Evaluation of solar irradiance on inclined surfaces models in the short-term photovoltaic power forecasting

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Abstract: Accurately forecasting photovoltaic (PV) power is a prerequisite for dispatching of power systems, which is also crucial to grid stability. In this study, an evaluation of different solar irradiance on inclined surfaces models in the short-term PV power forecasting was reported. First, combinations of decomposition and transposition models were used to estimate PV array irradiance from measured global horizontal irradiance. Then a short-term PV forecasting model was proposed according to the performance of PV array and inverter, and irradiance on inclined surfaces was applied to the model to obtain the final forecasts. Finally, numerous measured power data from a variety of climates were used to evaluate the forecasting results of five weather types (sunny day, cloudy day, rainy day, fog and haze day). Results suggest that different models lead to different results under the same weather type, and the forecasting accuracy strongly depends on the weather types.

1 Introduction

With the advancements in photovoltaic (PV) technology, large-scale PV power stations have been built around the world in recent years. By the end of 2015, the installed capacity of a new PV power generation total of 507 GW and increased by 26.5% compared with 2014 [1]. The accuracy of PV forecasting is essential for dispatching of power systems and improving safety and stability of electricity supply. Since the PV power generation critically depends on the variability of PV array irradiance, unexpected variations may cause an obstacle to the reliability of the grid. Accordingly, the accurate estimation of PV array irradiance is incredibly significant to the PV power forecasting [2].

The global horizontal irradiance ($E_h$) is provided by most meteorological stations and PV power plants, but they have less observation on the diffuse horizontal irradiance ($E_{h,d}$) and PV array irradiance. In the absence of these two parameters, models have to be used to decompose global horizontal irradiance into direct and diffuse and transpose into PV array irradiance. Many types of research focus on evaluating a combination of decomposition and transposition models used on the PV power forecasting in order to obtain a combination model applied to the area. Ineichen [3] compared and validated Erbs, DirInt, DirIndex and Skartveit decomposition models, and the performance of with a modification of the DirInt model was slightly improved accuracy compared to other models. Loutzenhiser et al. [4] investigated seven transposition models in four building energy simulation, the Munner and Perez model have a good agreement with the measured PV array irradiance. Padovan and Col [5] discussed the combined models of three decomposition models, and four transposition models (one isotropic and three anisotropic) by utilising measured global and diffuse horizontal irradiance and PV array irradiance of different surface tilt angle and orientation. Lave et al. [6] evaluated combination of 12 decomposition models and 4 transposition models by using measured global horizontal irradiance and coincident measured PV array irradiance from 12 meteorological stations within the United States, results suggest that Erbs and Dirint decomposition models showed the best performance, and the model combined with Hay–Davies transposition model had the smallest mean bias difference. Pelland et al. [7] explored 12 combination models by combining each of the decomposition model and the transposition model in order to evaluate the influence of the different combined models on the PV forecasting, and the results show that different combination models have little effect on the accuracy of PV power forecasting. However, this assessment did not explore the effect of different decomposition and transposition models in different weather types.

Accordingly, in this paper different combination of decomposition and transposition models are used to estimate PV array irradiance, and the PV forecasting model is established by combining the mathematical model of PV cell model and inverter performance model. The influence of different combination models on the accuracy and validity of the PV power forecasting in five different weather types (sunny day, cloudy day, overcast day, rainy day, fog and haze day) was analysed by using the measured power data of a PV power station.

2 Combination models of irradiance on inclined surfaces

The combination model of irradiance on inclined surfaces is composed of decomposition model and transposition model is used to estimate PV array irradiance by utilising numerical weather prediction (NWP) data, such as solar irradiance, ambient temperature, wind speed and atmospheric pressure.

2.1 Decomposition models

The decomposition model is decomposed global horizontal irradiance into direct normal irradiance ($E_n$) and diffuse horizontal irradiance. Clearness index ($k_T$) and diffuse fraction ($DF$) are two important physical quantities, $k_T = E_n / E_e$ ($E_e$ is the extra-terrestrial horizontal irradiance), $DF = E_{h,d} / E_h$, $k_T$ indicates the relative clearness of the atmosphere, $DF$ reflects the change of diffuse horizontal irradiance in global horizontal irradiance. The key to improving decomposition accuracy is how to accurately construct the functional relationship between $k_T$ and $DF$. Dozens of decomposition models were proposed by fitting large amounts of meteorological data. We considered the decomposition models shown in Table 1.
The above three decomposition models calculate DF by using $k_T$.
Because $E_{h,d}$ and $E_h$ are obtained by

$$E_{h,d} = E_h \times DF$$  \hspace{1cm} (1)

$$E_h = \frac{E_h - E_{h,d}}{\cos(Z_h)}$$  \hspace{1cm} (2)

