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A Coupled Model of Solar Irradiance and BP Neural Network for Photovoltaic Power Forecasting#

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ABSTRACT

The global horizontal irradiance (GHI), direct normal irradiance (DNI), temperature and other meteorological data are generally used for the photovoltaic (PV) power forecasting. Due to the multi-layered and complex factors between irradiance and PV power generation, a large amount of long-term operation data is required to train the model to achieve a high prediction accuracy. In order to reduce the data requirements, a coupled model based on solar irradiance and BP Neural Network is proposed in this paper. Firstly, the difference between the received irradiance and the GHI/DNI is clearly demonstrated. Moreover, the received irradiance of fixed photovoltaic panel is calculated. On this basis, according to the geographical location of the photovoltaic power plant, the received irradiance in a whole year is modelled and used as the input to train BP neural network. The prediction results show that, compared with the conventional prediction methods, the coupled model has a higher accuracy, which can reduce the mean squared error and root mean squared error by about 34% and 16%.

Keywords: solar irradiance, BP neural network, photovoltaic power forecasting, coupled model

NONMENCLATURE

Abbreviations	
BP	Back Propagation
GHI	Global Horizontal Irradiance
DNI	Direct Normal Irradiance
DHI	Diffuse Horizontal Irradiance
PV	Photovoltaic

Symbols	
$T_{ime,sun}$	Local time (hour)
LNG	Local longitude (°)
A_{time}	Solar time angle (°)
δ	Declination angle (°)
α	Solar altitude angle (°)
LAT	Local latitude (°)
A_z	Solar azimuth (°)
θ_z	Zenith angle (°)
Z	Array Tilt (°)
θ_{inc}	Angle of incidence between the Sun's rays and the PV array (°)
$A_{z,pv}$	Azimuth in the normal direction of the panel (°)
$I_{G,H}$	Value of global horizontal irradiance (W/m^2)
$I_{D,H}$	Value of diffuse horizontal irradiance (W/m^2)
$I_{N,B}$	Value of direct normal irradiance (W/m^2)
I_{cal}	Received irradiance of the PV panel (W/m^2)

1. INTRODUCTION

Fossil fuel power generation causes problems such as shortage of resources and serious pollution. Renewable energy power generation has attracted extensive attention. Solar energy, among other renewable sources of energy, is an ideal power generation energy source since it is everlasting and clean. However, due to the influence of weather, photovoltaic output shows volatility and randomness to some extent. , which causes mismatch between energy supply and demand in a power grid [1]. The power forecasting can provide the necessary data which will be helpful for the optimization dispatching strategy for solar power plant.

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According to the different data used by the prediction model, photovoltaic power prediction can be divided into physical model and data-driven model. The advantage of physical model is that it is widely applicable and historical data is not needed [2]. Some researchers have presented method to predict solar irradiance for all sky conditions [3]. To achieve high accuracy, the analysis is usually too complicated, which needs considerable computing resources [4]. In Ref.[5], physical models for irradiance-to-power forecast conversion are introduced. However, many meteorological conditions may exert an influence on each other, so it is difficult to model and determine the relationship between all these meteorological conditions and PV power output. At present, the application of physical model in photovoltaic power prediction research is less common.

Photovoltaic power forecasting based on data-driven methods has been extensively researched, such as BP neural network, support vector machine SVM, etc. The modeling is simple. However, to achieve higher accuracy, these methods not only need a large sets of historical data as training samples [6], but also have unsatisfying prediction precision [7]. Many researches have focused on the analysis of meteorological impact, such as daily and seasonal periodicities in PV power series [8] and similarity evaluation between two different days according to meteorological conditions [9], to achieve higher accuracy at the cost of complex data processing, feature analysis and scene division. However, the generation power of PV power plant is influenced by geographical location, meteorological conditions, seasons and other factors, while the data-driven methods only focus on meteorological conditions. These disturbing factors increase the difficulty of model training and reduce the prediction accuracy, which is also a problem faced by the conventional data-driven methods.

