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Research Article

Short-Term Photovoltaic Power Generation Forecasting Based on Multivariable Grey Theory Model with Parameter Optimization

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Owing to the environment, temperature, and so forth, photovoltaic power generation volume is always fluctuating and subsequently impacts power grid planning and operation seriously. Therefore, it is of great importance to make accurate prediction of the power generation of photovoltaic (PV) system in advance. In order to improve the prediction accuracy, in this paper, a novel particle swarm optimization algorithm based multivariable grey theory model is proposed for short-term photovoltaic power generation volume forecasting. It is highlighted that, by integrating particle swarm optimization algorithm, the prediction accuracy of grey theory model is expected to be highly improved. In addition, large amounts of real data from two separate power stations in China are being employed for model verification. The experimental results indicate that, compared with the conventional grey model, the mean relative error in the proposed model has been reduced from 7.14% to 3.53%. The real practice demonstrates that the proposed optimization model outperforms the conventional grey model from both theoretical and practical perspectives.

1. Introduction

With population growth, economic development, and nuclear confidence crisis, many countries are changing the energy structure and promoting the rapid development of renewable energy. Among them, the solar energy is being largely involved due to its highest sustainable development capability. However, photovoltaic power generation suffers from apparent intermittence and volatility resulting from illumination intensity, temperature, and so forth, which would cause alteration of both steady and transient characteristics of the power system when merged with current power grid. In this sense, the grid system planning, operation, and economic analysis will be largely impacted. As such, it is of great help to make accurate power output prediction of photovoltaic power station with the aim of coordination of conventional power and photovoltaic power, timely scheduling adjustment and proper power grid operation mode arrangement in advance. With the aid of prediction, on the one hand, the adverse effects of merging with photovoltaic power will be reduced, and the operational security and reliability of power system will be increased. On the other hand, by involving solar energy resource, the spinning reserve capacity and running cost of power system will be reduced as well as greater economic and social benefits being achieved.

Currently, a number of models are being applied for photovoltaic power generation prediction. In terms of prediction theory and methodology, they can be classified into three categories: neural network based model (NN) [1–4], time series model [5–7], and time trend extrapolation model [8]. Among these models, NN benefits from high prediction accuracy; however, it suffers from complex modeling together with high requirements of data samples, complicated training of models, and high cost. Time series model has less computational load; however, its prediction accuracy is not acceptable [5]. Markov model poses high requirement for classification scope, which is largely experience dependent. Generally speaking, the wider the scope, the simpler the model and, hence, the less accurate the prediction result, and vice versa [8].

Grey model (GM) is being widely used in data prediction due to lots of advantages. The main ones are that only few samples are needed and consideration of their distribution and variation trend is not necessary. In addition, the model benefits from low computational complexity, high accuracy of short-term prediction, easy checking, and so forth [9–15]. He and Li [10] proposed an enhanced residual error modifying GM$(1,1)$ model for power generation prediction for 5.6 kW photovoltaic system. However, the factor that the variation of daily power generation greatly depends on the system itself, external environment, and so forth was not considered in this model. Towards this issue, Zhong et al. [15] derived a GM$(1,N)$ model and obtained a good prediction result. It is reasonable to apply grey theory into photovoltaic prediction, in terms of the feature of grey theory and photovoltaic system. However, the existing model is not adapted to the photovoltaic system in this paper because of the difference of limited condition and photovoltaic data we have obtained. Therefore, how to improve the grey theory and make it applicable to the actual situation in this paper and perform better in prediction is the focus of this paper. In the further study, it is found that generation of background value in grey theory is of great importance in data prediction. Following up, Zhuang [16] verified that the prediction failed in the case of using GM$(1,1)$ model with $\theta = 0.5$ in background value formula if power generation fluctuated dramatically. Lin et al. [14] regenerated a novel background value formula and proposed an optimized multivariable grey model based on the formula. It is demonstrated that the proposed model performed well in road displacement prediction.

In this paper, an integrated particle swarm optimization and multivariable grey theory model is applied for ground value formula. It is expected that, by using this method, the prediction accuracy will be largely improved. Further, to verify the feasibility of the proposed model, large amounts of real data from two separate power stations are employed for verification. The experimental results demonstrate the full functionality of the proposed mathematical tool.

This paper is structured as follows. Section 2 discusses the fundamental principle of multivariable grey theory model as well as key issues of current model for forecasting. Section 3 describes the general forecasting procedure of using the proposed optimization model. The real data from power station and their prediction results by using both the proposed model and the old model are discussed in Section 4. In Section 5, conclusions are drawn.

2. The Multivariable Grey Theory Model with Parameter Optimization

2.1. Overview of Multivariable Grey Theory Model. The fundamental principle of multivariable grey theory is described as follows.

2.1.1. Accumulative Sequence Generation. Suppose $x_i^{(0)} = (x_i^{(0)}(1), x_i^{(0)}(2), x_i^{(0)}(3), \ldots, x_i^{(0)}(n))$, for $i = 1, 2, \ldots, N$, is the sample sequence, where $x_1^{(0)}$ is predicting sequence and $x_2^{(0)} \cdots x_N^{(0)}$ are correlative sequences. After the Accumulated Generation Operation (AGO), the sequence is expressed as

$$x_i^{(1)} = \left(x_i^{(1)}(1), x_i^{(1)}(2), x_i^{(1)}(3), \ldots, x_i^{(1)}(n)\right), \quad \text{for } i = 1, 2, \ldots, N, \tag{1}$$

where

$$x_i^{(1)}(k) = \sum_{m=1}^{k} x_i^{(0)}(m), \quad \text{for } k = 1, 2, \ldots, n. \tag{2}$$

2.1.2. Equation Establishment. The Albino equation of GM$(1, N)$ model is shown as follows:

$$\frac{dx_1^{(1)}}{dt} + a x_1^{(1)} = \sum_{i=2}^{N} b_i x_i^{(1)}, \tag{3}$$

where a is a parameter.

