

## Research Article

# Forecasting Chinese Wind Power Installed Capacity Using a Novel Grey Model with Parameters Combination Optimization

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Received 17 June 2021; Accepted 3 August 2021; Published 17 August 2021

Academic Editor: Lifeng Wu

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The intermittent and uncertain characteristics of wind generation have brought new challenges for the hosting capacity and the integration of large-scale wind power into the power system. Consequently, reasonable forecasting wind power installed capacity (WPIC) is the most effective and applicable solution to meet this challenge. However, the single parameter optimization of the conventional grey model has some limitations in improving its modeling ability. To this end, a novel grey prediction model with parameters combination optimization is proposed in this paper. Firstly, considering the modeling mechanism and process, the order of accumulation generation of the grey prediction model is optimized by Particle Swarm Optimization (PSO) Algorithm. Secondly, as different orders of accumulation generation correspond to different parameter matrixes, the background value coefficient of the grey prediction model is optimized based on the optimal accumulation order. Finally, the novel model of combinational optimization is employed to simulate and forecast Chinese WPIC, and the comprehensive error of the novel model is only 1.34%, which is superior to the other three grey prediction models (2.82%, 1.68%, and 2.60%, respectively). The forecast shows that China's WPIC will keep growing in the next five years, and some reasonable suggestions are put forward from the standpoint of the practitioners and governments.

## 1. Introduction

With the development of China's manufacturing, the rapid growth of energy consumption has become a major bottleneck affecting China's sustainable development of the economy. As a typical representative of green and environment-friendly energy, wind power is driven by international policies and led by the global development trend. It is of great significance to develop new power energy and to solve the shortage of power supply and consumption [1]. Wind turbines use installed capacity to describe how much electricity may be generated by a turbine in optimal wind conditions, describing how many watts of electricity the turbine hardware can possibly produce—generally measured in megawatts or kilowatts. The US Energy Information Administration (EIA) refers to capacity as the maximum

output of electricity that a generator can produce under ideal conditions.

Although China's wind power industry started late, it has achieved extremely rapid development since 2005, with the installed capacity of wind power (WPIC) doubling for five consecutive years. Wind generation is characterized by intermittency and volatility, which requires coordination and cooperation after large-scale access to the power grid, especially the continuous improvement of adaptability and stability [2].

However, the rapid development of China's wind power market does not make the grid connection improved on a par. The characteristics of reverse peak regulation and uneven distribution and the fluctuation of wind power have a significant impact on the safe operation and power quality of the power system. Unsuccessful grid-connected operation of

wind farms will result in a negative impact on the following aspects: the power quality, the voltage stability, the power grid security, etc. [3]. With the continuous expansion of the scale of wind farms, the impact of wind power's characteristics on the operation of conventional power systems is becoming more and more significant. The power grid security and risks have become serious constraints to energy supply and demand structure, even seriously wind abandoning phenomenon occurs, which will be resulting in a great waste of resources [4, 5].

As reported by National Energy Administration (NEA) 2019, China's wind power cumulative installed capacity reached 210.05 million kW, accounting for about 32.29% of the global total, and wind abandoning power was 16.9 billion kW. Especially in the following provinces (region) with more than 5% abandonment rate: Xinjiang province (14.0% abandonment rate, 6.61 billion kW), Gansu province (7.6% abandonment rate, 1.88 billion kW), and Inner Mongolia (7.1% abandonment rate, 5.12 billion kW). The abandoned wind power of these provinces (regions) totaled 13.6 billion kW, accounting for 81% of the abandoned wind power in the country. Therefore, accurate forecasting tools and scientific evaluation methods are necessary to support these environmental protection policies. The policy executors need more reliable predictive and assessment tools to predict and analyze installed capacity.

Considering that the development of the wind power industry in China is relatively short, the data available is relatively limited, and there are many factors affecting wind power generation. As a consequence, the prediction of wind power generation is essentially an uncertainty prediction problem based on the characteristics of a small sample and poor data. So far, there are many scholars who have carried out extensive research on prediction aspects of wind generation problems, such as the conventional grey prediction model, the ARMA model, the neural networks (including BP neural network and artificial network), the support vector machine (SVM) method, etc., these methods are presented as follows:

*1.1. Grey Prediction Model in Wind Power in Wind Power Industry Forecasting.* Ma et al. defined a new information priority accumulated grey model with time power to predict short-term wind turbine capacity [6]. Yang et al. put forward a method to enhance the prediction accuracy and robustness of the grey prediction model by introducing multisource information into traditional grey models [7]. Wu and Cong propose a novel method for short-term wind power forecasting, which combines the wavelet transform, particle swarm optimization dynamic grey model, and Lyapunov exponent prediction method [8]. Zhang et al. proposed a novel power-driven fractional accumulated grey model (PFAGM) to solve the wind energy consumption prediction problem. A heuristic intelligent algorithm WOA was used to search the optimal order and the least-square method to estimate linear parameters of the PFAGM model [9]. Qian and Wang proposed a seasonal GM (1, 1) method based on the HP filter for forecasting wind power generation in China

[10]. Duman et al. using optimized multivariate grey models to estimate the electronic waste [11].

*1.2. Application of SVM in Wind Power Industry Forecasting.* Vinothkumar and Deeba employ long short-term memory network model and variants of SVM models to predict the wind speed for the considered locations where the windmill has been installed [12]. Li et al. present a novel backward bat algorithm (BBA) for the parameter tuning of the SVM to forecast solar power and wind speed [13]. Yeh et al. built a long cycle maintenance of wind turbine predictive model based on the convolutional neural network and support vector machine [14]. Agasthian et al. nominate a method to decide the parameters for support vector machine (SVM) in wind turbine, called Cuckoo search optimization (CSO). They found that the CSO model based on the SVM algorithm accomplishes the most accurate fault detection than the past models [15].

*1.3. ARMA Model in Wind Power Industry Forecasting.* In order to address the static voltage stability issue and suppress the voltage fluctuation caused by the increasing integration of wind farms and solar photovoltaic (PV) power plants, Lu et al. proposed a two-tier reactive power and voltage control strategy based on ARMA power forecasting models for wind and solar plants [16]. Ergin and Shi proposed four approaches based on the autoregressive moving average (ARMA) method to forecasting short-term wind speed and direction tuple [17]. Chen et al. proposed a stochastic wind power model based on an autoregressive integrated moving average (ARIMA) process. This model takes into account the nonstationary and physical limits of stochastic wind power generation [18].