The received irradiance on a PV panel is used to quantify the incident irradiance on a given solar panel. Compared with the GHI and DNI in the environment where the photovoltaic panels are located, the received irradiance in the physical model is the irradiance on the photovoltaic panel, which is the parameter most directly related to the power output of a PV module. It is suitable for more accurate photovoltaic power prediction and the interference of geographical location and time on prediction results can bereduced. This paper establishes the model of solar irradiance on photovoltaic panel and takes the received irradiance as the input of BP neural network, which realizes the combination of physical model and data-driven model. The coupled model has the following advantages: wide applicability and simple modeling; lower requirements for historical data; including meteorological conditions, geographical location and seasons, which improves the overall prediction accuracy and reliability

2. METHODOLOGY

2.1 BP neural network

BP (back propagation) neural network is a multilayer feedforward network, which is composed of input layer, hidden layer and output layer.

The working process of BP neural network is as follows. Firstly, the input information is received by each neuron on the input layer, passed to the neurons on middle layer and finally exported by output layers. Secondly, the error between the actual output and the expected output is transferred to the reverse propagation, and the connection weights and thresholds of each layer are adjusted until the expected precision or predetermined training step is reached. The topology of BP neural network is shown in Fig.1.

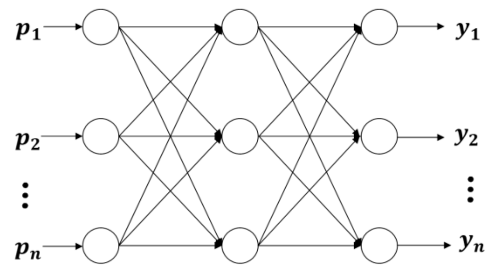

Fig. 1 The structure of the BP neural network

2.1.1 Input layer and output layer

Taking photovoltaic power as output, two models are established: GHI, DNI and other meteorological conditions (i.e., wind direction, wind speed, vertical wind speed, temperature, humidity and rainfall) as input; received irradiance on PV panels and other meteorological conditions as inputs, which are named as Model 1 and Model 2 respectively.

2.1.2 Hidden layer

The range of neurons in hidden layer is determined by empirical formula:

$$h=\sqrt{m+n}+p \quad \textbf{(1)}$$

where h is the number of neurons in hidden layer, m is the number of neurons in input layer, n is the number of neurons in output layer, p stands for a constant and $1 \le p \le 10$.

The number of neurons with the expected minimum average error in repeated tests are selected as the best number of hidden neurons.

2.2 DHI and received irradiance on PV panel

Calculate the solar position through longitude, latitude and local time, and then calculate the incident angle between solar irradiance and photovoltaic panel. Finally, a more accurate irradiance of photovoltaic panel can be obtained.

2.2.1 Solar position

The solar hour angle A_{time} can be expressed as:

$$A_{time} = 15 \times \left(T_{time,sun} - 12\right) \tag{2}$$

where $T_{time,sun}$ is the solar time, which is the time calculated based on the solar day.

Solar declination angle δ means the included angle between the equatorial panel of the earth and the connecting line which is drawn between the center of the sun and the earth. Declination angle δ can be calculated by the following equation:

$$\sin\delta_1 = 0.39795\cos\left[0.98563\left(N_{day} - 173\right)\right] \tag{3}$$

$$or \quad \sin\delta_2 = 23.45\sin\left(\left(284 + N_{day}\right)/365\right) \tag{4}$$

$$\begin{aligned} &or\ x_\delta = \left(N_{day} - 1\right)/365 \\ &\delta_3 = 0.3964\text{-}22.9133\cos x_\delta +\ 4.0254\sin x_\delta \text{-}0.3872\cos\left(2x_\delta\right) \\ &\quad +0.0520\sin\left(2x_\delta\right)\text{-}0.1545\cos\left(3x_\delta\right)+0.848\sin\left(3x_\delta\right) \end{aligned} \tag{5}$$

where N_{day} is the number of days in one year. The calculation equation δ_3 has higher accuracy. δ_1 and δ_2 can meet the general engineering requirements and the maximum deviation from δ_3 is 0.76%.

Solar altitude angle α is the angle between the incident direction of central ray from the sun and the horizontal plane, as shown in Fig. 2.

