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Research Article

Hybrid Power Forecasting Model for Photovoltaic Plants Based on Neural Network with Air Quality Index

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High concentration of greenhouse gases in the atmosphere has increased dependency on photovoltaic (PV) power, but its random nature poses a challenge for system operators to precisely predict and forecast PV power. The conventional forecasting methods were accurate for clean weather. But when the PV plants worked under heavy haze, the radiation is negatively impacted and thus reducing PV power; therefore, to deal with haze weather, Air Quality Index (AQI) is introduced as a parameter to predict PV power. AQI, which is an indication of how polluted the air is, has been known to have a strong correlation with power generated by the PV panels. In this paper, a hybrid method based on the model of conventional back propagation (BP) neural network for clear weather and BP AQI model for haze weather is used to forecast PV power with conventional parameters like temperature, wind speed, humidity, solar radiation, and an extra parameter of AQI as input. The results show that the proposed method has less error under haze condition as compared to conventional model of neural network.

1. Introduction

The solar energy is known as an ideal source of renewable energy power generation. Photovoltaic (PV) power generation is the main application pattern of solar energy, but the output of photovoltaic power station has high unpredictability, variation, and intermittent nature [1, 2]. Forecasting and energy scheduling are significant to ensure bulk power system reliability and dependable operations. PV forecasts can be integrated into daily demand schedules and used for real-time energy trading. PV power forecasting depends on solar radiation and other factors like humidity, wind speed, and temperature. Since, solar radiation at one location on the earth's surface indicates periodicity and nonstationary characteristic due to the effect of the earth's rotation and revolution. Output power data of photovoltaic power station indicates periodicity in one day. In other words, output power presents the growing trend before the noon, and presents the falling trend after the noon. If effective procedure is not adopted to reduce nonstationary characteristic of PV output power, conventional power forecast technique will not guarantee precision of forecasting results and algorithm convergence [3].

Several techniques, such as satellite cloud [4], numerical weather predictions (NWP) [5], have been adopted in PV output forecasting. The errors of short-term (one day, or 2 days) PV power output forecasting are in the range of 10 to 30%. But in the morning, foggy or under rainy weather, the forecasting accuracy is lower and sometimes the relative mean square error (RMSE) can be more than 40%. Data mining method deals with a lot of data, and if there is an error in predicting weather, the algorithm will not provide good results [6, 7]. Grey-Markov forecast model has good prediction, but it has inherent defect of not dealing with random and nonlinear data [8, 9]. Support vector machine (SVM) algorithm which is used for classification was applied also to predict solar power during four weather states which are classified as rainy, cloudy, sunny, and foggy days; the results were good only for the four states and could not deal with the other states of weather [10].

Another well-known method for PV forecasting is the artificial neural network (ANN) method [11]. The field of

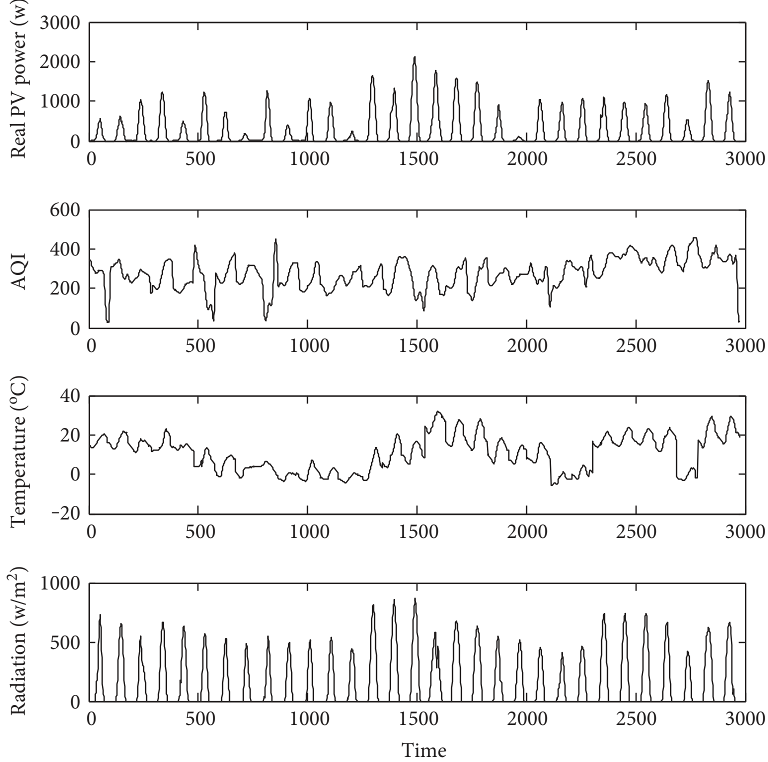

Figure 1: PV power and other meteorological parameters during haze weather.