The differential equation of GM$(1,N)$ is given by

$$x_1^{(0)}(k) + a z_1^{(1)}(k) = \sum_{i=2}^{N} b_i x_i^{(1)}(k), \tag{4}$$

where $z_1^{(1)}(k)$ is the background value, which is generated from $x_1^{(1)}(k)$:

$$z_1^{(1)}(k) = \theta x_1^{(1)}(k-1) + (1-\theta) x_1^{(1)}(k). \tag{5}$$

2.1.3. Parameter a Derivation. By using the Least Square (LS) algorithm, the parameters a in (4) can be obtained as

$$\alpha = \begin{bmatrix} a & b_1 & b_2 & \cdots & b_N \end{bmatrix}^T = \left(B^T B\right)^{-1} B^T Y, \tag{6}$$

where

$$B = \begin{bmatrix} -z_1^{(1)}(2) & -x_2^{(1)}(2) & \cdots & -x_N^{(1)}(2) \\ \vdots & \vdots & \ddots & \vdots \\ -z_1^{(1)}(n) & -x_2^{(1)}(n) & \cdots & -x_N^{(1)}(n) \end{bmatrix},$$
$$Y = \begin{bmatrix} x_1^{(0)}(2) & x_1^{(0)}(3) & \cdots & x_1^{(0)}(n) \end{bmatrix}^T. \tag{7}$$

2.1.4. Prediction Formula Generation. The approximate time response of GM$(1,N)$ model is given by

$$\widehat{x}_1^{(1)}(k) = \left(x_1^{(1)}(0) - \frac{1}{a}\sum_{i=2}^{n} b_i x_i^{(1)}(k)\right) e^{-a(k-1)} + \frac{1}{a}\sum_{i=2}^{n} b_i x_i^{(1)}(k) \quad \text{for } k = 0, 1, 2, \ldots. \tag{8}$$

The original data sequence can be retrieved by Inverse Accumulated Generation Operation (IAGO) when $x_1^{(1)}(0) = x_1^{(0)}(1)$:

$$\widehat{x}_1^{(0)}(k) = \widehat{x}_1^{(1)}(k) - \widehat{x}_1^{(1)}(k-1) \quad (k = 1, 2, 3, \ldots). \tag{9}$$

2.2. Problems of Multivariable Grey Theory Model. Assuming the existing data sequence is denoted as $x_1^{(1)}(k)$, $k = 1, 2, \ldots, n$, then, according to multivariable grey theory mentioned above, the background value of $x_1^{(1)}(k)$ can be obtained by average operation between neighboring data:

$$z_1^{(1)}(k) = 0.5x_1^{(1)}(k-1) + 0.5x_1^{(1)}(k), \quad (10)$$

where $x_1^{(1)}(k-1)$ is the last information and $x_1^{(1)}(k)$ is the latest information.

The coefficients of $x_1^{(1)}$ are the weights on old and new information. Note that the sum of the two coefficients will always be zero; the larger the value of one side is, the more important it is and the smaller the value of the other side is, and vice versa. It can be seen from (10) that $z_1^{(1)}(k)$ is generated under the condition of equal weight between old and new information. Generally speaking, with the lack of the old and new information's reliability, it is more likely to choose equal weights. However, accurate prediction can hardly be expected in this case [8]. From GM(1, 1), the parameter θ in background value can be derived:

$$\theta = \frac{1}{a} + \frac{1}{1-e^{a}}. \quad (11)$$

It can be seen that the limit of θ is 0.5 when a is approaching zero, while it deviates by 0.5 when the absolute value of a is large. Bringing (8) to (9), we can obtain

$$\begin{aligned} \hat{x}_1^{(0)}(k+1) &= be^{-ak} - ce^{-a(k-1)} \\ &\quad + \frac{1}{a}\sum_{i=2}^{n} b_i\left(x_i^{(1)}(k+1) - x_i^{(1)}(k)\right), \end{aligned} \quad (12)$$

where $b = x_1^{(1)}(0) - (1/a)\sum_{i=2}^{n} b_i x_i^{(1)}(k+1)$, $c = x_1^{(1)}(0) - (1/a)\sum_{i=2}^{n} b_i x_i^{(1)}(k)$; when bringing (12) and (5) into (4), we can get

$$\theta = \frac{1}{a} + \frac{be^{-ak}}{x_1^{(0)}(k+1)}. \quad (13)$$

According to (8),

$$\frac{1}{a}\sum_{i=2}^{n} b_i x_i^{(1)}(k+1) = \frac{\hat{x}_1^{(1)}(k+1) - x_1^{(1)}(0)\,e^{-ak}}{1-e^{-ak}}. \quad (14)$$

Then, bringing (14) into (13), the following equation is made:

$$\theta = \frac{1}{a} + \frac{\left(x_1^{(1)}(0) - x_1^{(1)}(k+1)\right)e^{-ak}}{x_1^{(0)}(k+1)\left(1-e^{-ak}\right)}. \quad (15)$$

It is well understood that both k and $(x_1^{(1)}(0) - x_1^{(1)}(k+1))/x_1^{(0)}(k+1)$ are constants when the sample sequence is determined. In addition, we can tell that parameter a in (4) is parameter θ dependent in (3).