*1.4. Neural Networks in Wind Power Industry Forecasting.* Luo et al. proposed a novel fault prediction method that is combined based on BP neural network and Pair-Copula model [19]. An artificial neural network (ANN) based model is investigated for short-term forecasting of the hourly wind speed, solar radiation, and electrical power demand [20]. In order to enhance the accuracy of short-term wind speed prediction, Wang et al. constructed an improved small-world BP neural (SWBP) based on the MI algorithm to predict short-term wind power [21]. Jahangir et al. proposed a short-term wind speed prediction framework based on Artificial neural networks [22]. Zhang et al. use the similar day data preprocess and unprocessed as the input of back propagation neural network optimized by genetic algorithm (GA-BP neural network) [23].

*1.5. Other Predictive Models.* In addition to the above research methods, scholars have adopted other predictive methods in the field of wind power. For instance, Tan et al. explored and developed the Salp Swarm Algorithm in the iterative process to optimize the input weight matrix and hidden layer deviation of the Extreme Learning Machine (ELM), in order to improve the adaptability and accuracy of

the prediction model [24]. Wang et al. build a hybrid PSO-SVM-ARMA prediction model for wind power prediction, and the covariance minimization method and PSO are employed to find the optimal weights [25]. Wang et al. designed a novel deep learning network stacked by independent recurrent autoencoder (IRAE) which, according to the characteristics of ultrashort-term wind power data, hereafter called SIRAE (staked independently recurrent autoencoder). This approach accommodates a sheer volume of data in the smart energy era and overcomes the effects of random changes in the natural environment [26]. Wang et al. proposed a hybrid model known as SAM-ESM-RBFN, which is used for capturing these different patterns and obtaining better prediction performance. This model is based on the seasonal adjustment method (SAM), exponential smoothing method (ESM), and radial basis function neural network (RBFN) [27].

The above research results are of great value to realize the scientific prediction of wind power installed capacity in China and to provide solutions for the healthy development of the wind power industry. Because of the randomness, volatility, and intermittence of wind power systems, the data characteristics of wind power prediction and installed capacity are consistent with the grey model of “small samples, poor information.” The techniques based on large samples, such as the SVM and neural network, are difficult to apply to the prediction of WPIC and the ARMA model is difficult to detect the complex nonlinear dynamic processes of power system and wind energy, so it can not accurately describe the real changes of a wind speed or wind farm power, which affects the performance of the prediction results. The artificial neural network forecasting model has a high predictive ability for nonlinear data, but it is difficult to search for the optimal solution so that it barely meets the accuracy requirements. The conventional grey prediction model has the advantages of small data modeling and can be used to predict the hosting capacity of wind power. However, the conventional GM (1, 1) model is the most primitive single variable grey model, and the limitation of the structure makes it difficult to meet the requirements of complex systems. As a consequence, the conventional GM (1, 1) model does not perform well in wind power industry. Another problem of the current grey model with the combination model is that no detailed optimization algorithm is used to seek the optimum solution of parameters [28–31]. Therefore, we establish an optimization model to search the parameters and use the PSO algorithm to determine the optimized values of the novel model. This paper intends to expand the structure and optimize the parameters of the conventional grey model, on the basis of which a more reasonable prediction model of wind power installed capacity is constructed.

The remainder of the paper is organized as follows: In Section 2, a new grey optimization model is proposed, which include optimization with background value and optimization with fractional order accumulation. In

Section 3, we simulate China’s WPIC from 2009 to 2016 by employing the WPICM (1, 1,  $r$ ,  $\xi$ ) model and compare its error with the other three conventional grey models. In Section 4, we use the WPICM (1, 1,  $r$ ,  $\xi$ ) model to forecast China’s WPIC for 2020–2024. According to the forecast results, some suggestions are provided for the policy-making of the Chinese government. Conclusions are presented in Section 5. The paper structure is presented in Figure 1.

## 2. WPICM (1, 1, $r$ , $\xi$ ) Model

This paper will study the predictive problem of the WPIC in China by using the combination grey prediction model. In order to construct a suitable grey forecast model for wind power installed capacity, we expand the structure of the traditional GM (1, 1) model and optimizes the model parameters. These will provide a methodological basis for forecasting the WPIC in China in Section 4.

### 2.1. Basic Form of the WPICM (1, 1) Model

*Definition 1* (see [32]). Assume that a raw sequence is  $W^{(0)} = (w^{(0)}(1), w^{(0)}(2), \dots, w^{(0)}(n))$ , where  $w^{(0)}(k) \geq 0$ ,  $k = 1, 2, \dots, n$ .  $W^{(1)}$  is the 1-AGO sequence of  $W^{(0)}$ , that is,

$$W^{(1)} = (w^{(1)}(1), w^{(1)}(2), \dots, w^{(1)}(n)), \quad (1)$$

where

$$W^{(1)} = \sum_{i=1}^k w^{(0)}, \quad k = 1, 2, \dots, n, \quad (2)$$

and  $Z^{(1)}$  is the mean sequence generated by consecutive neighbors of  $W^{(1)}$ , that is  $Z^{(1)} = (z^{(1)}(1), z^{(1)}(2), \dots, z^{(1)}(n))$ , where  $z^{(1)} = 0.5 \times [x^{(1)}(k) + x^{(1)}(k-1)]$ ,  $k = 1, 2, \dots, n$ . Then,

$$w^{(0)} + az^{(r)}(k) = 0.5(2k-1)b + c \quad (3)$$

is the common form of the WPICM (1, 1) model.

*Definition 2.* Assuming that  $W^{(0)}$ ,  $W^{(1)}$ , and  $Z^{(1)}$  are given by Definition 1, we have the following equation:

$$\frac{dw^{(1)}}{dt} + aw^{(1)} = bt + c, \quad (4)$$

which is named the whitenization equation of grey model WPICM(1,1) for short [32].

In equation (3), we can estimate the parameter  $a$  and  $b$  using the least-square method, which is as follows:

$$\hat{p} = (a, b, c)^T = (B^T B)^{-1} B^T Y, \quad (5)$$

where

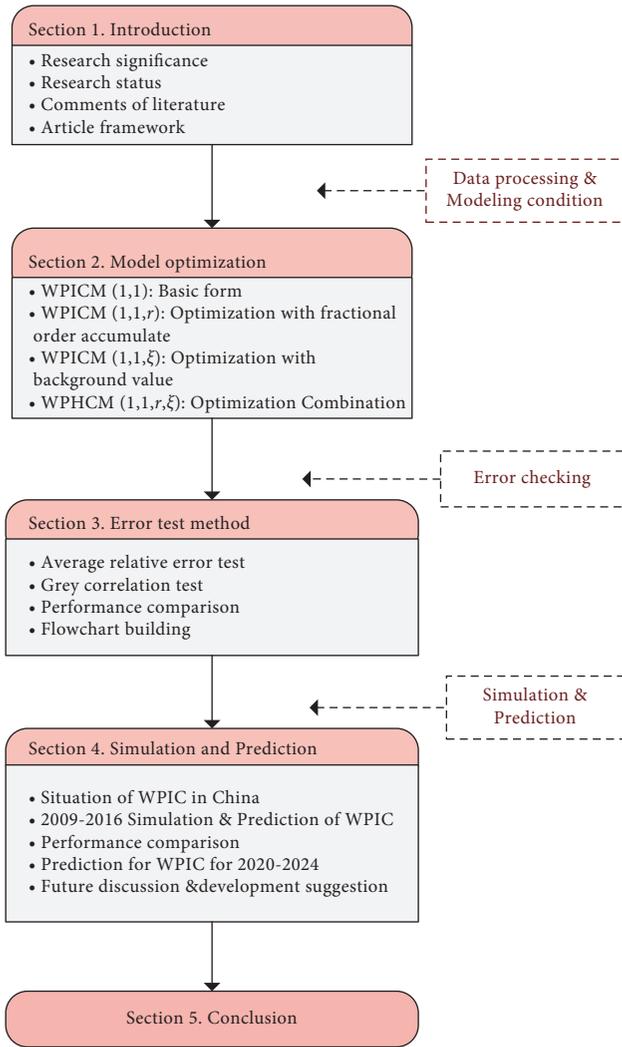


FIGURE 1: Paper structure.

$$Y = \begin{bmatrix} w^{(0)}(2) \\ w^{(0)}(3) \\ \vdots \\ w^{(0)}(n) \end{bmatrix},$$

$$B = \begin{bmatrix} -z^{(1)}(2) & \frac{3}{2} & 1 \\ -z^{(1)}(3) & \frac{5}{2} & 1 \\ \vdots & \vdots & \vdots \\ -z^{(1)}(n) & \frac{(2n-1)}{2} & 1 \end{bmatrix}. \tag{6}$$

**Theorem 1** (see [32]). Assuming that  $Y$ ,  $B$ , and  $\hat{p}$  are the same as those Definition 2, one can obtain that the time response sequence of WPICM(1,1) is given by the following:

$$\begin{aligned} \hat{w}^{(0)}(t) &= \hat{w}^{(1)}(t) - \hat{w}^{(1)}(t-1) \\ &= (1 - e^a) \left( w^{(0)}(1) - \frac{b}{a} + \frac{b}{a^2} - \frac{c}{a} \right) e^{-a(t-1)} + \frac{b}{a} \end{aligned} \tag{7}$$

Let

$$\begin{aligned} \alpha &= (1 - e^a) \left( w^{(0)}(1) - \frac{b}{a} + \frac{b}{a^2} - \frac{c}{a} \right), \\ \beta &= \frac{b}{a}. \end{aligned} \tag{8}$$

Equation (7) will be transformed as follows:

$$w^{(0)}(k) = \alpha e^{-a(k-1)} + \beta. \tag{9}$$

**2.2. Optimization with Fractional Order Accumulate.** In the process of constructing the grey prediction model, the fractional order accumulate  $r$  is an important tool to weaken the randomness of grey modeling sequence. Different orders have different effects on the performance of the grey prediction model. The traditional grey model is set  $r = 1$ , which largely limits the room for improving the performance of the model. In the actual modeling process,  $r$  can be accepted as a fraction, a negative number, or another integer [30, 33]. Hence, in this section, a new order optimization model  $r$  is discussed.

**Definition 3.** The raw sequence is proposed by Definition 1;  $W^{(r)}$  is the  $r$ -AGO (Accumulating Generation Operator) sequence of  $W^{(0)}$ , that is,

$$W^{(r)} = (w^{(r)}(1), w^{(r)}(2), \dots, w^{(r)}(n)), \tag{10}$$

where

$$w^{(r)}(k) = \sum_{i=1}^k \frac{\Gamma(r+k-i)}{\Gamma(k-i+1)\Gamma(r)} w^{(0)}(i), \quad k = 1, 2, \dots, n. \tag{11}$$

**Definition 4.** Assuming that  $W^{(0)}$  is given by Definition 1 and  $W^{(r)}$  is given by Definition 3,  $r \in R^+$ , then,  $Z^{(r)} = (z^{(r)}(1), z^{(r)}(2), \dots, z^{(r)}(n))$  is called the mean sequence generated by consecutive neighbors of  $W^{(r)}$ , where

$$z^{(r)}(k) = \frac{w^{(r)}(k) + w^{(r)}(k-1)}{2}, \quad k = 2, 3, \dots, n. \tag{12}$$

As the  $W^{(0)}$ ,  $W^{(r)}$ , and  $Z^{(r)}$  are known, then

$$w^{(r-1)} + az^{(r)}(k) = 0.5(2k-1)b + c \tag{13}$$

is the basic form of WPICM (1, 1, r).

$\hat{p} = (a, b, c)^T = (B^T B)^{-1} B^T Y$  is a sequence of parameters, and

$$Y = \begin{bmatrix} w^{(r-1)}(2) \\ w^{(r-1)}(3) \\ \vdots \\ w^{(r-1)}(n) \end{bmatrix}, \quad (14)$$

$$B = \begin{bmatrix} -z^{(r)}(2) & \frac{3}{2} & 1 \\ -z^{(r)}(3) & \frac{5}{2} & 1 \\ \vdots & \vdots & \vdots \\ -z^{(r)}(n) & \frac{(2n-1)}{2} & 1 \end{bmatrix}.$$

The least squares estimate sequence of WPICM (1, 1, r) satisfied  $\hat{p} = (a, b, c)^T = (B^T B)^{-1} B^T Y$ .

**2.3. WPICM (1, 1,  $\xi$ ) Model Optimization with Background Value.** When constructed a grey prediction model, the generation of the immediate means is a smooth processing method to weaken the influence of the extreme value on the size of the grey action in the 1-ago sequence, and the background value is the main parameter for the weight allocation of the two adjacent elements in the immediate mean sequence.

In the conventional grey modeling process, it is a simplification to set the background value generally as 0.5 [32, 34], in which  $z^{(1)}(k) = 0.5 \times w^{(1)}(k) + 0.5 \times w^{(1)}(k-1)$ . Under the condition of minimizing the sum of squares of the average simulation error, we optimize the background value on the basis of the WPICM (1, 1) model, which improves the performance of the grey prediction model to some extent.

**Definition 6.** The sequence of  $W^{(0)}$ ,  $W^{(1)}$ , and  $Z^{(1)}$  is given in Definition 1, assuming that background value is  $\xi$ ; then,

$$z_g^{(1)}(k) = \xi w^{(1)}(k) + (1 - \xi)w^{(1)}(k-1) \quad (15)$$

and

$$w^{(0)}(k) + a(\xi w^{(1)}(k) + (1 - \xi)w^{(1)}(k-1)) = 0.5(2k-1)b + c, \quad (16)$$

which is the basic form of WPICM (1, 1,  $\xi$ ) model.