Table 1: Pearson correlation between PV power and meteorological parameters under different AQI level.

AQI level	AQI	Radiation	Temperature	Humidity	Wind speed
0–100	−0.15001	0.916376	0.398646	−0.36733	0.223341
100–200	−0.2279	0.914026	0.367856	−0.35487	0.253726
200–450	−0.2667	0.886601	0.302601	−0.332359	0.171378

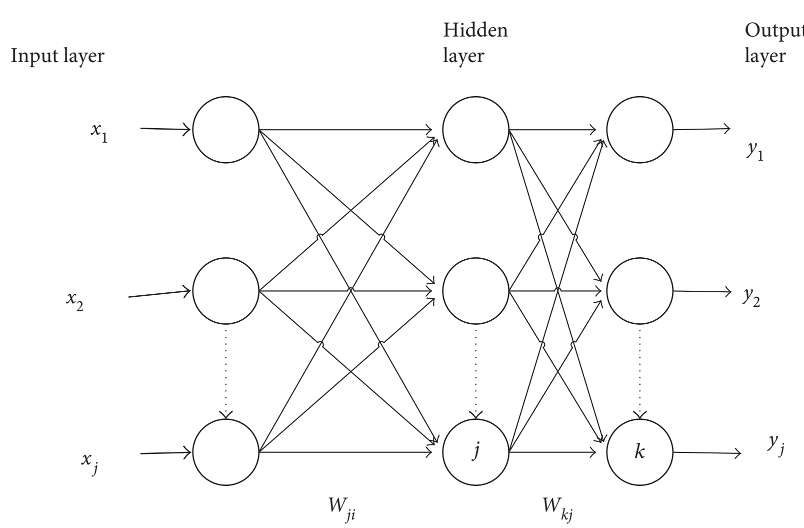

Figure 2: Structure of BP network.