By integrating (1) in the interval of $(k-1, k)$, we can obtain

$$\int_{k-1}^{k} \frac{dx_1^{(1)}}{dt}dt + \int_{k-1}^{k} ax_1^{(1)}dt = \int_{k-1}^{k} \sum_{i=2}^{N} b_i x_i^{(1)}dt. \quad (16)$$

Since the term $\sum_{i=2}^{N} b_i x_i^{(1)}(k)$ at the right side of (16) can be served as the grey constants, (16) can be rewritten as

$$x_1^{(1)}(k) - x_1^{(1)}(k-1) + a\int_{k-1}^{k} x_1^{(1)}dt = \sum_{i=2}^{N} b_i x_i^{(1)}, \quad (17)$$

$$x_1^{(0)}(k) + a\int_{k-1}^{k} x_1^{(1)}dt = \sum_{i=2}^{N} b_i x_i^{(1)}. \quad (18)$$

Combining (18) and (2), we can obtain

$$z_1^{(1)}(k) = \int_{k-1}^{k} x_1^{(1)}dt. \quad (19)$$

So, the real background value equals the integration of $x_1^{(1)}$ in the interval of $(k-1, k)$, derived from (19). And the background value in the simple model was generated from the neighboring average. We should not just let θ be equal to 0.5, which is the huge limitation in the simple multivariable grey theory model. At the same time, since $x_1^{(1)}$ is an ascending sequence, the value of θ is always between 0 and 1.

It is observed that when the time gap is small and data sequence keeps flat, conventional multivariable grey theory model is feasible to some extent. However, when the data changes fast and dramatically, this model may cause a large error [12]. In this paper, a kind of particle swarm algorithm was used for background value optimization. It is expected that, via this way, the better recovered results can be obtained and less error can be made.

2.3. The Particle Swarm Optimization. Particle swarm optimization (PSO) was first proposed by Kennedy and Eberhart in 1995 [17]. It is a kind of swarm intelligence algorithm and is being widely used in various disciplines as well as engineering area due to its simple structure, fast convergence, and robustness [18, 19]. The algorithm is described as follows.

Suppose there are m particles in D-dimensional space; first, randomly select the initial velocity $V_i = (V_{i1}, V_{i2}, \ldots, V_{iD})$ and position $X_i = (X_{i1}, X_{i2}, \ldots, X_{iD})$ of each particle. Then, update these two parameters by iteration that involves local extreme value $Pbest = (Pbest1, Pbest2, \ldots, PbestD)$ and global extreme value $Gbest = (Gbest1, Gbest2, \ldots, GbestD)$. Finally, the velocity $V_{id}(k+1)$ and position $X_{id}(k+1)$ of the $(k+1)$th time can be given by

$$\begin{aligned} V_{id}(k+1) &= wV_{id}(k) + c_1 r_1 \left(Pbestd - X_{id}(k)\right) \\ &\quad + c_2 r_2 \left(Gbestd - X_{id}(k)\right) \\ X_{id}(k+1) &= V_{id}(k+1) + X_{id}(k), \end{aligned} \quad (20)$$

where w is the inertia weight factor, c_1 and c_2 are the training coefficients, and r_1 and r_2 are random numbers between 0 and 1.

3. The Optimization Model Based Algorithm Design

There are a number of factors that impact daily photovoltaic power generation volume. They are usually classified into two categories: systematic factors and external factors. The former include efficiency of transformation between solar energy and battery and inclination of battery panel and power capacity, while the latter consist of air temperature, solar radiation intensity, weather, evaporation, and so forth. The impact of systematic factors has been considered in historic power generation already and thus can be omitted in the following prediction in this paper, while the external factors such as solar radiation intensity and air temperature are the main concerns for daily power generation volume [20, 21], which is of high priority in our modeling. Owing to the existence of historical data in our system database, in this paper, two parameters, that is, solar radiation intensity and air temperature, are being used as correlative inputs into portfolio model for prediction of daily photovoltaic power generation.

According to correlation analysis as well as fundamentals of multivariable grey model and PSO algorithm, the procedure of the proposed algorithm is described as follows:

(a) Extract all the historic power generation volume, air temperature (average for day time), and illumination intensity from archive (the data of power generation volume comes from the inverter; solar radiation intensity and air temperature come from environmental monitor).

(b) Generate sample matrix and accumulative sequence subsequently.

(c) Set parameters of PSO, including training factors, weight, lower and upper bounds of position and velocity, number of initial particles, and maximum number of iterations.

(d) Obtain the Fitness Function of PSO, which is given by deviation between fitted values and real values of the sample sequence:

$$\text{fitness} = \sum_{i=2}^{s}\left(\frac{\sum_{i=2}^{s}\left|\left(\widehat{x}_1^{(0)}(i) - x_1^{(0)}(i)\right)/x_1^{(0)}(i)\right|}{s-1} - \left|\left(\widehat{x}_1^{(0)}(i) - x_1^{(0)}(i)\right)/x_1^{(0)}(i)\right|\right)^2. \tag{21}$$

(e) Initialize the position and velocity of each particle as well as its local extreme and global extreme and then calculate the level of fitness of each particle.

(f) Update local extreme and global extreme of each particle according to its level of fitness.

(g) Iterate and update particle's position and velocity based on (12) and (13) every loop.

(h) Iteration continues until the number of iterations exceeds the max number. Then, the particle position θ can be obtained in terms of global extreme.

(i) The prediction is achieved by inputting θ to multivariable grey model.