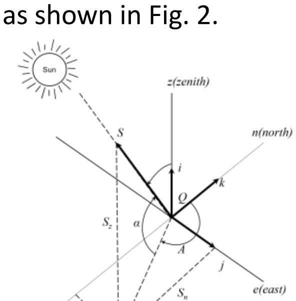

Fig. 2 Solar altitude angle α and solar azimuth A

The solar altitude angle can be calculated by the following equation:

$$\sin\alpha = \cos\delta\cos A_{time}\cos\left(LAT\right) + \sin\delta\sin\left(LAT\right) \tag{6}$$

where LAT is the local latitude.

The solar azimuth A_z is the azimuth angle of the sun, which is 0° in the due north and is positive in the clockwise direction. For example, at 12 o'clock solar time (noon), the solar azimuth is A_z=180°. The calculation equation are as follows:

$$\begin{aligned} &\cos x_{Az} = \left(-\cos\delta\cos A_{time} \times \sin\left(LAT\right) + \sin\delta\cos\left(LAT\right)\right)/\cos\alpha \\ &\text{IF}\ \ \sin A_{time} > 0,\ A_z = 360 - x_{Az} \\ &\text{IF}\ \ \sin A_{time} \le 0,\ A_z = x_{Az} \end{aligned} \tag{7}$$

$$or\ \ \cos A_z = \frac{\sin\left(LAT\right)\sin\alpha - \sin\delta}{\cos\alpha\cos\left(LAT\right)} \tag{8}$$

2.2.2 Incident angle of fixed PV panel

For the PV panel (as shown in Fig. 3) with due south orientation and panel tilt of Z, the incident angle θ_{inc} can be calculated by the following equation:

$$\cos\theta_{inc} = \sin\alpha\cos Z + \cos\alpha\sin Z\cos\left(A_{z,pv} - A_z\right) \tag{9}$$

where Z stands for panel tilt and $A_{z,pv}$ is the azimuth in the normal direction of the panel, which is 0° when the panel is arranged horizontally and is 180° when the panel is arranged obliquely.

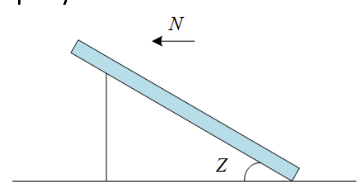

Fig. 3 Fixed PV panel

2.2.3 Irradiance

Since the global horizontal irradiance, direct normal irradiance and diffuse horizontal irradiance meet the equation:

$$I_{G,H} = I_{D,H} + I_{N,B} \times \cos\theta_z \tag{10}$$

where $I_{G,H}$ is the value of global horizontal irradiance, $I_{D,H}$ is the value of diffuse horizontal irradiance, $I_{N,B}$ is the value of direct normal irradiance, and θ_z is the zenith angle.

Therefore, when the global horizontal irradiance $I_{G,H}$ and direct normal irradiance $I_{N,B}$ are known and the zenith angle θ_z is calculated, the diffuse horizontal irradiance $I_{D,H}$ can be calculated. On this basis, irradiance of the PV panel can be calculated as follows:

$$I_{cal} = I_{D,H} \times \frac{1 + cos\left(LAT\right)}{2} + I_{N,B} \times cos\theta_{inc} + \rho_r \times I_{G,H} \times \frac{1 - cos\left(LAT\right)}{2} \tag{11}$$

where I_{cal} is the received irradiance of the PV panel, LAT stands for local latitude, θ_{inc} is the angle of incidence between the Sun's rays and the PV array and ρ_r is ground reflection coefficient.

The flow chart is shown in Fig.4.

3. CASE STUDY

3.1 Data screening and normalization

This paper uses the data from Desert Knowledge Australia Solar Centre (DKASC) as the experimental sample [10]. The plant is located in Alice Springs, Australia (23.7624°S, 133.8754°E). The output power data of a PV array is with 4.95 kW rating capacity. The data sets include the output power data of the photovoltaic array, irradiance data (i.e. GHI, DNI) and other meteorological conditions (i.e. wind direction, wind speed, vertical wind speed, temperature, humidity and rainfall). The data has been collected over the period of one year, from January 1, 2020 to December 31, 2020, with an interval of 5 minutes. The specifications of the array are shown in Table 1.

In order to improve the prediction accuracy, it is necessary to exclude abnormal data and normalize the rest of the data. The data with low output power is also excluded.