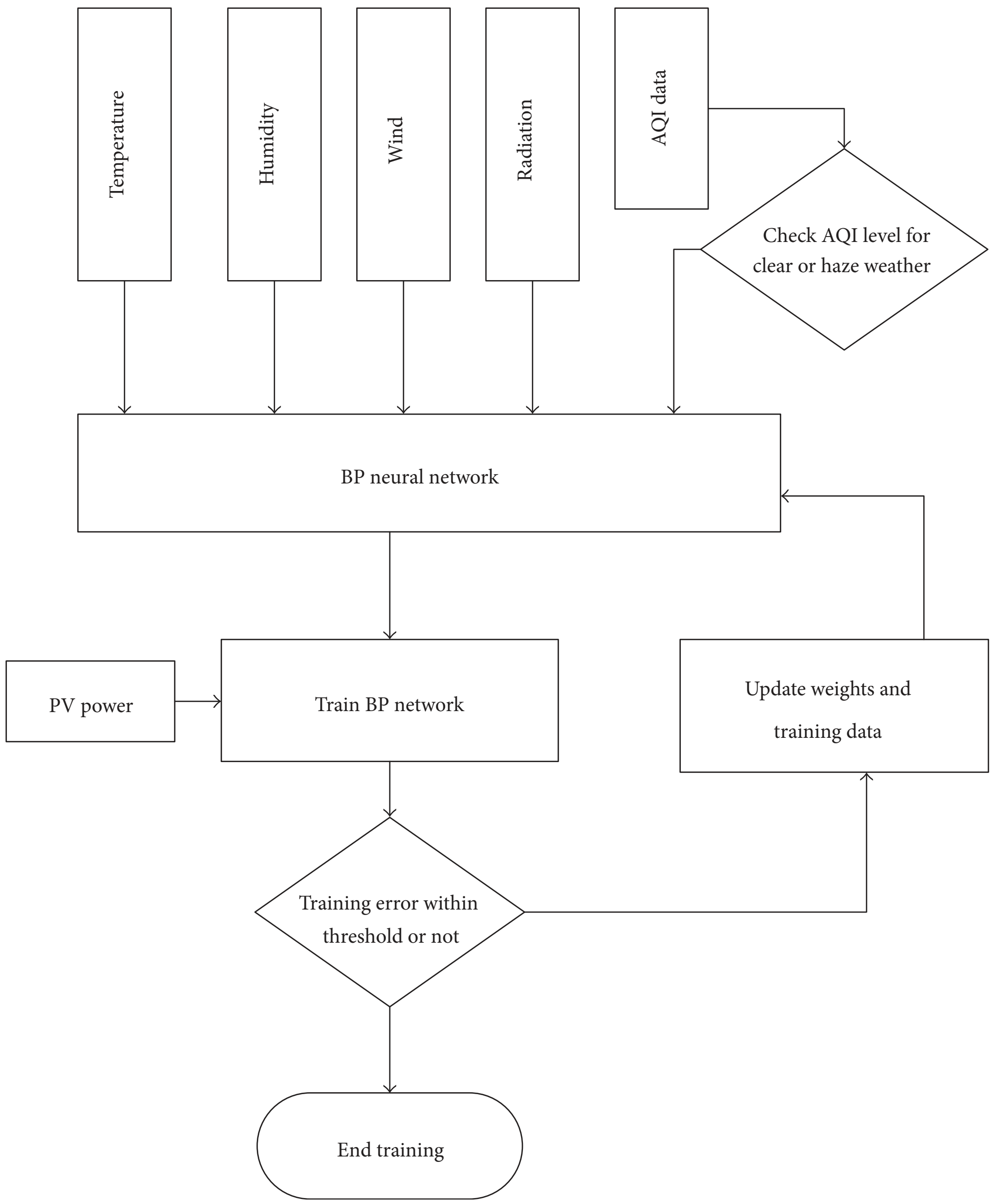

Figure 3: Training network with historic input data.

neural networks has a history of some five decades but has established solid application only in the past fifteen years, and the field is still developing quickly. Neural networks can be trained to solve problems that are difficult for conventional computers or human beings. One of the ANN-related methods, back propagation (BP) neural network, has been more commonly used because of its best nonlinear mapping function, especially appropriate for solving difficult regression problems [12]. Back propagation is a particular method for implementing gradient descent in weight space for a multilayer perceptron. Well-trained back propagation networks tend to deliver reasonable answers when provided with inputs that they have never seen. Some of the advantages of BP neural network are to tackle simulation of nonlinear systems and handle large amount of input data, learning the complex problem well enough. But on the other side, there are some drawbacks of BP network. Execution time is large which can slow down the learning rate using this approach. Sometimes, BP network technique falls in local minimum due to gradient descent technique. Existence of local minimum condition does not guarantee an approximation so there are many situations in which it will oscillate forever [13, 14].

This paper predicts PV power during haze and clear weather. A hybrid forecasting method based on conventional BP network for clear weather and AQI model for haze weather is proposed to forecast PV power. If the average value of AQI for one day exceeds threshold value (in this paper, the threshold value for AQI is 150) then BP AQI model is proposed to predict PV power. If AQI value is less

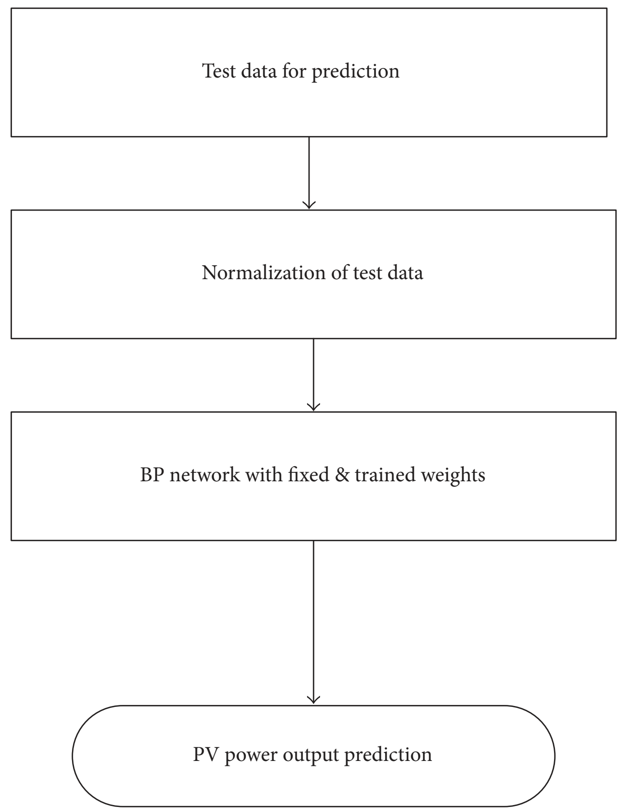

Figure 4: Prediction of PV power by trained network.

than the threshold value, then conventional BP neural network with no AQI is proposed. The output of PV power is not only effected by radiation, wind, temperature, and humidity but also to some extent on Air Quality Index which has not been taken as meteorological parameter to forecast PV power in urban areas.

