PV power forecasting is shown in Fig. 1.

3 Combination models of solar irradiance on inclined surfaces

It is known that PV array irradiance is a prerequisite for PV power forecasting, but most meteorological stations provide only global horizontal irradiance and fewer observations of direct normal irradiance or diffuse horizontal irradiance. Therefore, this section selects the typical decomposition model and transposition model for detailed analysis and combines them one into one model to the calculate PV array irradiance. The typical model selection is based on the following criteria: (i) The model formula and the coefficient are fixed. (ii) The input parameters are easy to obtain. (iii) The calculation results have been recognised in a large number of documents.

3.1 Decomposition models

The clearness index ($kT$) and the diffuse fraction (DF) are two important physical quantities, defined by $kT = E_{b,d}/E_b$ ($E_b$ is the extraterrestrial horizontal irradiance) and $DF = E_{b,d}/E_h$. $kT$ indicates the relative clearness of the atmosphere, and DF reflects the change of the diffuse horizontal irradiance in the global horizontal irradiance. The crucial factor in improving the decomposition accuracy is how to accurately construct the functional relationship between $kT$ and DF. By referring to the documents, the Erbs model, the DIRINT model, and the Reindl2 model are selected for comparison and analysis. The reason is that their parameters are easier to obtain, with high accuracy and representativeness.

3.1.1 Erbs model: Erbs et al. [15] constructed a three-stage polynomial model using measured irradiance data from five US
meteorological stations (31.08° N to 42.42° N, 71.48° W to 80.6° W). The formula is as follows:

\[
DF = \begin{cases} 
1.0 - 0.09k_T & (k_T \leq 0.22) \\
0.9511 - 0.1604k_T + 4.388k_T^2 & (0.22 < k_T \leq 0.80) \\
-16.638k_T^2 + 12.336k_T^3 & (k_T > 0.80)
\end{cases}
\] (1)

3.1.2 DIRINT model: Perez et al. [16] constructed a dynamic model based on the DISC model by 58,000 radiation data observed at 18 sites in North America and Europe. The correlation formula is as follows (2)-(5):

\[
E_b = E_{b-disc} \cdot X(k_T, Z_S, W, \Delta k_T)
\] (2)

\[
k_T = \frac{k_T}{1.031 \cdot \exp[-1.47(0.9 + 9.4/m)] + 0.1} 
\] (3)

\[
\Delta k_T = 0.5 \cdot (k_T - k_{T-1}) + |k_T - k_{T-1}|
\] (4)

\[
W = \exp(0.07 \cdot T_g - 0.075)
\] (5)

where the subscripts \(i\), \(i+1\), and \(i-1\) refer to the current, the next, and the previous hourly record, respectively, \(E_{b-disc}\) is the direct normal irradiance estimated by the DISC model, \(X(k_T, Z_S, W, \Delta k_T)\) a coefficient function of the four insolation condition parameters, \(\Delta k_T\) a stability index, \(m\) the air mass, \(Z_S\) the solar zenith angle, \(k_T\) the modified clearness index, \(W\) the atmospheric precipitable water, and \(T_g\) the surface dew-point temperature.

3.1.3 Reindl2 model: Reindl et al. [17] constructed three kinds of decomposition models by 22,000 radiation data from five sites in North America and Europe (28.4° N to 59.56° N, 73.8° W to 80.6° W, 10.0° E to 12.6° E): Reindl1, Reindl2, and Reindl3. Compared with the Reindl1 single-factor model, the Reindl2 model introduces the solar elevation angle factor, and there are fewer input variables. Therefore, the simulation results are better than Reindl1 by (3)-(6):

\[
DF = \begin{cases} 
1.02 - 0.254k_T + 0.012 \sin \alpha & (k_T \leq 0.3) \\
1.4 - 1.749k_T + 0.177 \sin \alpha & (0.3 < k_T < 0.78) \\
0.486k_T - 0.182 \sin \alpha & (k_T \geq 0.78)
\end{cases}
\] (6)

where \(\alpha\) is the solar elevation angle.