3.2 Design of BP neural network prediction model

To better compare the prediction results under different input of Model 1 and Model 2, the parameters of BP neural network are consistent, which are as follows: the number of hidden layer is 1, the number of neurons in hidden layer is 9, the training method is trainlm, the learning rate is 0.1, the training goal is 0.00004, and the maximum iteration is 300.

Table 1. Specifications of the PV system

Item	Value
Array Rating	4.95kW
Panel Rating	165W
Number Of Panels	30
Panel Type	BP 3165
Array Area	37.75 m²
Type Of Tracker	N/A
Inverter Size / Type	6 kW, SMA SMC 6000A
Installation Completed	Tue, 11 Nov 2008
Array Tilt/Azimuth	Tilt = 20, Azi = 0 (Solar North)

4. COMPARISON AND ANALYSIS

The 80th, 163rd, 266th and 310th days are selected to represent one of the sunny days near the autumnal equinox, the winter solstice, the vernal equinox and the summer solstice respectively. Through Fig. 6, it can be seen that the predicted power curve of Model 2 is closer to the actual power curve than that of Model 1. To be specific, on the 163rd day (near the winter solstice), the fluctuation of GHI and DHI are shown in Fig. 5(b). In Fig. 6(b), the predicted power curve of Model 2 is closer to the actual power curve, and the predicted power of Model 1 is lower.

From the 80th day near autumnal equinox to the 163rd day near winter solstice, as shown in Fig. 6(a) and Fig. 6(b), the difference of measured power maximum and predicted power maximum of Model 1 becomes bigger. However, the deviation of predicted power curve of Model 1 is more obvious than Model 2 and the measured power maximum and predicted power maximum of Model 2 are closer in both figures, which shows the importance of prediction combined with solar irradiance model.

In order to better compare the prediction effects of BP neural network under different inputs, each experiment is carried out 20 times independently. The average evaluation metrics (MSE, RMSE, MRE, MAE, R) in 2020 are shown in the Table 2. Compared with Model 1, the prediction error of Model 2 is smaller and the fitting coefficient of Model 2 is higher.

Table 2. Performance metrics of Model 1 and Model 2

Metrics	MSE	RMSE	MAPE	MAE	R
Model 1	0.1635	0.4043	0.2973	0.2772	0.9448
Model 2	0.1223	0.3489	0.3732	0.2140	0.9613

5. CONCLUSIONS

In this paper, the solar irradiance model is established. Combined with BP neural network, a suitable photovoltaic power forecasting model is obtained. According to the simulation results, when the inputs of other meteorological conditions are consistent, compared with taking GHI and DNI as inputs as inputs, when using the received irradiance of PV panel as inputs, the prediction error is smaller and the fitting coefficient is higher.

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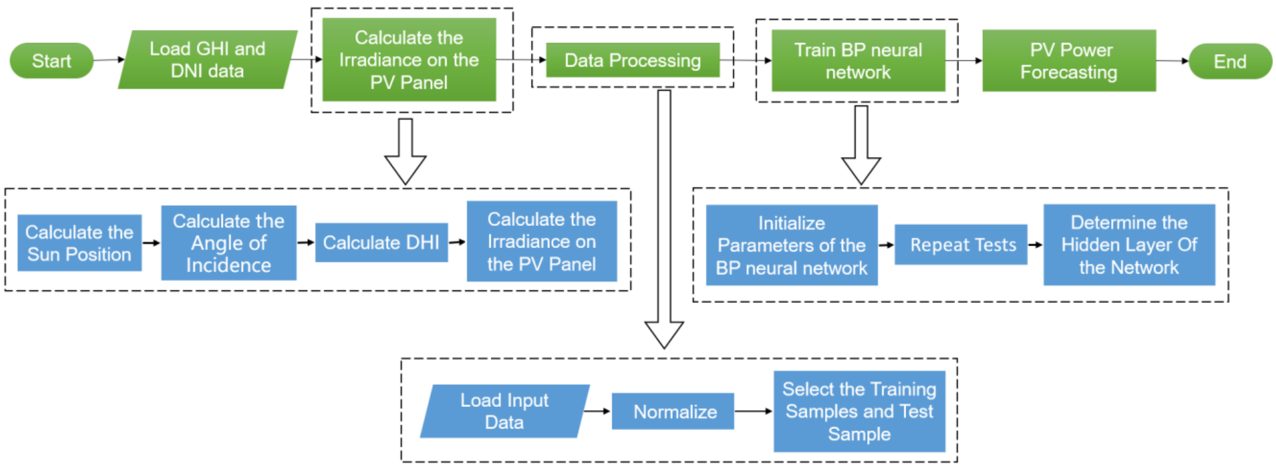