This paper explains nonlinear features of the output power of photovoltaic power stations by studying the output characteristics of photovoltaic power stations with temperature, humidity, wind speed, AQI, and solar radiation. This paper adopts historical data to train BP feed-forward neural network and combines theoretical weather prediction information to forecast the output power of photovoltaic power station. The results show that the photovoltaic power prediction method based on the calculation of average AQI for 24 hours and BP network has good forecasting precision.

2. Effect of Haze and Other Factors on PV Power

2.1. Effect of Meteorological Parameters on PV Power. The output of photovoltaic power station is not just directly affected by solar radiation but other meteorological parameters (such as temperature, humidity, wind direction, wind speed, AQI, and cloud) will also lead to variations of photovoltaic power. It is known from Figure 1 that output power curve is affected by earth rotation with a period of 24 hours; the output is 0 at night and rises in the afternoon and then declines. Affected by meteorological factors, output power of photovoltaic power station shows different features every day. However, it is known from Figure 1 that since the output of photovoltaic power station is directly affected by solar radiation received by the ground and meanwhile air temperature, humidity, AQI, and other meteorological parameters impose indirect effect on the output of photovoltaic module; the output of the photovoltaic power station has random variations and intermittency.

2.2. Effect of Haze on Output of PV Plant. To study the effect of haze on PV power, AQI is introduced. "AQI" may be defined as a single number for reporting the air quality with respect to its effects on the human health. In most elaborate form, it combines many pollutant concentrations in some mathematical expression to arrive at a single number for air quality. Particulate concentrations of Beijing city have reached to high level due to rapid urbanization and neighboring coal-based factories in Hebei province [15]. Therefore, the level of AQI of Beijing sometime reaches to 500 (which indicates hazardous situation). Sunlight is reflected back by these pollution particles, and hence attenuation of radiation occurs when AQI is high. This paper explains the effect of AQI on PV power and the forecasting precision of PV power by combining meteorological parameters using an artificial neural network.

This paper introduces correlation coefficient to discuss the correlation among photovoltaic power, meteorological