The above three decomposition models calculate DF by using \(k_T\), where \(E_{b-disc}\) and \(E_b\) are obtained by

\[
E_{b-disc} = E_b \times DF 
\] (7)

\[
E_b = \frac{E_b - E_{b-disc}}{\cos(Z_S)} 
\] (8)

3.2 Transposition models

The transposition model transposes \(E_b\) and \(E_{b-disc}\) into \(E_c\). \(E_c\) can be divided into three components: (i) the direct normal component of PV array irradiance \((E_{c,d})\); (ii) the sky diffuse component of PV array irradiance \((E_{c,d})\); and (iii) the reflected ground diffuse component of PV array irradiance \((E_{c,g})\).

\[
E_c = E_{c,b} + E_{c,d} + E_{c,g}
\] (9)

The Liu–Jordan model is the most typical isotropic sky model and gives an isotropic sky assumption. Its diffuse component is composed of the uniform irradiance from the sky dome and the irradiance reflected from the ground

\[
E_c = E_{c,b} \cos(\theta) + E_{c,d} \left(1 + \frac{\cos(\beta)}{2}\right) + E_{c,g} \left(1 - \frac{\cos(\beta)}{2}\right)
\] (10)

where \(\theta\) is the incidence angle between solar beam and surface. It is calculated by (11)

\[
\theta = \cos^{-1}\left(\cos(\beta) \cos(Z_S) + \sin(\beta) \sin(Z_S) \cos(AZ_5 - AZ_T)\right)
\] (11)

where \(\beta\) is the surface tilt angle from horizon, \(AZ_S\) the azimuth angle of sun, \(AZ_T\) the azimuth angle of PV array, and \(\rho\) the ground albedo assumed as \(\rho = 0.2\).

In the Hay–Davies model, the sky diffuse component is composed of the circumsolar diffuse irradiance and the rest-of-sky diffuse irradiance that uses an isotropic assumption. The total irradiance can be calculated using the following equation:

\[
E_c = E_{c,b} \cos(\theta) + E_{c,d} \left(1 - A \left(1 + \frac{\cos(\beta)}{2}\right)\right) + E_{c,g} \left(1 - \frac{\cos(\beta)}{2}\right)
\] (12)

where \(A\) is the anisotropic index which represents the transmittance through atmosphere for direct irradiance, \(A = E_{b-disc}/E_b\) is the direct extraterrestrial normal irradiance, \(R_0 = \cos(\theta) \cos(Z_S)\), is the ratio between the direct irradiance on inclined plane and the direct irradiance on horizontal plane, and \(\rho\) is dealt with like in the Liu–Jordan model.

The horizon brightening component of diffuse irradiation from the sky is considered in the Reindl model on the basis of the Hay–Davies model

\[
E_c = E_{c,b} \cos(\theta) + E_{c,d} \left(1 - A \left(1 + \frac{\cos(\beta)}{2}\right)\right) \times \left(1 + \frac{E_{b-disc} \cos(Z_S)}{E_{b-disc} \cos(Z_S)} \sin(\beta) \frac{1}{2} + E_{c,g} \left(1 - \frac{\cos(\beta)}{2}\right)\right)
\] (13)

where \(\rho\) is again dealt with like in the Liu–Jordan model.

The above three kinds of transposition models assume \(\rho = 0.2\). Formula (13) used an albedo equation that was empirically fit to data from Albuquerque, as shown in (14), where the \(E_{c,b}\) and \(E_{c,d}\) calculation method is consistent with the Liu–Jordan model

\[
\rho = 0.012 \cdot Z_S - 0.04
\] (14)

In order to estimate the PV array irradiance from the measured global horizontal irradiance and test the influence of the models used on the PV power forecasting, we explored 12 combination models by combining three decomposition models and four transposition models.

4 Mathematical model of PV power system

The typical grid-connected PV power system is mainly composed of a PV array and a grid-connected inverter. The critical factor in accurate PV power forecasting is to accurately simulate the mathematical model of the PV cell and inverter. Therefore, this paper establishes a mathematical model of the PV cell and the PV inverter with high simulation precision to calculate the performance output of PV system at different irradiances and ambient temperature.

4.1 PV cell model

The PV cell is the core component of the PV power system. It is very important to establishing the PV power forecasting model. The PV cell equivalent circuit [18] is shown in Fig. 2 and the I–V characteristic is described in (8)

\[
I = I_{ph} - I_A \left\{ \frac{q(V + I_R)}{nkT} - 1 \right\} - \frac{V + I_R}{R_p}
\] (15)
where $I_{ph}$ is the light-generated current, $I_0$ the reverse saturation current, $q$ the elementary charge, $q = 1.602 \times 10^{-19} \text{C}$, $k$ is Boltzmann's constant, $k = 1.381 \times 10^{-23} \text{J/K}$, $n$ the diode ideality factor, $T$ the absolute temperature, $R_s$ the cell series resistance, and $R_p$ the cell parallel resistance.