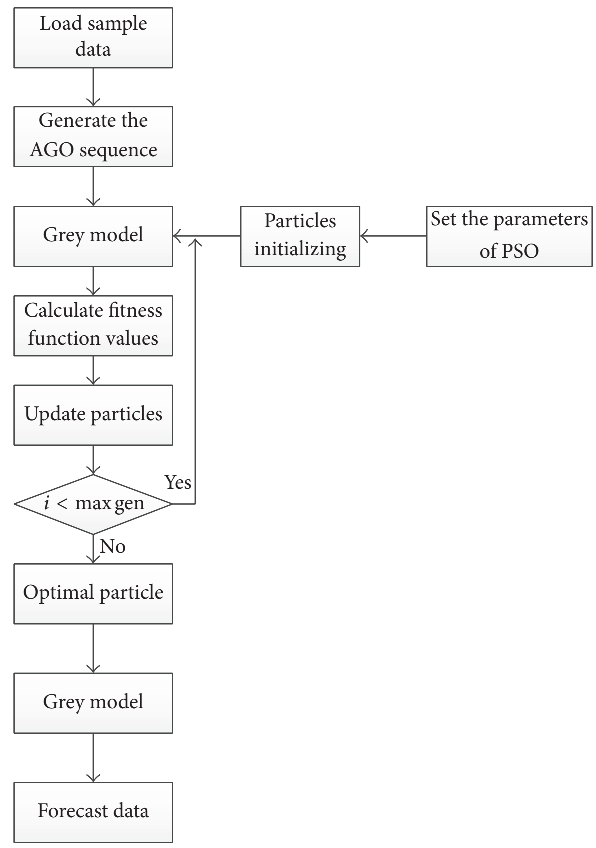

Figure 1: The flowchart of the optimization model.

The detailed flowchart of the proposed model is shown in Figure 1.

In the conventional grey theory model, θ is set to a fixed value such as 0.5. However, in the optimization model, the sample sequence is iterated through the PSO algorithm until the global optimal solution is found, and then θ is put into the multivariable grey theory for subsequent predictions. Compared with pure grey theory, the background value obtained by PSO algorithm is more reasonable and also shows a better prediction effect in actual prediction.

4. Forecasting Results and Discussions

To validate the proposed prediction model, in this paper, the real data samples from number 4 inverter (SG100KTL, made by Sungrow Power Supply Co., Ltd.) in Wuhan International Exhibition Center from July 25 to Oct. 12 were employed. The daily power generation volume forecasting was made from 8 days' datum starting from July 25. The experimental results from both the proposed model and the old model are shown in Figure 2.

Figure 2 shows the forecasting error by using the proposed model, the old model, and comparison between the two. Several conclusions can be drawn from these figures. Firstly, from Figures 2(a) and 2(b), it is observed that both models demonstrate their functionalities from variation trend perspective, especially in September. Secondly, from

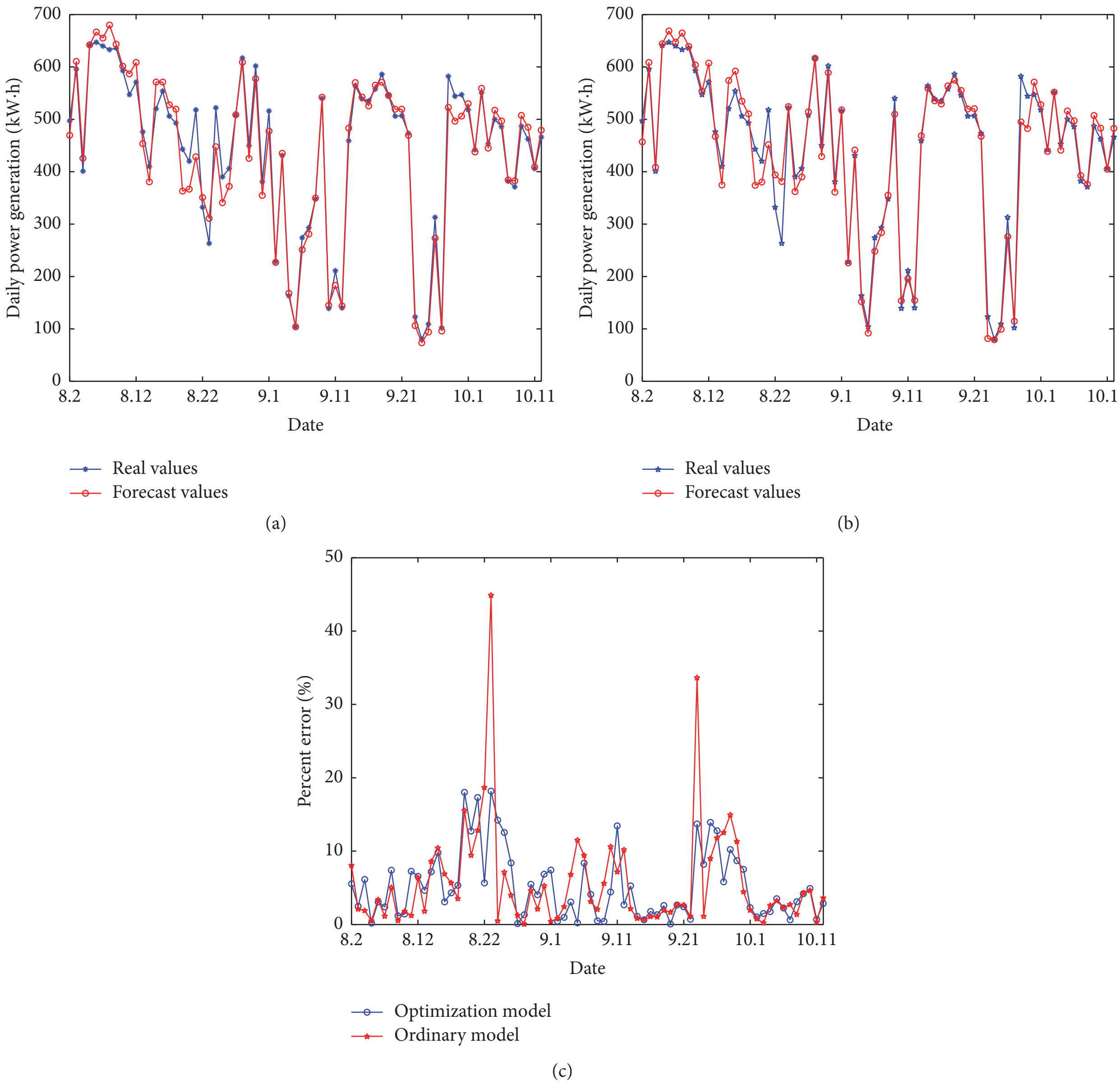

Figure 2: The forecasting results by using (a) the proposed model, (b) old model, and (c) comparison of the percent error between two models.