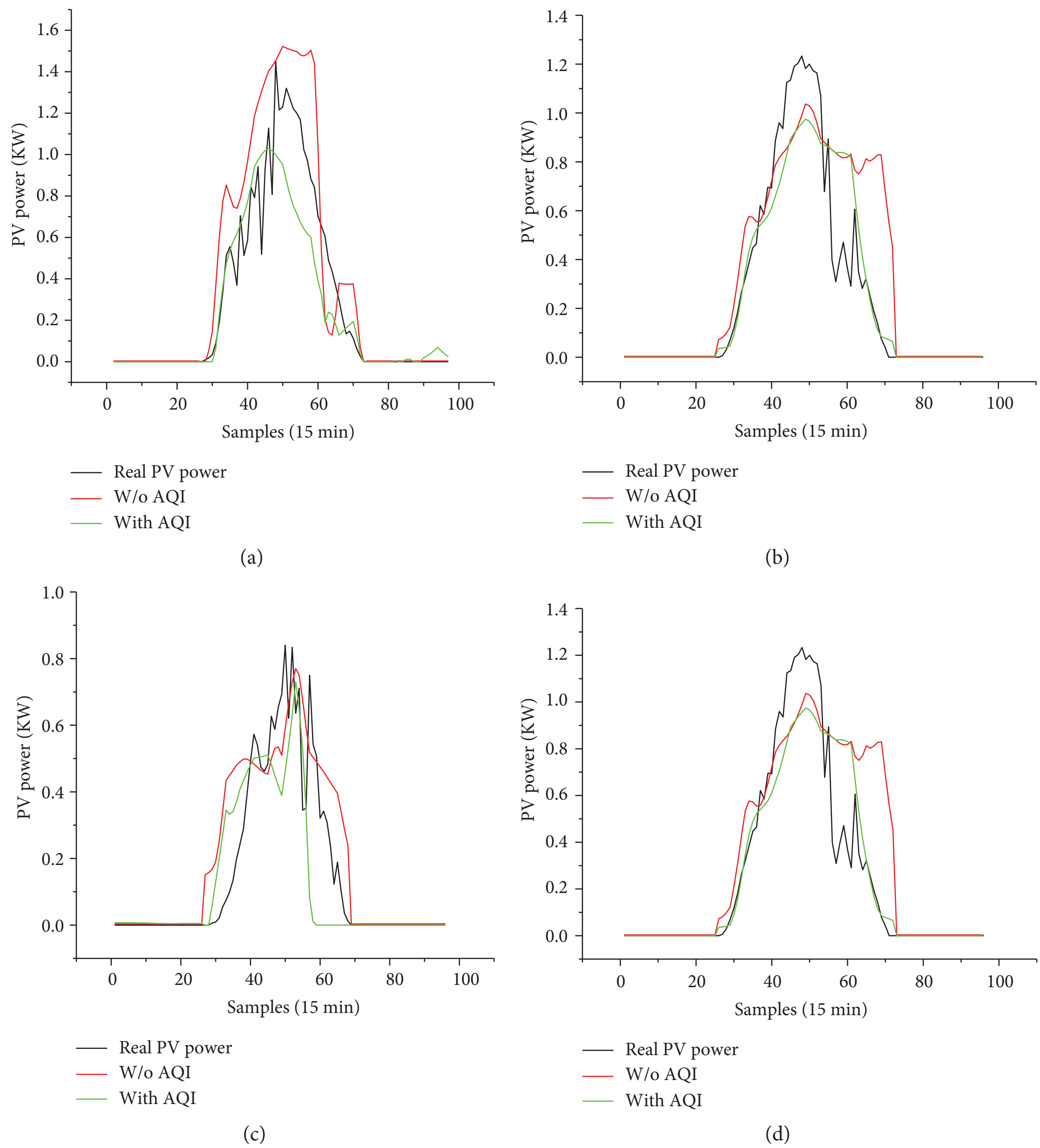

Figure 5: Haze weather forecasts ((a) day 1, (b) day 2, (c) day 3, and (d) day 4).

Table 2: Errors in KW during haze weather.

Time	MAE w/o AQI	MAE with AQI	RMSE w/o AQI	RMSE with AQI
Day 1	0.14044854 KW	0.096534 KW	0.232316302 KW	0.176328656 KW
Day 2	0.13411647 KW	0.077101 KW	0.236197228 KW	0.15172456 KW
Day 3	0.07473093 KW	0.073215 KW	0.128569197 KW	0.121601796 KW
Day 4	0.11309781 KW	0.067048 KW	0.233118235 KW	0.143950562 KW

parameters, and AQI. Correlation coefficient is an important indicator indicating linear correlation of different parameters. This paper just carries out simple correlation analysis. Pearson correlation coefficient is used to describe the relationship degree and trend of the two parameters. The formula is

$$r = \frac{\text{cov}(X, Y)}{\sqrt{\text{cov}(X, x)}\sqrt{\text{cov}(Y, Y)}}, \quad (1)$$

where correlation coefficient $r > 0$ shows that the two parameters have correlation and both parameters are directly proportional to each other, where $r < 0$ means that the two parameters are inversely related. Where r tends to be 1, the two have a close relationship; $r = 0$ means that the two are not related to each other.

One year data of PV power and other meteorological parameters has been analyzed to obtain the relationship between PV power and meteorological parameters under different AQI levels by using Pearson correlation coefficient as shown in Table 1. Pearson coefficient is widely used to find a linear connection between the two parameters. Pearson coefficient of AQI and PV power has a minus value as shown in Table 1 which means a larger AQI value will produce less PV power.

3. BP Network

3.1. Fundamentals of BP Network. Learning algorithm which is frequently used is called back propagation (BP). A BP network learns from the data and target data, which means that we have to provide two types of data that comprise of some input examples and the known precise output for each example [16]. The kind of behavior which we expect from the network is totally dependent on these input-output combinations, and the network is allowed to adapt by BP algorithm. The BP learning procedure is performed in iterations and produces the output on the current state of weights. The output of the network is calculated, compared with the known output of the training set, and error signal (mean squared error) is computed. The error signal is passed backwards to the network to bring some changes in the weights of each layer. The weight changes are computed to reduce the error, and the procedure is repeated for each set of input-output and then back to the first input-output set. The cycle is repeated to reduce the error below or equal to some threshold value. When the error reaches to threshold value, we say that the network has learned "well enough."