It is hard to determine the five parameters $I_{ph}$, $I_0$, $n$, $R_s$, and $R_p$ in the above equation. Therefore, the equivalent circuit model is simplified by a compensation coefficient to approximately calculate four parameters under an arbitrary $E_i$ and a cell temperature ($T_c$).

$$
I_{dc} = I_{acel} [1 + a(T_c - T_{ref})] \frac{E_i}{E_{ref}}
$$

$$
V_{dc} = V_{acel} [1 + b(T_c - T_{ref})] \ln[e + c(E_i - E_{ref})]
$$

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5 Modified forecasting model

5.1 Solar spectral modified

5.1.1 Effect of air mass: Absolute air mass $AM_a$ is the ratio of the mass of atmosphere through which beam radiation passes to the mass it would pass through if the sun were located at the zenith [20], and the formula is

$$
AM_a = \frac{P}{P_0} \left[ \cos(Z_s) + 0.5057 \cdot (96.080 - Z_s)^{-1.854} \right]^{-1}
$$

where $P$ is the atmospheric pressure, kPa; $P_0$ for the standard atmospheric pressure, $P_0 = 101.325$ kPa.

From (19), as the ZS increases, the propagation path of solar radiation in the atmosphere becomes longer, and the shortwave radiation reaching the Earth's surface decreases due to the increase in $AM_a$.

Fig. 3 shows the solar spectrum irradiance at different air masses. It shows the solar radiation observed by the ground when $AM_a = 1.5$ (typically sunny sunlight is irradiated to the general ground, when a portion of the wavelength of sunlight has been scattered and absorbed). The peak solar radiation spectrum is distributed at a wavelength of 300–2500 nm with an energy peak of ~500 nm. However, the spectral response of a typical silicon cell is 300–1200 nm, and the response peak is ~900 nm. The peak conversion efficiency is difficult to match with the solar spectrum. In addition, the increase in $AM_a$ leads to significant changes of spectral intensity in different wavelengths. Owing to the different proportions of solar energy in different wavelengths, the change of $AM_a$ will affect the absorption efficiency of PV cells, which will affect the accuracy of PV power forecasting.

Fig. 4 shows the air mass under five different weather types in East China. It can be seen that the difference in $AM_a$ is obvious under different weather types, which is particularly significant at foggy and hazy days when the long spectrum will increase. The result is that most of the solar irradiance in the actual photoelectric conversion is transmitted, reflected or converted into heat, so that the solar irradiance actually absorbed and converted by the array is reduced.

5.1.2 Solar spectral modified function: In order to modify the effect of solar spectrum change on effective irradiance by the solar spectrum, the ASTM spectral mismatch ($M$) [21] is introduced. The formula is
where $R_\theta(\theta)$ is the spectral response of reference cell, $R_a(\lambda)$ the spectral response of PV device, $E_a(\lambda)$ the reference spectral irradiance, $E(\lambda)$ the spectral irradiance, $\lambda_1-\lambda_4$ for the integration interval, and the cell spectral response wavelength range. Fanney et al. [22] constructed the modified spectral response function ($f_a(\lambda)$) by using a large number of $M$ at the spectral response value of different cell types

$$f_a(\lambda) = a_0 + a_1 \cdot \lambda + a_2 \cdot \lambda^2 + a_3 \cdot \lambda^3 + a_4 \cdot \lambda^4$$

where $a_0-a_4$ are the regression coefficient and are related to the type of PV cell.

5.2 Incidence angle modified

5.2.1 Effect of incidence angle: The incidence angle indicates the angle between the solar incident light and the array slope normal, which is determined by the solar azimuth, the solar zenith angle, the tilt, and the azimuth angle of the PV array, and is related to the geographical location of the PV power plant. From (9), we can see that $\theta$ affects the amount of global horizontal irradiance because as the incidence angle increases, the amount of direct normal irradiance reflected increases.

Fig. 5 shows the incidence angle under different weather types in East China. It can be seen that the change of $\theta$ is different under different weather types and different times. The amount of $E_0$ is decreased when $\theta$ increases, and foggy and hazy days are especially significant.

5.2.2 Incidence angle modified function: In order to modify the influence that $\theta$ affects the amount of direct normal irradiance, the modified incidence function ($f_\theta(\theta)$) is introduced. The formula is as follows [23]:

$$f_\theta(\theta) = \frac{(E_{sc} / I_{ref}) \cdot I_a(\lambda)_{ref} = 1.5, T_1 = 25^\circ C) - E_{th,d}}{E_b \cdot \cos(\theta)}$$

where $I_{sc}$ is the measured short circuit current at a given angle of incidence adjusted to the reference temperature and absolute air mass.