**Theorem 2.** The sequence of  $W^{(0)}$ ,  $W^{(1)}$ , and  $Z^{(1)}$  is given in Definition 1,  $\hat{p} = (a, b, c)^T = (B^T B)^{-1} B^T Y$  is a sequence of parameters, and

$$Y = \begin{bmatrix} w^{(0)}(2) \\ w^{(0)}(3) \\ \vdots \\ w^{(0)}(n) \end{bmatrix},$$

$$B = \begin{bmatrix} [-\xi w^{(1)}(2) + (1 - \xi)w^{(1)}(1)] & \frac{3}{2} & 1 \\ [-\xi w^{(1)}(3) + (1 - \xi)w^{(1)}(1)] & \frac{5}{2} & 1 \\ \vdots & \vdots & \vdots \\ [-\xi w^{(1)}(n) + (1 - \xi)w^{(1)}(1)] & \frac{(2n-1)}{2} & 1 \end{bmatrix}. \quad (17)$$

The least squares estimate sequence of WPICM(1,1, $\xi$ ) satisfied  $\hat{p} = (a, b, c)^T = (B^T B)^{-1} B^T Y$ .

The background value corresponds to different array distance B, and the undetermined value  $\xi$  in array distance B can be calculated by the PSO algorithm through MATLAB to obtain the optimal coefficient  $\xi$ . The calculation process is similar to the WPICM (1, 1, r) model and will not be repeated here.

**2.4. WPICM (1, 1, r,  $\xi$ ) Optimization Combination.** From the perspective of parameter optimization, the three basic parameters  $a$ ,  $b$ , and  $c$  of the grey prediction model are important metrics that affect its simulation and prediction accuracy. On the basis of the model structure optimized by the individual parameters, the fractional order accumulates  $r$  and the background value  $\xi$  have a direct influence on the parameters  $a$ ,  $b$ , and  $c$ . Therefore, the fractional order accumulates and the background value can greatly improve the performance of the grey prediction model.

**Definition 7.** Assuming that  $W^{(0)}$ ,  $W^{(1)}$ , and  $Z^{(r)}$  are given by Definition 4, then sequence  $W^{(0)} = (w^{(0)}(1), w^{(0)}(1), \dots, w^{(0)}(n))$ , which  $w^{(0)}(k) \geq 0, k = 1, 2, \dots, n$ ;  $W^{(r)} = (w^{(r)}(1), w^{(r)}(2), \dots, w^{(r)}(n))$   $r \in R^+$ , where

$$w^{(r)}(k) = \sum_{i=1}^k \frac{\Gamma(r+k-i)}{\Gamma(k-i+1)\Gamma(r)} w^{(0)}(i), \quad k = 1, 2, \dots, n, \quad (18)$$

$Z^{(r)} = (z^{(r)}(1), z^{(r)}(2), \dots, z^{(r)}(n))$  is called the mean sequence generated by consecutive neighbors of  $W^{(r)}$ , where

$$z_g^{(r)}(k) = \xi w^{(r)}(k) + (1 - \xi)w^{(r)}(k-1). \quad (19)$$

Then,

$$w^{(r-1)}(k) + a(\xi w^{(r)}(k) + (1 - \xi)w^{(r)}(k-1)) = 0.5(2k-1)b + c \quad (20)$$

is the basic form of WPICM (1, 1, r,  $\xi$ ).

We solve its whitening differential equation and the final restored expression can be formulated as follows:

$$\hat{w}^{(0)}(t) = \hat{w}^{(0)}(t) = (\hat{w}^{(r)}(t))^{(-r)} = (1 - e^a) \left( w^{(0)}(1) - \frac{b}{a} + \frac{b}{a^2} - \frac{c}{a} \right) e^{-a(t-1)} + \frac{b}{a} \quad (21)$$

Let  $\alpha = (1 - e^a)(w^{(0)}(1) - (b/a) + (b/a^2) - (c/a))$ , and  $\beta = (b/a)$ .

Then, the time response sequence of WPICM  $(1, 1, r, \xi)$  is  $\hat{w}^{(0)}(k) = \alpha e^{-a(k-1)} + \beta$ .

**Theorem 3.** The sequence of  $W^{(r-1)}$ ,  $W^{(r)}$ , and  $Z_g^{(r)}$  is given in Definition 1,  $\hat{p} = (a, b, c)^T = (B^T B)^{-1} B^T Y$  is a sequence of parameters, and

$$Y = \begin{bmatrix} w^{(r-1)}(2) \\ w^{(r-1)}(3) \\ \vdots \\ w^{(r-1)}(n) \end{bmatrix}, \quad B = \begin{bmatrix} -\xi w^{(r)}(2) + (1 - \xi)w^{(r)}(1) & \frac{3}{2} & 1 \\ -\xi w^{(r)}(3) + (1 - \xi)w^{(r)}(1) & \frac{5}{2} & 1 \\ \vdots & \vdots & \vdots \\ -\xi w^{(r)}(n) + (1 - \xi)w^{(r)}(1) & \frac{(2n-1)}{2} & 1 \end{bmatrix} \quad (22)$$

The least squares estimate sequence of WPICM  $(1, 1, r, \xi)$  satisfied  $\hat{p} = (a, b, c)^T = (B^T B)^{-1} B^T Y$ .

### 3. Error Checking Method for WPICM $(1, 1, r, \xi)$

In order to test whether a forecasting model could meet the prediction requirements of one system, we use the average relative error test and grey correlation test to examine the performance of the combinatorial optimization model. Usually, start with the relative percentage error. For giving a threshold value  $\alpha$ , which is set according to the specific situation of a system, when  $\bar{\Delta} < \alpha$  holds true, the grey model is said to be error-satisfactory. The relative average percentage error includes two parts: mean relative simulated percentage error and mean relative forecasted percentage error.

**Definition 8.** Assume a raw sequence  $W^{(0)} = (w^{(0)}(1), w^{(0)}(2), \dots, w^{(0)}(n), w^{(0)}(n+1), \dots, w^{(0)}(n+t))$ . Then, simulation sequence  $\hat{S}^{(0)}$  is as follows:

$$\hat{S}^{(0)} = (\hat{w}^{(0)}(1), \hat{w}^{(0)}(2), \dots, \hat{w}^{(0)}(n)). \quad (23)$$

We use the WPICM  $(1, 1, r, \xi)$  model to forecast the latter  $t$ -step data and the predictive sequence is as follows:

$$\hat{F}^{(0)} = (\hat{w}^{(0)}(n+1), \hat{w}^{(0)}(n+2), \dots, \hat{w}^{(0)}(n+t)). \quad (24)$$