The back propagation learning algorithm can be divided into two phases: propagation and weight update. Propagation stage involves forward propagation of a training set and backward propagation of error to output layer and hidden layer. Weight update stage comprises to update weights in the negative gradient direction. A training set $\{(x_1, t_1), \ldots, (x_n, t_n)\}$ consisting of n-ordered pairs, pattern x_i from the training set is presented to BP network; it creates an output y_i different from the target t_i. The network makes y_i and t_i identical for $i = 1, \ldots, p$, by using a learning algorithm. More precisely, we want to minimize the error function of the network, defined as

$$E = \frac{1}{2}\sum_{i=1}^{i=p} \|t_i - y_i\|^2. \quad (2)$$

The weights in the network are the only factors that can be changed to make the quadratic error E as small as possible.

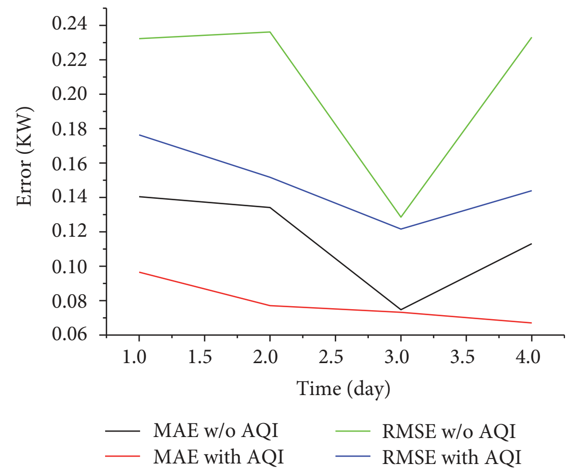

FIGURE 6: Errors during haze weather.

Because E is computed by the long network through composition of the node functions, it is a continuous and differentiable function of the weights $w_1, w_2, \ldots, w_l$ in the network. We can thus lessen E by using an iterative process of gradient descent, for which we need to calculate the gradient

$$\nabla E = \left(\frac{\partial E}{\partial w1}, \frac{\partial E}{\partial w2}, \ldots, \frac{\partial E}{\partial wl}\right). \quad (3)$$

Weights are updated with a learning rate (which is a proportionality factor that defines the step size of each iteration) that is introduced. With the introduction of this factor, the entire learning problem now depends on calculating the gradient of the network function with respect to its weights. The change in weight Δw_i, which is added to the old weight, is equal to the product of the learning rate "α" and the gradient, multiplied by -1.

$$\begin{aligned}\Delta w_i &= -\alpha\frac{\partial E}{\partial w_i},\\ w_i &= w_i - \alpha\frac{\partial E}{\partial w_i}.\end{aligned} \quad (4)$$

The gradient can adjust the network weights iteratively. By updating the weights in this manner, a point of minimum of the error function is reached, where $\nabla E = 0$.

Input of each layer is multiplied by a different weight value. The weighted inputs are summed and broadcasted to all neurons in the next layer to solve a problem as shown in Figure 2.

3.2. Hybrid Forecasting Method. The BP network algorithm is divided into two steps. First is to train BP network with training input data of wind speed, humidity, temperature, and PV power and AQI (for haze weather) or no AQI (for clear weather) data to train the network as shown in Figure 3, and then the network is used to predict PV power for four-day test data ahead as shown in Figure 4. Normalization of each input (A) is given by (5) with $B_{\max}$ and $B_{\min}\{1, -1\}$.