time series aspect, it is calculated that the Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) during Aug. 2 and Oct. 11 are 5.2352% and 28.83 (kW·h), respectively, which are far less than those of the old model. In addition, from Figure 2(c), it is easily seen from prediction errors of two single dates, that is, Aug. 23 and Sep. 23, that the proposed model yields 18.17% and 13.95% individually, while the prediction errors of the old model are 44.87% and 33.63%. The reason of the invalidity of the old model in this case is that θ is always equal to 0.5 in (5), which, however, may not fit in some harsh scenarios. The proposed model calculates the value of θ adaptively according to historic records, and thus it is able to improve the prediction accuracy. The Key Parameter Indicators (KPIs) of two weeks mentioned above are listed in Tables 1 and 2.

From Tables 1 and 2, it can be seen that the regenerating data from the proposed model is far more accurate than that from the old model in most scenarios. In few cases, however, the old model behaves better. The reason is that the proposed model took actions on the whole samples rather than every individual data, which results in that few data may not be covered by optimization model. Further, it is calculated that the Mean Absolute Percentage Errors of data recovering from Tables 1 and 2 are 5.83% and 1.14%, respectively, via the proposed model, which are much smaller than those from the old model, that is, 9.57% and 3.91%.

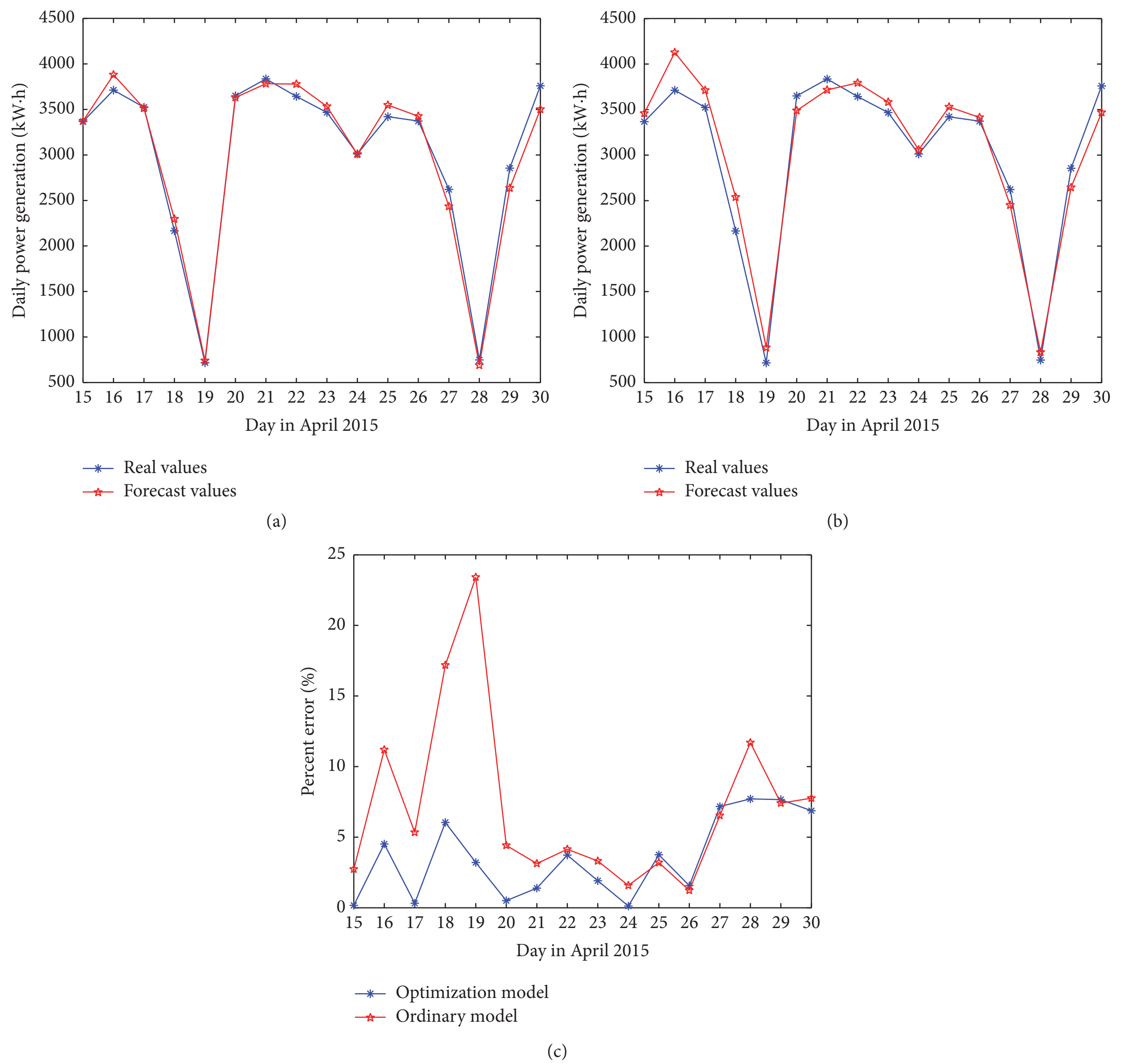

FIGURE 3: The forecast results of the optimization model (a) and ordinary model (b) and the comparison of the percent error (c) in April 2015.