5.3 Soiling factor

In addition, PV module surface fouling will also affect the component transmittance and power generation due to haze, dust, and other reasons. The results show that the average dust density in the summer is 0.239 g/m$^2$, and the output power is reduced by 2.823%. The average dust density in the autumn is 0.867 g/m$^2$, and the output power is reduced by 7.156% [24]. In East China in January 2014 to December 2015, there was rain a total of 694 days, accounting for 38%, with more rain on the PV array surface to play the role of scouring. Therefore, the soiling factor of 0.95 is selected.

5.4 Modified model of irradiance on inclined surfaces

As mentioned above, the effective irradiance is affected by the change of the solar spectrum caused by the AM$^4$ change, and the change of the optical losses of the array surface is caused by $\theta$ and the surface soiling. It can be seen that the use of the PV array irradiance calculated by (9), (12) and (13) directly predicts the lack of PV power. Therefore, the modified model of irradiance on inclined surfaces is used to improve the prediction accuracy.

In this paper, the modified spectral response function, the modified incidence angle function and the soiling factor are introduced in the PV array calculation, and the modified model of irradiance on inclined surfaces is established to calculate the effective irradiance. The direct normal component is subjected to modified spectral response and soiling factor, and the direct radiation of the solar radiation is modified for the incidence angle. The computational formula of the modified model of irradiance on inclined surfaces is as follows:

$$E_{i,d} = f_a(\lambda) \cdot \{E_{i,b} \cdot f_\theta(\theta) + (E_{i,d} + E_{i,g}) \} \cdot SF$$

where $E_{i,b}$ is the effective irradiance, $E_{i,b}$, $E_{i,d}$, $E_{i,g}$ are different parts of the effective irradiance, $f_a(\lambda)$ is the solar spectral modified, $f_\theta(\theta)$ is the incidence angle modified, SF is the soil factor, SF = 0.95.

Based on the above analysis, the modified physical method is based on the traditional physical model to increase the modified model of irradiance on inclined surfaces. Its framework is shown in Fig. 6. The procedure used for forecasting PV power can be summarised as follows:

(i) Collect data such as meteorological data, PV power station location information, and the characteristics of the PV array and inverter from their datasheets.

(ii) Based on the above data, the decomposition model is used to estimate diffuse horizontal irradiance, and PV array irradiance is estimated by transposition model.

(iii) Considering the $f_a(\lambda)$, $f_\theta(\theta)$, and SF at different moments of the prediction day, the effective irradiance is calculated by using the slope correction model.

(iv) PV array irradiances are input to the PV cell model and inverter model to forecast the PV power, and the different forecasted results are tested and evaluated by the measured values.

6 Results and discussion

6.1 Data

Data of solar irradiance, ambient temperature, wind speed, atmospheric pressure, and power measured in real time in July
2010 to January 2015 were collected for a PV power plant in East China (30.77° N, 120.76° E). The influence of the 12 kinds of combination models on the forecasting results of the PV power system was analysed. Two forecasting models to predict the output power of four typical weather types of PV power plants were compared.

The data was collected every 15 min, conducting quality checks on data and eliminating unreasonable data to retain reliable data in the data application stage in order to improve the accuracy of the assessment.

6.2 Performance metrics

In this paper, the root-mean-square error (ERMSE) and the mean-absolute error (EMAE) are used as the performance metrics. The formulas are shown in (24) and (25)

\[
E_{\text{RMSE}} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left( \frac{P_{\text{mi}} - P_{\text{fi}}}{C_{\text{api}}} \right)^{2}} \quad (24)
\]

\[
E_{\text{MAE}} = \frac{1}{n} \sum_{i=1}^{n} \frac{|P_{\text{mi}} - P_{\text{fi}}|}{C_{\text{api}}} \quad (25)
\]

where \( P_{\text{mi}} \) is the measured power output, \( P_{\text{fi}} \) is the predicted power output, \( C_{\text{api}} \) is the capacity of analysed PV plants, and \( n \) is the total number of data.

6.3 Evaluation results of combination models

A summary of ERMSE and EMAE of the PV forecasting results of 12 combination models is shown in Table 1. It can be noticed that the average ERMSE and EMAE for combined models with the Liu–Jordan model are always smaller. Owing to the increase in aerosol particles and the anisotropy of the sky tended to be isotropic, solar irradiation is weakened. Therefore, the forecasted power is closer to the measured power. Compared to the King model, the Hay–Davies model, or the Reindl model, the average ERMSE of combined models with the Liu–Jordan model was reduced by 7.01, 13.01, and 13.50%, respectively, and EMAE was also reduced. It indicated the validity of combination models with Liu–Jordan model. On sunny days, the accuracy of each combination model is higher than that of other weather types, and the Erbs + Liu–Jordan model has the highest accuracy with ERMSE and EMAE values of 13.38 and 12.13%, respectively. The forecasting accuracy of the cloudy days is lower than that of other weather types, and its average ERMSE is >25%. All combination models had little impact on the forecasting errors in overcast and rainy days. The average ERMSE and EMAE varied in the ranges 22.93–25.37 and 18.39–20.82%, respectively, in overcast days, and the average ERMSE and EMAE ranged from 19.13 to 20.98% and from 15.28 to 17.03%, respectively, in rainy days.