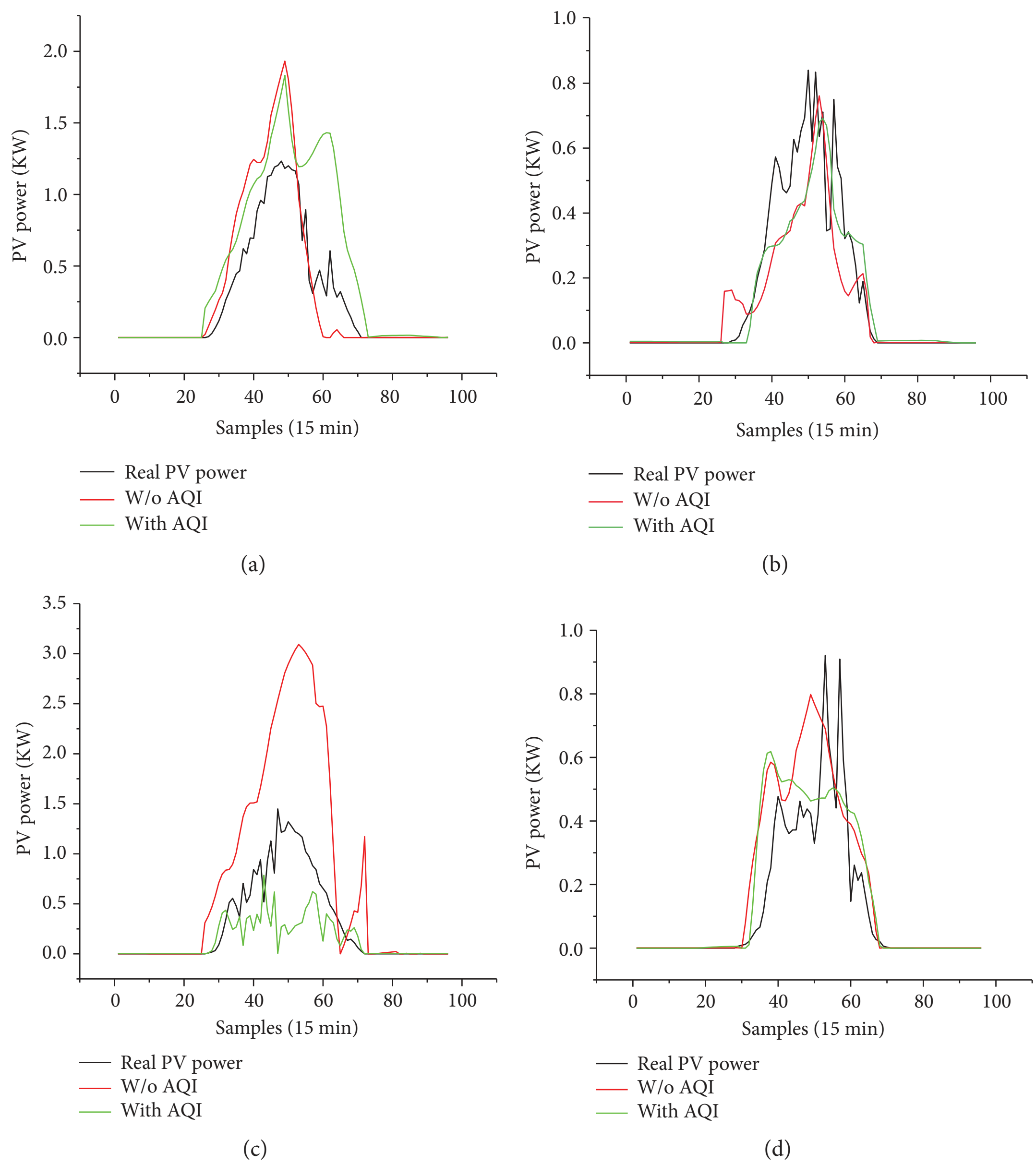

FIGURE 7: (a) Day 1, (b) day 2, (c) day 3, and (d) day 4.

$$B = \frac{(B_{\max} - B_{\min})(A - A_{\min})}{(A_{\max} - A_{\min}) + B_{\min}}. \quad (5)$$

4. Simulation Results

Simulations are carried out by Matlab to implement forecasting process of BP network. The data are from photovoltaic Power Station of the State Key Laboratory of Electrical Power System with Renewable Energy Sources in North China Electric Power University (NCEPU) in Changping District, Beijing, with installed capacity of 3 KW and sampling interval of 15 minutes. For example, verification four days ahead of PV power is predicted with well-trained network. Weather is classified in two categories: the first one in which AQI is high or there is haze, and the second one is when AQI is normal or the haze factor is less. In this paper, AQI model and conventional model (No AQI as input) are tested on both weather conditions. The prediction results are evaluated through root mean square error (RMSE) and mean absolute error (MAE).

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (P_{Mi} - P_{Pi})^2}{n}}, \qquad \text{MAE} = \frac{\sum_{i=1}^{n} |P_{Mi} - P_{Pi}|}{n}, \quad (6)$$

where P_{Mi} is real power at i time, P_{Pi} is predicted power at i time, and n is the number of samples which are taken at 15 min interval; for one day, n is 96.