TABLE 1: Analysis of forecasting results on August 23.

	Date	Real value (kW·h)	Ordinary model		Optimization model	
			Recovered value (kW·h)	Percent error (%)	Recovered value (kW·h)	Percent error (%)
Sample data	8.15	520	520	0	520	0
	8.16	554	457.99	17.33	527.63	4.76
	8.17	506	566.16	11.89	512.51	1.28
	8.18	493	527.17	6.93	508.11	3.06
	8.19	443	443.45	0.10	402.98	9.03
	8.20	420	425.27	1.25	387.56	7.72
	8.21	518	454.49	12.26	443.20	14.44
	8.22	332	389.29	17.26	330.28	0.52
Forecasting data	8.23	263	381.01	44.87	310.80	18.17

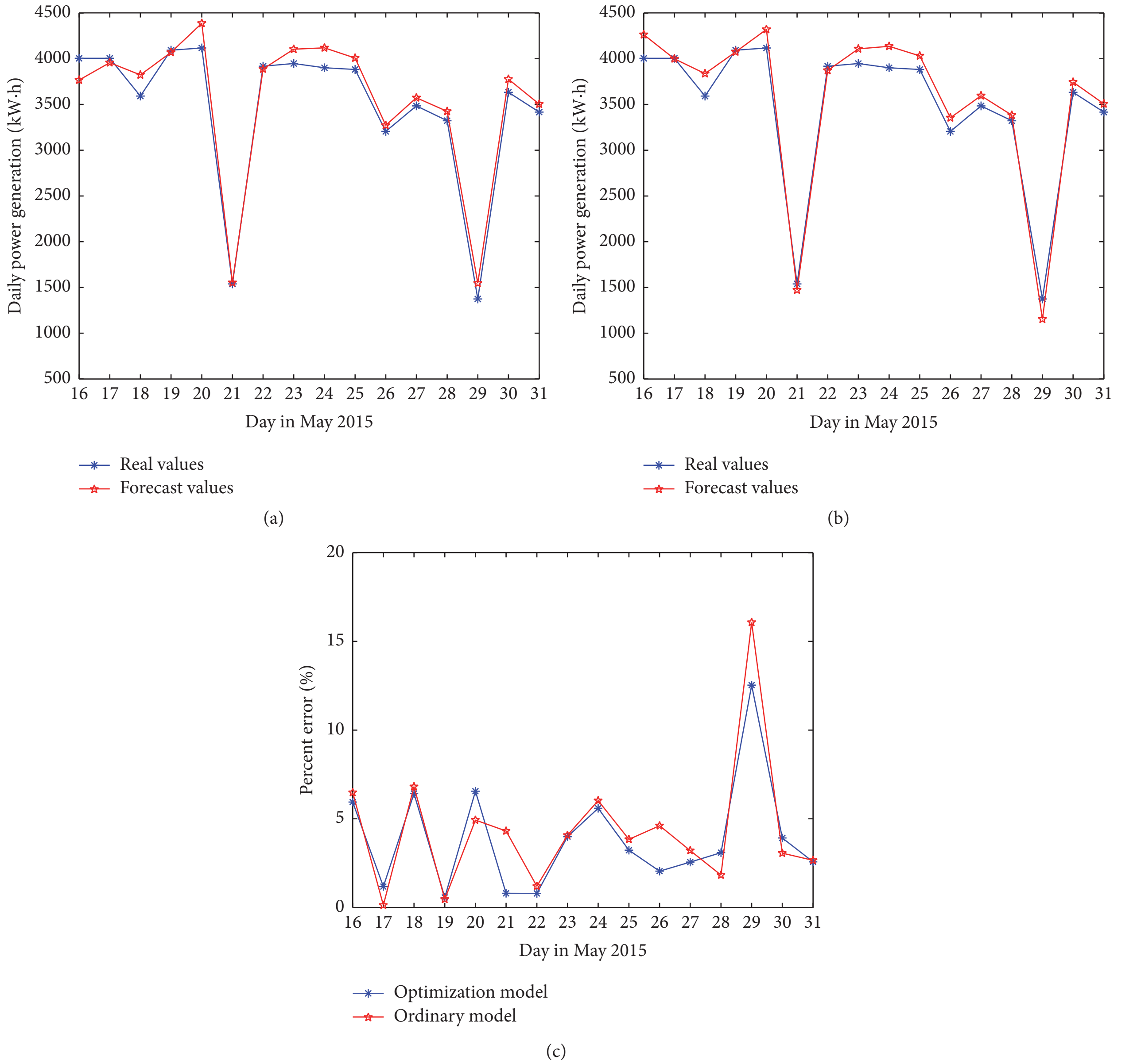

Figure 4: The forecast results of the optimization model (a) and ordinary model (b) and the comparison of the percent error (c) in May 2015.

Table 2: Analysis of forecasting results on September 23.