2.2 Transposition models

The transposition model is transposed $E_h$ and $E_{h,d}$ into PV array irradiance ($E_i$). $E_i$ can be divided into three components: (i) the direct normal component of PV array irradiance ($E_{i,n}$), (ii) the sky diffuse component of PV array irradiance ($E_{i,d}$) and (iii) the reflected ground diffuse component of PV array irradiance ($E_{i,g}$) [4]

$$E_i = E_{i,n} + E_{i,d} + E_{i,g}$$  \hspace{1cm} (3)

Liu–Jordan model is the most typical isotropic sky model and gives an isotropic sky assumption. It’s a diffuse component being composed of uniform irradiance from the sky dome and irradiance reflected from the ground

$$E_i = E_h \cos(\theta) + E_{h,d} \left( \frac{1 + \cos(\beta)}{2} \right) + E_{h,g} \rho \left( \frac{1 - \cos(\beta)}{2} \right)$$  \hspace{1cm} (4)

where $\theta$ is the incidence angle between solar beam and surface, it is calculated by

$$\theta = \cos^{-1}\left[ \cos(\beta) \cos(Z_h) + \sin(\beta) \sin(Z_h) \cos(\Delta Z_h - \Delta Z_t) \right]$$  \hspace{1cm} (5)

where $\beta$ is the surface tilt angle from the horizon, $\Delta Z_h$ is the azimuth angle of the sun, $\Delta Z_t$ is the azimuth angle of PV array, $\rho$ is the ground albedo, usually assume $\rho \approx 0.2$.

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

$$E_i = E_h \cos(\theta) + E_{h,d} \left( AR_h + (1 - A) \frac{1 + \cos(\beta)}{2} \right) + E_{h,g} \rho \left( \frac{1 - \cos(\beta)}{2} \right)$$  \hspace{1cm} (6)

where $A$ is the anisotropic index which represents the transmittance through atmosphere for direct irradiance, $A = E_{d}/E_h$ ($E_h$ is the direct extra-terrestrial normal irradiance, $R_h$ is the ratio between the direct irradiance on inclined plane and the direct irradiance on horizontal plane, $R_h = \cos(\theta) \cos(Z_h)$, $\rho$ 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 Hay–Davies model

$$E_i = E_h \cos(\theta) + E_{h,d} \left( AR_h + (1 - A) \frac{1 + \cos(\beta)}{2} \right) \times \left[ 1 + \frac{E_{h,d} \cos(Z_h)}{E_h} \sin^2 \left( \frac{\beta}{2} \right) \right] + E_{h,g} \rho \left( \frac{1 - \cos(\beta)}{2} \right)$$  \hspace{1cm} (7)

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

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

3 PV cell model

The PV cell is the core component of the PV power system, it is becoming more and more important to establish the PV power forecasting model. The PV cell equivalent circuit [11] is shown in Fig. 1 and the $I–V$ characteristic is described as

$$I = I_{ph} - I_0 \left[ \exp \left( \frac{q(V + IR)}{nkT} \right) - 1 \right] - \frac{V + IR}{R_p}$$  \hspace{1cm} (8)

where $I_{ph}$ is the light-generated current, $I_0$ is the reverse saturation current, $q$ is the elementary charge, $q = 1.602 \times 10^{-19} C$, $k$ is the Boltzmann’s constant, $k = 1.381 \times 10^{-23} K/J$, $n$ is the diode ideality factor, $T$ is the absolute temperature, $R_t$ is the cell series resistance, $R_p$ is the cell parallel resistance.

It is very difficult to determine the five parameters of $I_{ph}$, $I_0$, $n$, $R_t$ and $R_p$ in the above equation, which inconvenience applied to engineering. Therefore, the equivalent circuit model is simplified and the compensation coefficient is introduced to approximate calculate four parameters under the arbitrary $E_i$ and cell temperature ($T_c$)

$$\begin{align*}
I_{sc} &= I_{ocref} \left[ 1 + a(T_c - T_{ref}) \right] E_{ref} \\
V_{oc} &= V_{ocref} \left[ 1 + b(T_c - T_{ref}) \right] \ln[c(e + c(E_i - E_{ref}))] \\
I_{mp} &= I_{mpref} \left[ 1 + a(T_c - T_{ref}) \right] E_{ref} \\
V_{mp} &= V_{mpref} \left[ 1 + b(T_c - T_{ref}) \right] \ln[c(e + c(E_i - E_{ref}))]
\end{align*}$$  \hspace{1cm} (9)

where $E_{ref}$ is the reference irradiance, $E_{ref} = 1000 W/m^2$, $T_{ref}$ is the reference temperature, $T_{ref} = 25^\circ C$, $e$ is the base of natural logarithms, $e \approx 2.718$, $a$, $b$ and $c$ are the compensation coefficients, $a = 0.0025/\%C$, $b = -0.0028/\%C$, $c = 0.0005/W/m^2$. 