Based on the above analysis, if the forecasting accuracy is not high, the combination models with the Liu–Jordan model were chosen as the best performing models to forecast PV power, and...
the Erbs + Liu–Jordan combination model was selected if the precision is high.

### 6.4 Forecasting results

Figs. 7–10 show a comparison between measured values and forecasting results of traditional and modified forecasting models in sunny, cloudy, overcast and rainy days, respectively.

It can be seen from Figs. 7–10 that the modified physical model can achieve a better prediction than the traditional physical model can. On a sunny day (24 October 2014), the two models can well follow the measured power curve, but after 12:00, the traditional model deviates from the measured value by 19 kW, and the prediction effect is decreased, because it does not take into account the influence of aerosol concentration on PV array effective irradiance. Owing to dramatic changes of cloud thickness and movement trends in a cloudy day (1 October 2014), none of the two forecasting models reflect the abrupt changes, such as at 9:15, 10:00, 10:15, 13:00. The forecasting result of the modified model in the period of 10:00–14:00 is obviously better than that of the traditional model. PV power generation has more uncertainty and randomness in an overcast day (21 October 2014) and a rainy day (29 October 2014); the modified forecasting model curve is closer to the actual curve in the period of 8:00–13:00.

Table 2 compares ERMSE and EMAE of the PV forecasting results of the two forecasting models under different weather types, and the three typical days for each of the four weather types.

| Weather type | Date               | ERMSE | EMAE |
|--------------|--------------------|-------|------|
| Sunny day    | 24 October 2014    | 13.16 | 11.97|
|              | 23 October 2014    | 12.70 | 10.87|
|              | 25 October 2014    | 13.42 | 12.21|
| Cloudy day   | 1 October 2014     | 25.08 | 19.50|
|              | 12 October 2014    | 21.16 | 16.47|
|              | 19 October 2014    | 20.08 | 17.17|
| Overcast day | 21 October 2014    | 22.93 | 18.39|
|              | 27 October 2014    | 16.85 | 11.75|
|              | 14 September 2014  | 20.26 | 16.16|
| Rainy day    | 29 October 2014    | 19.13 | 15.28|
|              | 19 September 2014  | 20.41 | 17.51|
|              | 22 September 2014  | 18.22 | 14.59|

It can be seen from Table 2 that the forecasting accuracy of the modified model is significantly higher than that of the traditional model for the same weather type, and the modified model reduces the average ERMSE by 28% and EMAE by 30% compared with the traditional model in these five weather types. On sunny days, the two models are more accurate than for other weather types. However, on cloudy and overcast days, the average ERMSE of the traditional model was 22.11% and 20.01%, respectively, and the ERMSE of traditional model does not meet the requirements because the performance metric is >20%. The average ERMSE of the modified model was 17.00 and 14.99% to meet the requirements. The average ERMSE and EMAE of the modified model were 12.91 and 10.04%, respectively, so the forecasting accuracy was 33 and 36% higher, respectively, than that of the traditional model.

### 7 Conclusion

The PV power forecasting model by utilising combination models, the PV cell model, and the inverter performance model have been presented. Based on the measures of the power produced by a PV power station located in East China, 12 combination models of irradiance on inclined surfaces were compared and showed a good forecasting performance for the Erbs + Liu–Jordan combination model. If the precision is not demanded, the Liu–Jordan combination model can be used to predict the PV power in all weather types in the area. On the contrary, choosing the Erbs + Liu–Jordan combination model, the predicted power value gets closer to the measured value.

Based on the traditional forecasting model, the influence on effective irradiance of air mass, incidence angle of sunlight, and soiling factor are analysed, and the modified model of irradiance on inclined surfaces is established. The forecasting results show that the modified physical model has higher forecasting accuracy than the traditional model has and is more suitable for different weather types. The modified physical forecasting model does not need a lot of historical data to support it. Not only can it be used for new PV power plant power forecasting, but it can also be used for old PV power stations when real-time power data acquisition...
fails. Meanwhile, the PV power of the area can also be calculated based on historical meteorological data, which can provide a reliable basis for constructing a new PV power station.

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