	Date	Real value (kW·h)	Ordinary model		Optimization model	
			Recovered value (kW·h)	Percent error (%)	Recovered value (kW·h)	Percent error (%)
Sample data	9.15	539	539	0	539	0
	9.16	535	455.31	14.89	522.15	2.40
	9.17	558	596.68	6.93	558.37	0.07
	9.18	586	594.22	1.40	583.68	0.39
	9.19	546	550.63	0.84	552.39	1.17
	9.20	506	509.53	0.70	514.81	1.74
	9.21	507	512.50	1.08	517.88	2.15
	9.22	473	465.98	1.48	472.72	0.06
Forecasting data	9.23	123	81.65	33.62	105.84	13.95

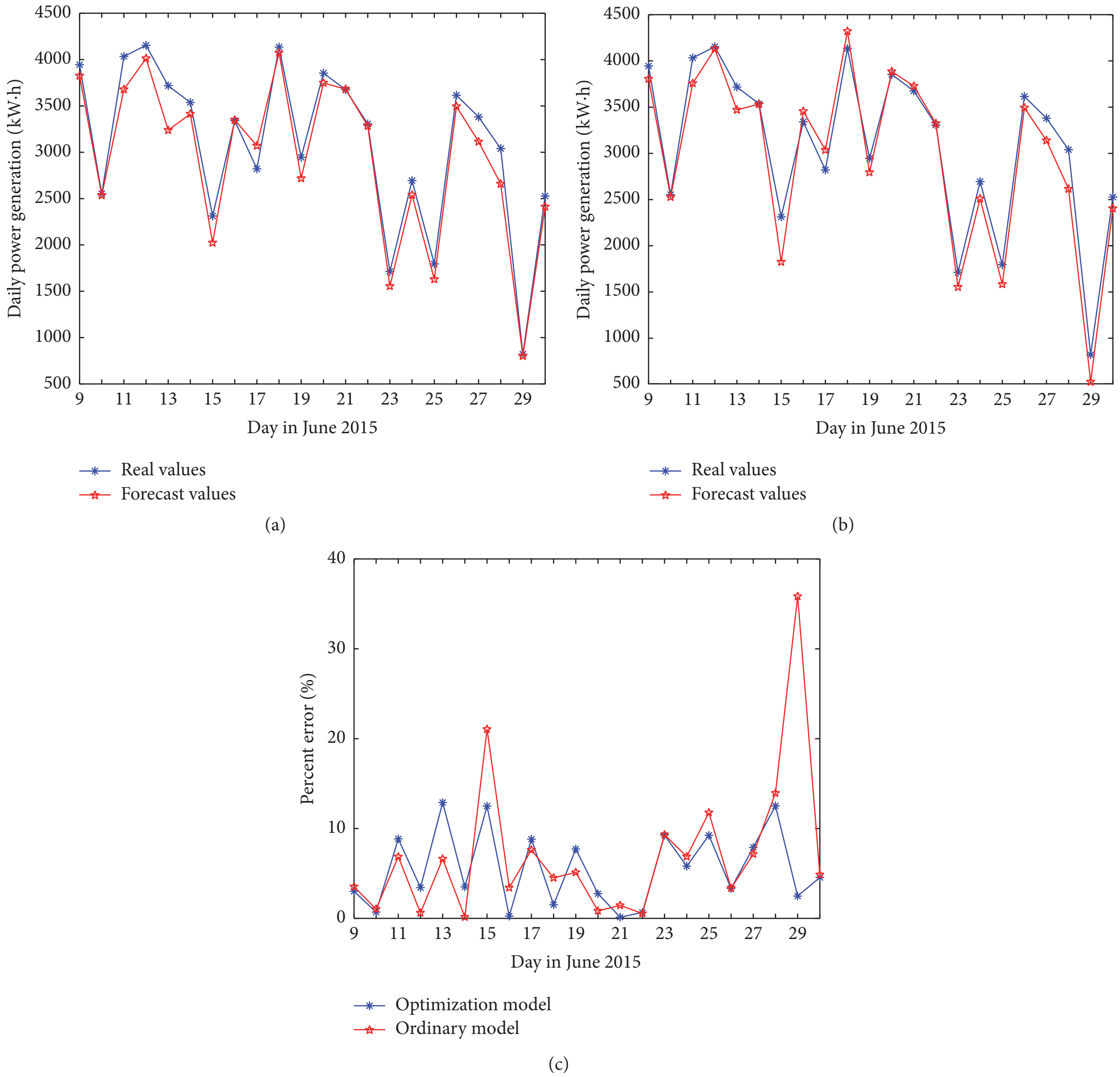

Figure 5: The forecast results of the optimization model (a) and ordinary model (b) and the comparison of the percent error (c) in June 2015.

In addition, the source data from number 117 inverter (SG630KTL, made by Sungrow Power Supply Co., Ltd.) in Bao Ya power station (located in Dezhou, Shandong province) was also employed for daily power generation volume prediction. The results are shown in Figures 3, 4, and 5.

It is unreasonable to use the proposed model for continuous long-term prediction, since the solar radiation intensity and average temperature from April 3 to 6 and from May 2 to 7 cannot be obtained from our database. As such, we divided three months into three time slots and tried to make prediction within each. For April, May, and June, we started from April 7, May 8, and June 1 individually and extracted the data samples of the following eight days to make prediction of the power generation volume of the ninth day.

It is observed from Figures 3 and 4 that when the photovoltaic power generation volume kept stable, for example, in April and May, the prediction accuracy of the old model stayed in a relatively high level. However, there were still some days when the power generation volume varies greatly; in this case, the old model was invalid and an accurate prediction can only be achieved by the proposed model. From Figure 5, it can be seen that, due to the large fluctuation of power generation in June, the prediction errors from both new and old models are larger than those in April and May. In addition, however, the maximum error of the proposed model is 14.37% and that of the conventional model is 37.32%. Thus, the prediction effect of the optimization model is much better than the original one.

Table 3: Prediction performance of the optimization and ordinary model from April to June 2015.