![Fig. 1 Equivalent circuit of a PV cell](image-url)
4 Inverter performance model

The efficiency of the European efficiency in the inverter datasheet is the weight conversion efficiency, which takes into account different loads. Very few inverters have achieved this efficiency due to its own power loss. There is a large error if the European efficiency is directly used to calculate the output power of the inverter. In this paper, the inverter performance model of Sandia National Laboratories is considered, and the model not only considers its own power loss but also has high accuracy [12]. Equation (10) is represented by the basic equations describing this model

\[ P_{ac} = \left[ \frac{P_{dc0}}{A - B} - C \cdot (A - B) \right] \cdot (P_{dc} - B) + C \cdot (P_{dc} - B)^2 \]  

where

\[
\begin{align*}
A &= P_{dc0} \cdot \left[ 1 + C_1 \cdot (V_{dc} - V_{dc0}) \right] \\
B &= P_{dc0} \cdot \left[ 1 + C_2 \cdot (V_{dc} - V_{dc0}) \right] \\
C &= C_0 \cdot \left[ 1 + C_3 \cdot (V_{dc} - V_{dc0}) \right]
\end{align*}
\]  

where \( P_{ac} \) is the AC output power from inverter, \( P_{dc0} \) is the maximum AC power rating for inverter at reference operating condition, \( P_{dc} \) is the DC power input to inverter, \( P_{dc0} \) is the DC power level at which the AC power rating is achieved at reference operating condition, \( V_{dc} \) is the DC voltage level at which the AC power rating is achieved at reference operating condition, \( C_0 \sim C_4 \) are empirical coefficients, can be obtained by further experiments.

5 PV power forecasting model

Based on the above analysis, the framework of PV power forecasting model is shown in Fig. 2. The procedure used for forecasting PV power can be summarised as follows:

Step 1: Collect data such as meteorological data, PV power station location information, and the characteristics of the PV array and inverter from their datasheet.

Step 2: Three decomposition models are used to estimate diffuse horizontal irradiance, and PV array irradiance was estimated by combining three different transposition models.

Step 3: PV array irradiance of nine different combination models 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

PV power station is located in Jiaxing, China, whose geographical coordinates are latitude 30.77°N and longitude 120.76°E. Using the Suntech STP270S-24/Vb PV modules and STC PVS-100(208 V) inverters, and the surface tilt angle is 27° and the azimuth angle is 180°. To verify the presented forecasting model under different weather types, the measured power and meteorological data were used for evaluating. The climate data are global horizontal irradiance, ambient temperature, wind speed and atmospheric pressure.

Root mean square error (\( E_{\text{RMSE}} \)) and mean absolute error (\( E_{\text{MAE}} \)) are used to assess the performances of different combination models used in the PV power forecasting. They are obtained as

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

\[ E_{\text{MAE}} = \frac{1}{n} \sum_{i=1}^{n} \left( \frac{|P_{\text{fi}} - P_{\text{gi}}|}{C_{\text{api}}} \right) \]

where \( P_{\text{fi}} \) is the forecasted value, \( P_{\text{gi}} \) is the measured value. \( C_{\text{api}} \) is the capacity of the PV power station, \( n \) is the number of forecasting points.

A summary of \( E_{\text{RMSE}} \) and \( E_{\text{MAE}} \) of the PV forecasting results of nine combination models used on the PV power forecasting is shown in Table 2. It can be noticed that the average \( E_{\text{RMSE}} \) and \( E_{\text{MAE}} \) for combined models with Liu–Jordan model are always smaller than combination models with Hay–Davies model or Reindl model. Its average \( E_{\text{RMSE}} \) was reduced by 18 and 19% and \( E_{\text{MAE}} \) was reduced by 21 and 22% in the five weather types relative to other combination models, and it indicated the validity of combination models with Liu–Jordan model. On sunny days, the accuracy of each combination model is higher than other weather types, and Erbs + Liu–Jordan model has the highest accuracy and its \( E_{\text{RMSE}} \) and \( E_{\text{MAE}} \) are 8.41 and 7.67%. The forecasting accuracy of the cloudy days is lower than other weather types and its average \( E_{\text{RMSE}} \) >20%. All combination models had little impact on the forecasting errors in overcast and rainy days. The average \( E_{\text{RMSE}} \) and \( E_{\text{MAE}} \) varied in the range 16.26–17.90 and