**Definition 9.** Assume that the residual sequence of  $\hat{S}^{(0)}$  and  $\hat{F}^{(0)}$  is  $\varepsilon_s$  and  $\varepsilon_F$ , respectively, which is as follows:

$$\begin{aligned} \varepsilon_s &= (\varepsilon_s(1), \varepsilon_s(2), \dots, \varepsilon_s(n)), \\ \varepsilon_F &= (\varepsilon_F(n+1), \varepsilon_F(n+2), \dots, \varepsilon_F(n+t)), \end{aligned} \quad (25)$$

then

$$\begin{aligned} \varepsilon_s(u) &= |x^{(0)}(u) - \hat{x}^{(0)}(u)|, \quad u = 1, 2, \dots, n, \\ \varepsilon_F(v) &= |x^{(0)}(v) - \hat{x}^{(0)}(v)|, \quad v = n+1, n+2, \dots, n+t. \end{aligned} \quad (26)$$

**Definition 10.** The relative simulated percentage error (RSPE) of the simulated sequence is  $\Delta_s$ , and  $\Delta_s = (\Delta_s(1), \Delta_s(2), \dots, \Delta_s(n))$ , where

$$\Delta_s(u) = \left| \frac{\varepsilon_s(u)}{x^{(0)}(u)} \times 100\% \right|, \quad u = 1, 2, \dots, n. \quad (27)$$

The mean relative simulated percentage error (MRSPE) of the simulation sequence  $\bar{\Delta}_s$  is as follows:

$$\bar{\Delta}_s = \frac{1}{n} \sum_{u=1}^n \Delta_s(u). \quad (28)$$

**Definition 11.** The relative forecasted percentage error (RFPE) of the forecasted sequence is  $\Delta_F$ , and  $\Delta_F = (\Delta_F(n+1), \Delta_F(n+2), \dots, \Delta_F(n+t))$ , where  $\Delta_F(u) = |(\varepsilon_F(v)/x^{(0)}(v)) \times 100\%|$  and  $v = n+1, n+2, \dots, n+t$ .

The mean relative simulation percentage error (MRSPE) of predicted sequence  $\bar{\Delta}_F$  is as follows:

$$\bar{\Delta}_F = \frac{1}{t} \sum_{v=n+1}^{n+t} \Delta_F(v), \quad v = n+1, n+2, \dots, n+t. \quad (29)$$

The comprehensive average relative percentage error of the model is recorded as  $\Delta$  (CMRPE), where

$$\Delta = \frac{n \cdot \bar{\Delta}_s + t \cdot \bar{\Delta}_F}{n+t}. \quad (30)$$

The grey absolute correlation degree is an important tool to measure the degree of difference between different time series. When evaluating the error of the forecast model, it

can effectively check the degree of deviation of the original data before and after the modeling process. For giving a threshold value  $\delta$ , in which the threshold is set according to the specific situation of a system. When  $\delta_0 < \delta$  holds true, the grey model is said to be error satisfactory [29, 34, 35].

*Definition 12* (see [35]). Assume that sequence  $X^{(i)} = (x^{(i)}(1), x^{(i)}(2), \dots, x^{(i)}(n))$ , where  $x^{(i)}(k)d = x^{(i)}(k) - x^{(i)}(1)$ ,  $k = 1, 2, \dots, n$ ; then,  $X_i D = X_i^0 = (x_i^0(1), x_i^0(2), \dots, x_i^0(n))$  is the zero image of the starting point of  $X_i$ .

*Definition 13* (see [29]). Let the sequence of  $X_i^0$  and  $X_j^0$  be equidistant and of the same length; then,

$$\varepsilon^{ji} = \frac{1 + |s_j| + |s_i|}{1 + |s_j| + |s_i| + |s_i - s_j|}, \quad (31)$$

which is called absolutely correlation degree of  $x^{(j)}$  and  $x^{(i)}$ , where

$$\begin{aligned} |S_j| &= \left| \sum_{j=2}^{n-1} x_i^0(k) + \frac{1}{2} x_j^0(n) \right|, \\ |S_i| &= \left| \sum_{j=2}^{n-1} x_i^0(k) + \frac{1}{2} x_j^0(n) \right|. \end{aligned} \quad (32)$$

#### 4. Forecasting with the WPICM (1, 1, $\xi$ , $r$ ) Model

The data in the Statistical Communique of the People's Republic of China on Energy indicates that the growth rate of wind power generation is the highest, compared with hydropower, nuclear power, and solar photovoltaic power. Therefore, wind power has become one of the most popular clean energy sources, which effectively alleviates the energy supply pressure borne by fossil fuels [36].

On the basis of China's actual situation, it is of great practical significance to forecast the future wind power generation and clarify the seasonal characteristics of wind power generation evolution. On the one hand, it could reasonably allocate power resources, optimize the design of the power grid and power dispatching, and ensure the efficient use of power. On the other hand, it could accelerate the upgrading of energy consumption structure, reduce the use of fossil fuels, and finally achieve the coordinated development of the economy and environment. The data source of this paper is the original data (Table 1) of China's wind power installed capacity released by the Global Wind Energy Council (GWEC) in 2019.

As reported by China Renewable energy Association, the WPIC of China 2015 is 30.5 million kW. Affected by the reduction in the price of wind power benchmarking, there was a significant rush to install wind power projects. It increased by 31.5% compared with the same period last year, and the scale of new installed capacity is obvious. That is the reason in Figure 2 there is an inflection point in 2015, which slows down the WPIC in 2016–2017. Affected by the reduction in the price of wind power benchmarking, there was

a significant rush to install wind power projects. It increased by 31.5% compared with the same period last year, and the scale of new installed capacity is obvious. Moreover, the structure of the application section is provided in Figure 3.

*4.1. Simulation and Forecasting.* Considered as an alternative to fossil fuels, wind energy has been highly valued as renewable energy around the world. However, due to the intermittency, fluctuant, and random probability, the wind power grid connection is limited, resulting in wind curtailment. Large-scale access leads to serious threats to the stability and security of the power system and inevitably affects the reliability of grid operation. Consequently, power quality is not guaranteed. To address this challenge, wind power installed capacity prediction, manual guidance of wind farm operation, and reasonable scheduling are valid methods to lessen the effect of wind power upon the grid when it is connected to the grid [37, 38].

We use the WPICM(1, 1) model and its parameter optimization models WPICM(1, 1,  $r$ ), WPICM(1, 1,  $\xi$ ), WPICM(1, 1,  $r, \xi$ ) to predict and analyze China's wind power installed capacity. In the processing of data sets,  $k = 1, 2, \dots, 6$  are taken as in-sample data to test the simulation performance, and the data of the last two time points  $k = 7$  are taken as out-of-sample data to test the prediction performance. The results are shown in Table 2. We find that the model with optimized order and background value simultaneously has better performance than the other two models with optimized parameters alone. Moreover, the flowchart of constructing the WPICM(1, 1,  $r, \xi$ ) combination model is presented in Figure 4.