	April		May		June	
	Optimization model	Ordinary model	Optimization model	Ordinary model	Optimization model	Ordinary model
MRE (%)	7.71	23.41	12.53	16.07	12.89	35.84
ARE (%)	3.53	7.14	3.86	4.35	5.53	7.10
RMSE (kW·h)	123.58	200.34	148.86	155.34	206.75	210.37

Table 3 presents the power generation prediction performance during April to June 2015 from both novel model and conventional model in terms of Maximum Percent Error (MPE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE), respectively. It is obvious that the proposed model outperforms the old model from all the three perspectives. In addition, the MRE during the three months is merely 12.89%, which is highly acceptable according to practical requirements.

5. Conclusions

The experimental results and analysis indicate that though the conventional multivariable grey theory model is feasible for photovoltaic power generation, however, its error rate increases when the generation fluctuates dramatically. In this paper, the proposed PSO algorithm is applied for background value optimization and its accuracy is well verified. Thus, the proposed model can be better applied to the short-term photovoltaic power generation forecasting in the PV system. The optimization model proposed in this paper is optimized for the whole sample data, which greatly improves the prediction accuracy. However, how to effectively improve the prediction precision of each data will be the focus of further research.

Competing Interests

The authors declare that they have no competing interests.

References

[1] S. Alam, S. C. Kaushik, and S. N. Garg, "Assessment of diffuse solar energy under general sky condition using artificial neural network," *Applied Energy*, vol. 86, no. 4, pp. 554–564, 2009.

[2] B. Amrouche and X. Le Pivert, "Artificial neural network based daily local forecasting for global solar radiation," *Applied Energy*, vol. 130, pp. 333–341, 2014.

[3] A. Mellit and A. M. Pavan, "A 24-h forecast of solar irradiance using artificial neural network: application for performance prediction of a grid-connected PV plant at Trieste, Italy," *Solar Energy*, vol. 84, no. 5, pp. 807–821, 2010.

[4] A. Chaouachi, R. M. Kamel, and K. Nagasaka, "Neural network ensemble-based solar power generation short-term forecasting," *World Academy of Science, Engineering and Technology*, vol. 54, pp. 54–59, 2009.

[5] Y. Cui, Y. C. Sun, Z. L. Chang et al., "A review of short-term solar photovoltaic power generation prediction methods," *Resources Science*, vol. 35, no. 7, pp. 1474–1481, 2013.

[6] Y. Li, Y. Su, and L. J. Shu, "An ARMAX model for forecasting the power output of a grid connected photovoltaic system," *Renewable Energy*, vol. 66, pp. 78–89, 2014.

[7] G. Reikard, "Predicting solar radiation at high resolutions: a comparison of time series forecasts," *Solar Energy*, vol. 83, no. 3, pp. 342–349, 2009.

[8] Y. Li, L. He, and J. Niu, "Forecasting power generation of grid-connected solar PV system based on Markov chain," *Acta Energiae Solaris Sinica*, vol. 35, no. 4, pp. 611–616, 2014.

[9] V. Bianco, O. Manca, S. Nardini, and A. A. Minea, "Analysis and forecasting of nonresidential electricity consumption in Romania," *Applied Energy*, vol. 87, no. 11, pp. 3584–3590, 2010.

[10] L. He and Y. Z. Li, "Short-term forecasting for photovoltaic power system based on advanced residual error modified GM(1, 1) model ," *Journal of Beijing University of Civil Engineering and Architecture*, vol. 24, no. 4, pp. 61–65, 2008.

[11] J. Kang and H. Zhao, "Application of improved grey model in long-term load forecasting of power engineering," *Systems Engineering Procedia*, vol. 3, pp. 85–91, 2012.

[12] S. Bahrami, R.-A. Hooshmand, and M. Parastegari, "Short term electric load forecasting by wavelet transform and grey model improved by PSO (particle swarm optimization) algorithm," *Energy*, vol. 72, pp. 434–442, 2014.

[13] X. Liu, H. Peng, Y. Bai et al., "Tourism flows prediction based on an improved grey GM(1, 1) Model," *Social and Behavioral Sciences*, vol. 138, pp. 767–775, 2014.

[14] C.-S. Lin, F.-M. Liou, and C.-P. Huang, "Grey forecasting model for CO_2 emissions: A Taiwan Study," *Applied Energy*, vol. 88, no. 11, pp. 3816–3820, 2011.

[15] Z. F. Zhong, C. Y. Yan, T. J. Zhang, and M. Tian, "Design of photovoltaic power generation forecasting model based on multivariable grey theory," *Advanced Materials Research*, vol. 953-954, pp. 3–7, 2014.

[16] H. Y. Zhuang, "Modeling mechanism and prerequisites for GM(1, 1) and the Revised methods," *Systems Engineering-Theory Methodology Applications*, vol. 2, no. 3, pp. 56–62, 1993.

[17] J. Kennedy and R. Eberhart, "Particle swarm optimization," in *Proceedings of the IEEE International Conference on Neural Networks*, pp. 1942–1948, Perth, Australia, December 1995.

[18] R. C. Eberhart and Y. Shi, "Particle swarm optimization: developments, applications and resources," in *Proceedings of the Congress on Evolutionary Computation*, pp. 81–86, May 2001.

[19] J. H. Liu, *The Research of Basic Theory and Improvement on Particle Swarm Optimization*, Central South University, 2009.

[20] X. M. Lv, H. Zhu, and J. D. Wang, "The influence of meteorological factors on the photovoltaic daily generation," *Renewable Energy Resources*, vol. 10, no. 10, pp. 1423–1428, 2014.

[21] J. Hernandez, G. Gordillo, and W. Vallejo, "Predicting the behavior of a grid-connected photovoltaic system from measurements of solar radiation and ambient temperature," *Applied Energy*, vol. 104, pp. 527–537, 2013.