Fig. 4 The flow chart of coupled model of solar irradiance and BP neural network

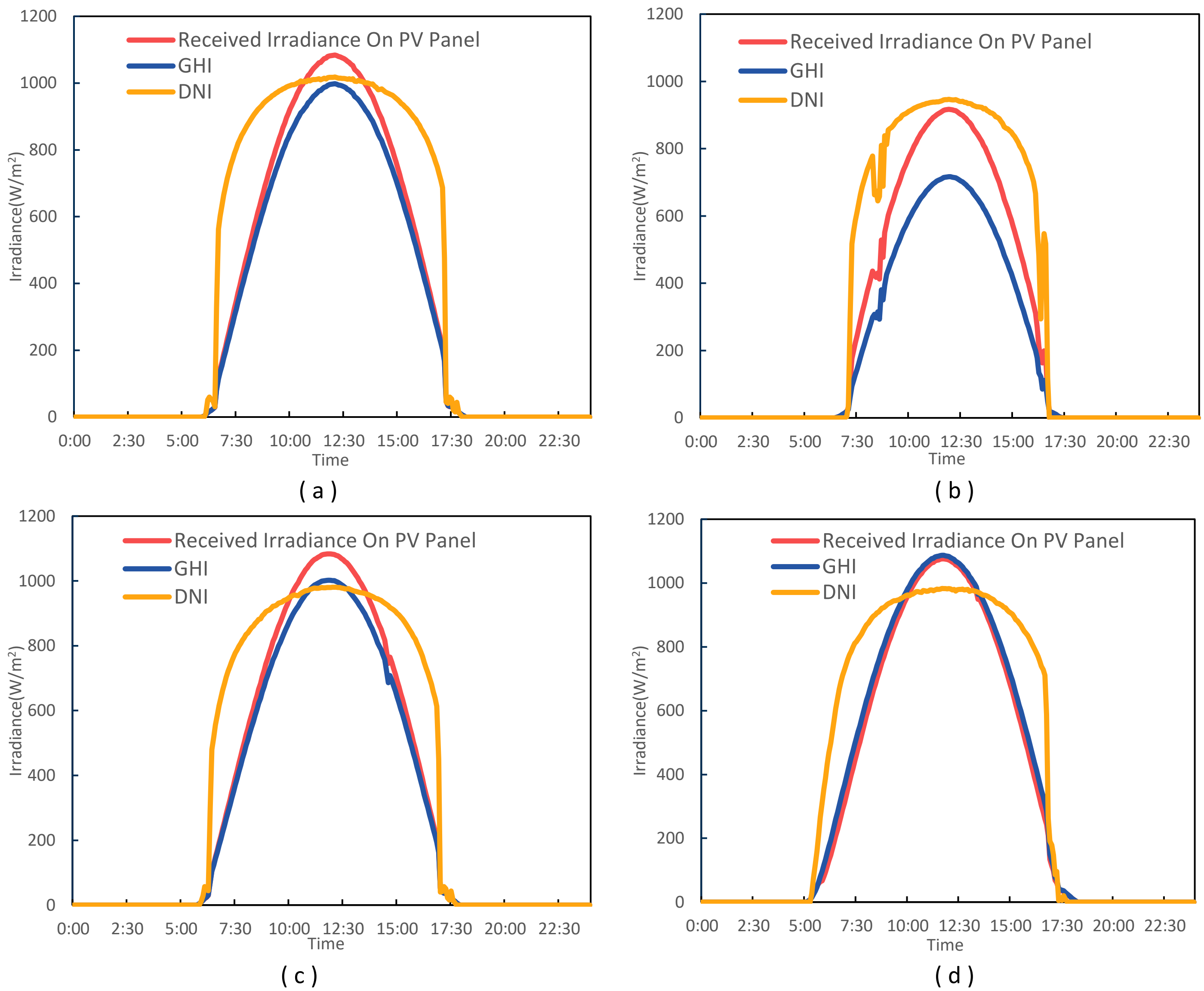

Fig. 5 GHI, DNI and received irradiance on PV panel. (a) The 80th day; (b) The 163rd day; (c) The 226th day; (d) The 310th day