We use MATLAB to find parameters for these four models. Corresponding parameters are shown in Table 3.

*4.2. Performance Comparison.* In order to compare these four models' simulated and forecasted performance, three metrics are selected, namely, MRSPE, MRFPE, RSPE, CRMPE. The model's performance evaluation metrics and meanings are shown in Table 4.

Table 2 shows the model WPICM(1, 1,  $r, \xi$ )'s performance is better than the WPICM(1, 1) model and the WPICM(1, 1,  $\xi$ ) model, in terms of simulation and prediction. In order to clearly compare the performance of the four models, we drew the simulation/prediction errors curves of the four models based on the data in Tables 2 and 3, and the results are plotted in Figure 5.

In order to test the simulation and prediction performance of different prediction models on the WPIC in China, the performance evaluation metrics in Table 4 is employed. The raw data and computational result are plotted in Figures 6 and 7. It can be seen from the combination model, WPICM(1, 1,  $r, \xi$ ) is better than no optimization WPICM(1, 1), or only optimizing a single parameter (WPICM(1, 1,  $\xi$ ) and WPICM(1, 1,  $r$ )). Moreover, the results reveal that the combinatorial optimization model shows a more stable prediction performance. The simulation accuracy is 99.23%, the prediction accuracy is 97.26%. The grey absolute correlation is 0.9878%,  $\varepsilon^{ji} = 0.9878 > 0.9$ ; the mean relative

TABLE 1: China’s WPIC from 2009 to 2018 (ten thousand of kW).

Year	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
WPIC	25810	44730	62360	75320	91410	114610	145360	168730	188390	209533

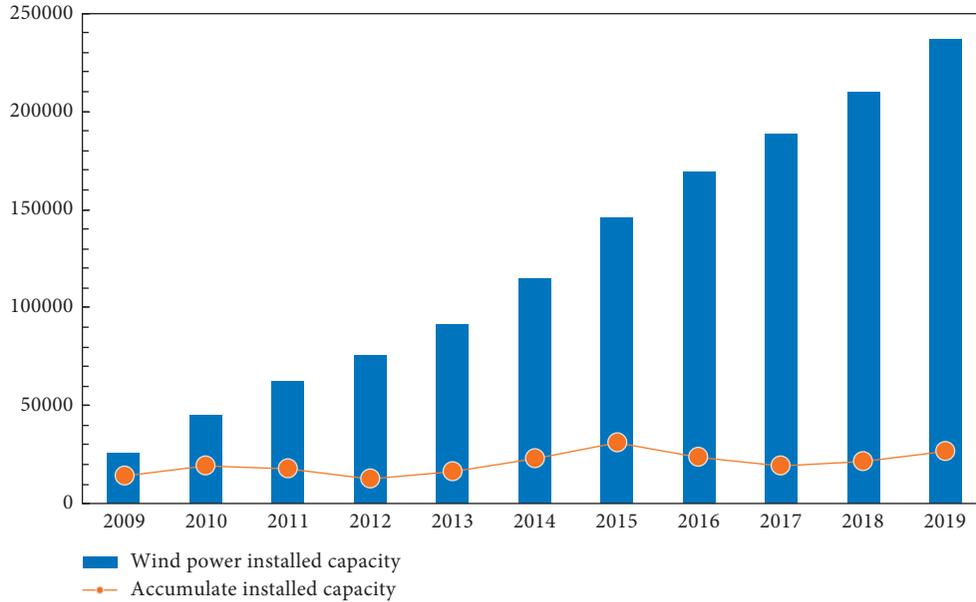


FIGURE 2: WPIC of China for 2009–2018 (ten thousand of kW).

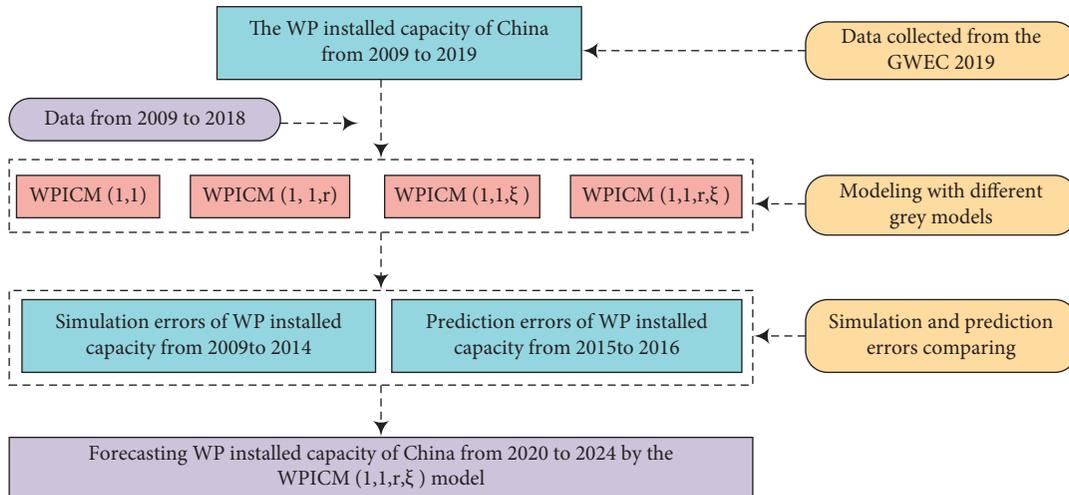


FIGURE 3: Structure chart of application.

simulated percentage error  $\bar{\Delta}_S$  is 0.77%,  $\bar{\Delta}_S = 0.77\% < 1\%$ , which makes the WPICM (1, 1, r,  $\xi$ ) model error satisfactory (Table 5).

4.3. Forecasting China’s WPIC for 2020–2024. As can be seen from the earlier simulated and predicted results of China’s WPIC, comparing to the conventional grey models, the novel WPICM (1, 1, r,  $\xi$ ) model proposed in this paper has a relatively optimal simulation and prediction performance.

Hence, in this section, we will use the WPICM (1, 1, r,  $\xi$ ) model to forecast and analyze the WPIC for 2020 to 2024.

In this section, the WPICM (1, 1, r,  $\xi$ ) combination model is built to forecast the demand of wind power capacity in China during 2020–2024, providing a picture of the demand conditions for the upcoming years. Based on this, the government can judge the status of supply and demand according to domestic output and take some preventive measures in advance to maintain the balance of supply and demand for WPIC.

TABLE 2: Simulated/forecast results of wind power installed capacity with different models.