![Fig. 2 Framework of PV power forecasting model](image-url)
12.50–13.42% in overcast days, and the average $E_{\text{RMSE}}$ and $E_{\text{MAE}}$ range from 13.04 to 13.37% and 10.50 to 10.67% in rainy days. On fog and haze days, the average $E_{\text{RMSE}}$ and $E_{\text{MAE}}$ of combined models with Liu-Jordan model increased by 26 and 29% compared to other models. Based on the above analysis, the combination models with Liu–Jordan model were chosen as the best performing models to forecast PV power.

Figs. 3–7 show a comparison between measured values and forecasting results of Erbs + Liu–Jordan model, Dirint + Liu–Jordan model, and Reindl2 + Liu–Jordan model in a sunny day, cloudy day, rainy day, fog and haze day, respectively. In recent years, solar irradiation is weakened by the increase of aerosol particles and the anisotropy of the sky tended to be isotropic, therefore the forecasted power of combined models with Liu–Jordan model is closer to the measured power. On a sunny day, the forecasted power values of Reindl2 + Liu–Jordan model have good agreement with the measured power during the morning from 6 to 12,

| Decomposition model | Transposition model | Sunny day | Cloudy day | Overcast day | Rainy day | Fog and haze |
|---------------------|---------------------|-----------|------------|--------------|-----------|--------------|
|                     |                     | $E_{\text{RMSE}}$ | $E_{\text{MAE}}$ | $E_{\text{RMSE}}$ | $E_{\text{MAE}}$ | $E_{\text{RMSE}}$ | $E_{\text{MAE}}$ |
| Erbs                | Liu–Jordan          | 8.41      | 7.67       | 19.92        | 13.08      | 16.30        | 12.61        | 13.04        | 10.50       | 13.61        | 11.48        |
|                     | Hay–Davies          | 14.45     | 13.26      | 23.54        | 17.49      | 17.49        | 13.33        | 13.19        | 10.56       | 17.59        | 15.29        |
| Dirint              | Liu–Jordan          | 9.01      | 8.30       | 20.22        | 13.50      | 16.26        | 12.50        | 13.14        | 10.52       | 12.44        | 10.44        |
|                     | Hay–Davies          | 15.10     | 13.80      | 23.61        | 17.40      | 17.44        | 13.20        | 13.32        | 10.59       | 16.54        | 14.39        |
| Reindl2             | Liu–Jordan          | 15.22     | 13.90      | 23.72        | 17.55      | 17.63        | 13.32        | 13.37        | 10.62       | 16.65        | 14.50        |
|                     | Hay–Davies          | 15.39     | 11.90      | 21.39        | 15.42      | 16.49        | 12.59        | 13.12        | 10.53       | 10.29        | 8.21         |
|                     | Reindl              | 22.21     | 18.93      | 25.89        | 20.06      | 17.71        | 13.29        | 13.27        | 10.61       | 14.58        | 12.28        |

Fig. 3  Forecasting results of different combination models in sunny day

Fig. 4  Forecasting results of different combination models in cloudy day

Fig. 5  Forecasting results of different combination models in overcast day

Fig. 6  Forecasting results of different combination models in rainy day

Fig. 7  Forecasting results of different combination models in fog and haze day

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however, the forecasted power curve gradually deviated from the measured power curve after 12:00. None of the three combination models reflect the abrupt changes because of the dramatic changes in cloud thickness and movement trends in a cloudy day. PV power generation has more uncertainty and randomness in overcast and rainy day, therefore the forecast curves of the three combination models deviate from the actual curve. On fog and haze day, the AQI index is up to 209 and it belongs to moderate pollution, and 3 combination models forecasted results are too large due to the failure to consider the effects of aerosol on solar irradiation.

7 Conclusion

The PV power forecasting model by utilising combination models of irradiance on inclined surfaces, PV cell model, and inverter performance model has been presented. A comparison between the measures of the power produced by a PV power station located in Jiaxing and the forecasted power of nine combination models of irradiance shows a good forecasted performance for combined models with Liu–Jordan model. It has been found that forecasted values are greater than the measured values because the local air pollution is not considered in different weather types. In conclusion, the main advantage of the PV forecasting model that is possible to obtain the power output as historical power data is not needed and provides a reliable basis for the new PV power station.

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