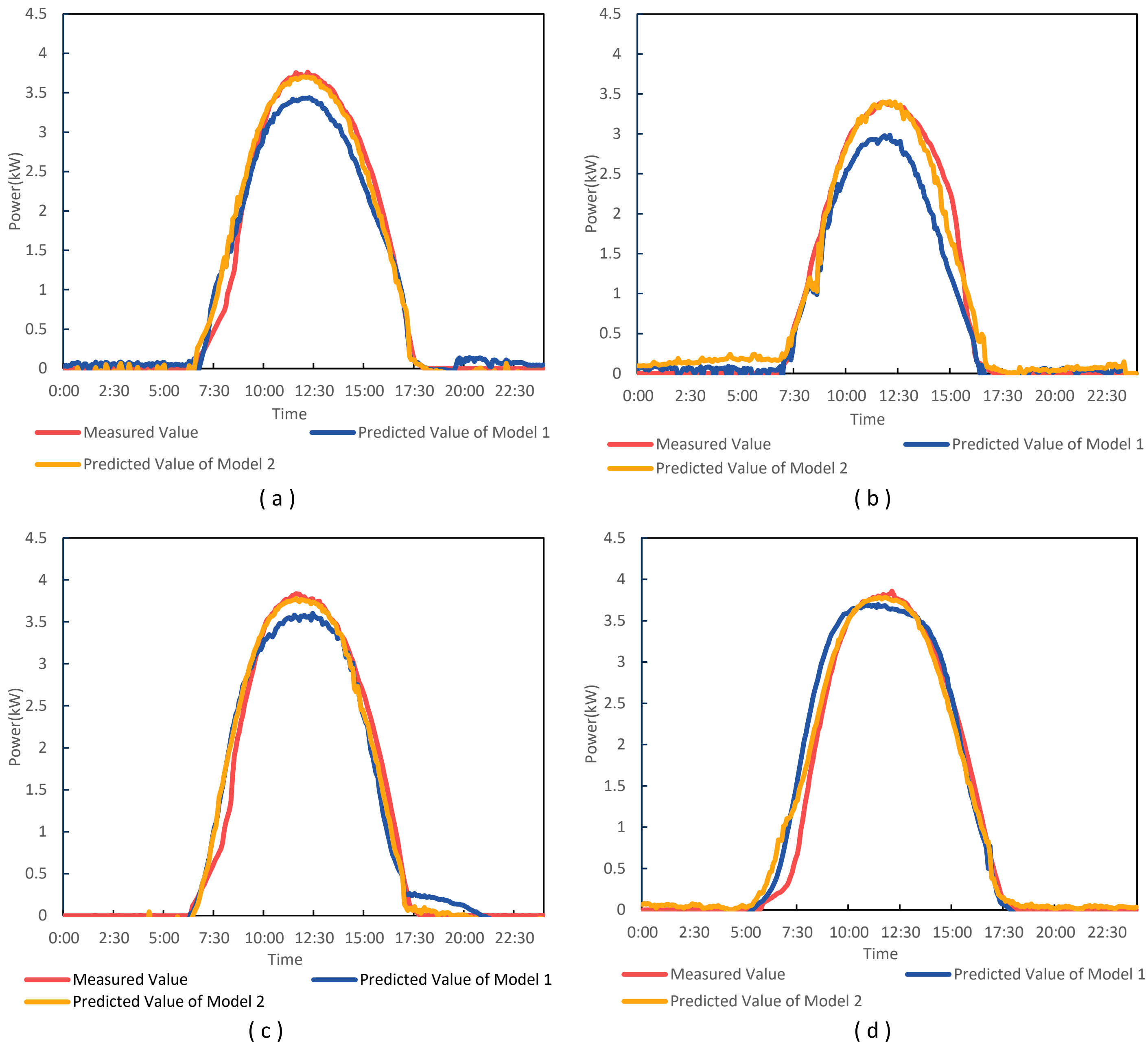

Fig. 6 Prediction result of Model 1 and Model 2. (a) The 80th day; (b) The 163rd day; (c) The 226th day; (d) The 310th day

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