Year	Raw data	WPICM(1, 1)		WPICM(1, 1, $r$ )		WPICM(1, 1, $\xi$ )		WPICM(1, 1, $r, \xi$ )	
	$w^{(0)}(k)$	$\hat{w}^{(0)}(k)$	RSPE (%)	$\hat{w}^{(0)}(k)$	RSPE (%)	$\hat{w}^{(0)}(k)$	RSPE (%)	$\hat{w}^{(0)}(k)$	RSPE (%)
<i>In-sample</i>									
2009	25810	25810	0	25810	0	25810	0	25810	0
2010	44730	45935.00	2.69	44071.24	1.47	46297.13	3.50	44730.00	0.00
2011	62360	59636.23	4.37	61020.49	2.15	60183.19	3.49	61752.99	0.97
2012	75320	75249.90	0.09	74840.64	0.64	76010.17	0.91	75870.77	0.73
2013	91410	93042.95	1.79	91733.92	0.35	94049.37	2.89	93158.78	1.91
2014	114610	113319.57	1.13	112410.27	1.92	114610.00	2.01	114355.56	0.22
$\bar{\Delta}_S$			2.01		1.31		2.16		0.77
<i>Out-sample</i>									
2015	145360	136426.44	6.15	137726.78	5.25	138044.50	5.03	140354.90	3.44
2016	168730	162758.61	3.54	168729.99	0.00	164754.56	2.36	172250.14	2.09
$\bar{\Delta}_F$		4.84		2.63		3.69		2.76	
CRMPE		2.82		1.68		2.60		1.34	

Table 6 shows that with the support of existing policies, China's hosting capacity of wind power keeps expanding. By 2020, China's cumulative hosting capacity of wind power can reach 390,578.90 kW, and the total development target of wind power in the 13<sup>th</sup> Five-Year Plan can be achieved.

*4.4. Future Discussion and Development Suggestion.* Wind energy is one of the most important renewable resources in the world and plays a vital role in reducing carbon emission and solving the global warming problem. In order to promote the development of the wind energy industry, China has formulated corresponding energy policies based on the production, consumption, and distribution of wind energy.

In this paper, we focus on forecasting wind energy consumption from a macro perspective. From the above forecast trend, it can be seen that the WPIC will increase significantly from 2020 to 2024, and the installed capacity of wind power in China will reach 885,423.10 kW by 2024. On this basis, the following suggestions are made.

*4.4.1. Strengthen the National Power Grid.* According to the demand for economic development, power grid enterprises need to revise the existing power grid development plan. Power grid structures in remote areas, such as transmission, distribution, and energy storage facilities, should be built in a focused and step-by-step manner. They should create a larger regional electricity market. Through interprovincial and interregional power grid interconnection, so that the wind power consumption market can be found in the regional power grid and even outside the regional power grid.

*4.4.2. Innovative Wind Power Grid Connection Technology and Application.* The grid-connected technology of wind power in China still needs in-depth research and innovation to improve the consumption level of wind power to realize the efficient utilization of wind power. For this reason, the government should actively support the transmission investment needed for wind power development and integration into the power grid while maintaining the system's stability and reliability.

*4.4.3. Strengthen Risk Control of Wind Power Project.* National power regulatory authorities should pay attention to the mutual influence between wind farms and power grids. The International Development and Reform Commission should strictly approve and carefully examine and approve the application projects of large wind power. Authorities should unify planning and use it to avoid excessive wind power capacity caused by repeated construction.

*4.4.4. Innovate the Utilization Mode of Wind Power.* On the basis of focusing on solving the problem of wind power transmission in major development areas such as Inner Mongolia, Hebei province, Jilin province, and Gansu province, authorities should continue to develop heating and agricultural water-lifting irrigation to flexibly use electricity load. Through these ways, the government could promote the local consumption and utilization of wind power to ensure the sustained and healthy development of China's wind power industry.

*4.4.5. Accelerate the Development of Green and Low Carbon.* Relevant departments should strengthen land space planning and use control, implement space control boundaries such as ecological protection, basic farmland, and urban development, and reduce the occupation of natural space by human activities. The legislature should strengthen the legal and policy guarantee of green development, develop green finance, support green technological innovation, promote cleaner production, develop environmental protection industries, and promote the green transformation of key industries and important areas. Relevant departments should strengthen land space planning and use control, implement space control boundaries such as ecological protection, basic farmland, and urban development, and reduce the occupation of natural space by human activities. The legislature should strengthen the legal and policy guarantee of green development and promote the green transformation of key industries and important areas. The Chinese government should continue to promote clean, low-carbon, safe, and efficient use of energy.