Table 3: Errors in KW during clear weather.

Time	MAE w/o AQI	MAE with AQI	RMSE w/o AQI	RMSE with AQI
Day 1	0.556935472 KW	0.681523136 KW	0.801264019 KW	0.879952702 KW
Day 2	0.139607957 KW	0.213452279 KW	0.238803266 KW	0.359465769 KW
Day 3	0.06406909 KW	0.054085026 KW	0.106858401 KW	0.1024408844 KW
Day 4	0.062984087 KW	0.071846739 KW	0.129994319 KW	0.136200512 KW

Weather is classified in two categories on average AQI value. Average AQI value above 150 is called haze weather and below 150 is clear weather. In this paper, hybrid model (conventional + AQI model) is tested on clear and haze weather conditions. The proposed model is trained with AQI and without AQI. If the average AQI of the data for future prediction is more than 150 then the BP AQI model is triggered and if the AQI value for future data is less than 150 then the conventional BP model is used.

4.1. Haze Weather or High AQI Tests. When the average AQI for one day is above 150, the proposed model predicts the PV power more accurately than the conventional model. The errors calculated in predicting PV power with the AQI model are minimum. In this case, the BP AQI model has less errors as compared to the conventional BP model. Therefore, for haze weather, the BP AQI model is proposed. The performance of predicting PV power is significantly improved by the proposed model. The output of both models is shown as follows in Figure 5. Calculated errors are given at Table 2 and Figure 6.

4.2. Clear Weather Tests. During clear weather, when the average AQI is below 150, the outputs of both AQI model and conventional BP model are compared, which show that the conventional BP model has less errors as compared to the BP AQI model. Therefore, for clear weather or low AQI, the conventional BP model is proposed to predict the PV power. The results are shown in Figure 7, and calculated errors are given at Table 3 and Figure 8.

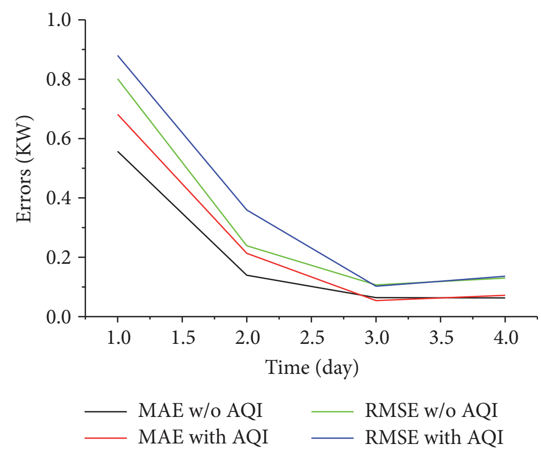

Figure 8: Errors during clear weather.

5. Discussion

From the results of Figures 5 and 7, it is evident that the proposed hybrid model can perform well especially in haze weather, while other forecasting models have less precision during haze weather. The threshold value of AQI in this paper is 150, from which above BP with AQI and below conventional BP model are used, respectively. From Tables 2 and 3, it is evident that for clear weather, the conventional BP model has less errors while for haze weather or high AQI value, BP with AQI model has less errors. The hybrid model is tested on haze weather and clear weather conditions. Results of Tables 2 and 3 verify the precision of the proposed model. The errors calculated in Table 2 for four days ahead show that the accuracy is high during haze weather, and the proposed model is appropriate for weather of Beijing where haze factor is considerable. Output of PV power is negatively impacted by AQI which has never been considered as a meteorological parameter in the previous models of forecasting of PV power.

6. Conclusions

In this paper, four days ahead PV power is predicted with well-trained hybrid model with the introduction of additional meteorological factor AQI. The model is trained with the average AQI values ranging from 0 to 400, one month data of PV power and meteorological parameters. After training, four days ahead data is then normalized and fed to the trained network to predict PV power. For the average AQI value of 150 or below the conventional BP neural network and for AQI value above 150, BP with AQI model is used to predict PV power, thus, enhancing the precision and accuracy even during haze weather and clear weather, which proves precision and practicability of this approach. Errors are calculated by MAE and RMSE to verify the forecasting errors of the proposed method. Precision of this model can offer reference basis for forecasting PV power grid generation plan.

Conflicts of Interest

The authors declare no conflict of interest.

Authors' Contributions

Idris Khan is the first author of the manuscript who performed the simulation and wrote the paper. All the authors contributed to prepare the manuscript.

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