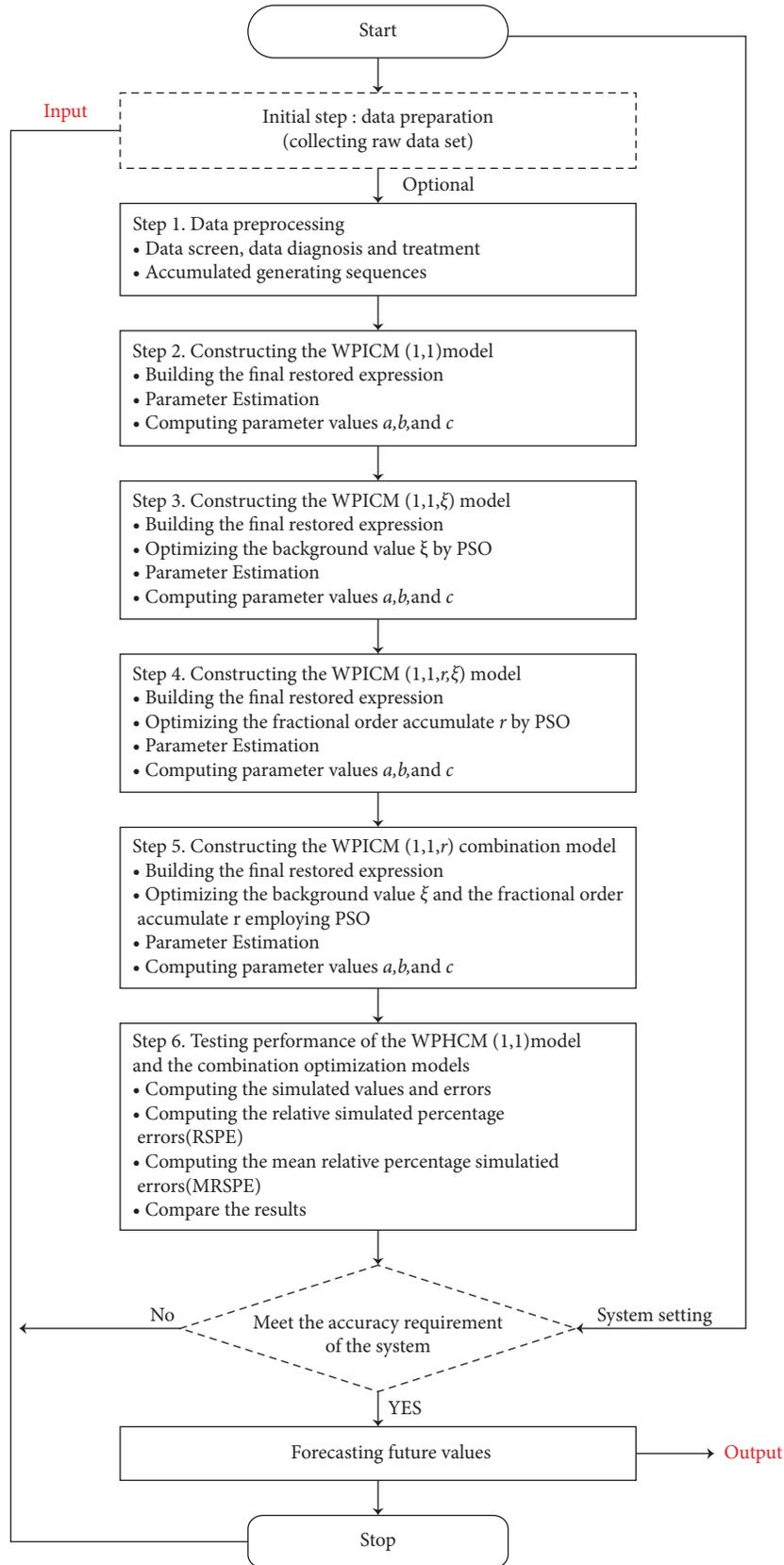


FIGURE 4: Flowchart of constructing the WPICM(1, 1, r, ξ) combination model.

TABLE 3: Parameters of the prediction model.

Model	$r$	$\xi$	$a$	$b$	$c$	$\alpha$	$\beta$
WPICM(1,1)	1	0.5	-0.20282	40655.3559	-2604.1104	2.2060	-2.0044
WPICM(1,1, $r$ )	1.9955	0.5	-0.20283	40658.27	-2607.5377	2.2060	-2.0045
WPICM(1,1, $\xi$ )	1	0.44	-0.13083	6940.3893	29622.9115	8.7162	-5.3048
WPICM(1,1, $r,\xi$ )	1.9954	0.46	-0.20457	41006.4157	-2627.3167	2.20762	-20045

TABLE 4: Table model performance evaluation metrics.

Metrics	Symbol	Formula
MRPE	MRPE	$MRPE(k) =  (w^{(0)}(k) - \hat{w}^{(0)}(k))/w^{(0)}(k)  \times 100\%$
MRSPE	$\bar{\Delta}_S$	$\bar{\Delta}_S = (1/n) \sum_{k=1}^n MRPE(k), k \text{ in in-sample}$
MRFPE	$\bar{\Delta}_F$	$\bar{\Delta}_F = (1/t) \sum_{k=n+1}^{n+t} MRPE(k), k \text{ in out-sample}$
CRMPE	$\Delta$	$\Delta = (n \cdot \bar{\Delta}_S + t \cdot \bar{\Delta}_F) / (n + t)$

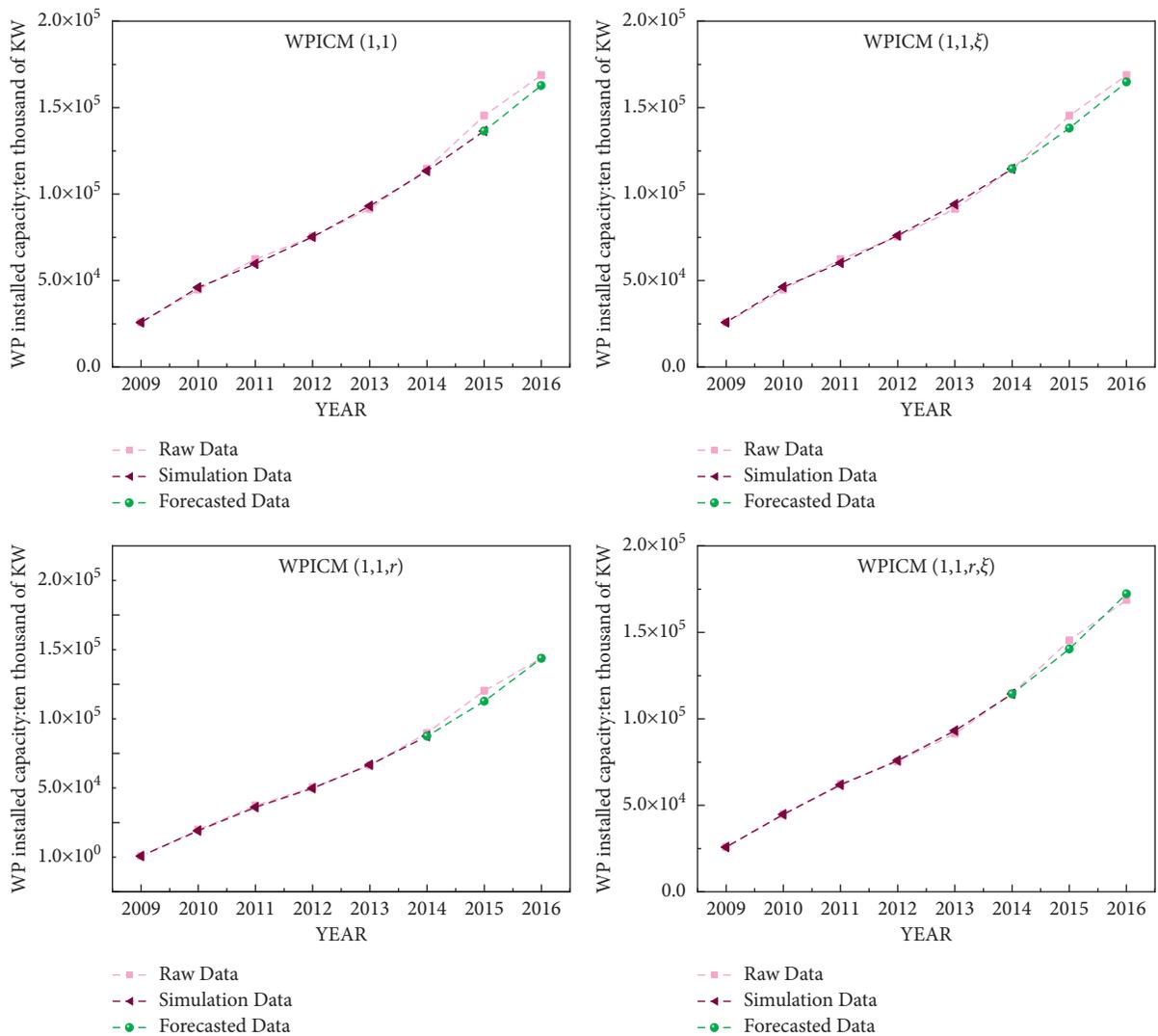


FIGURE 5: Performance comparison.

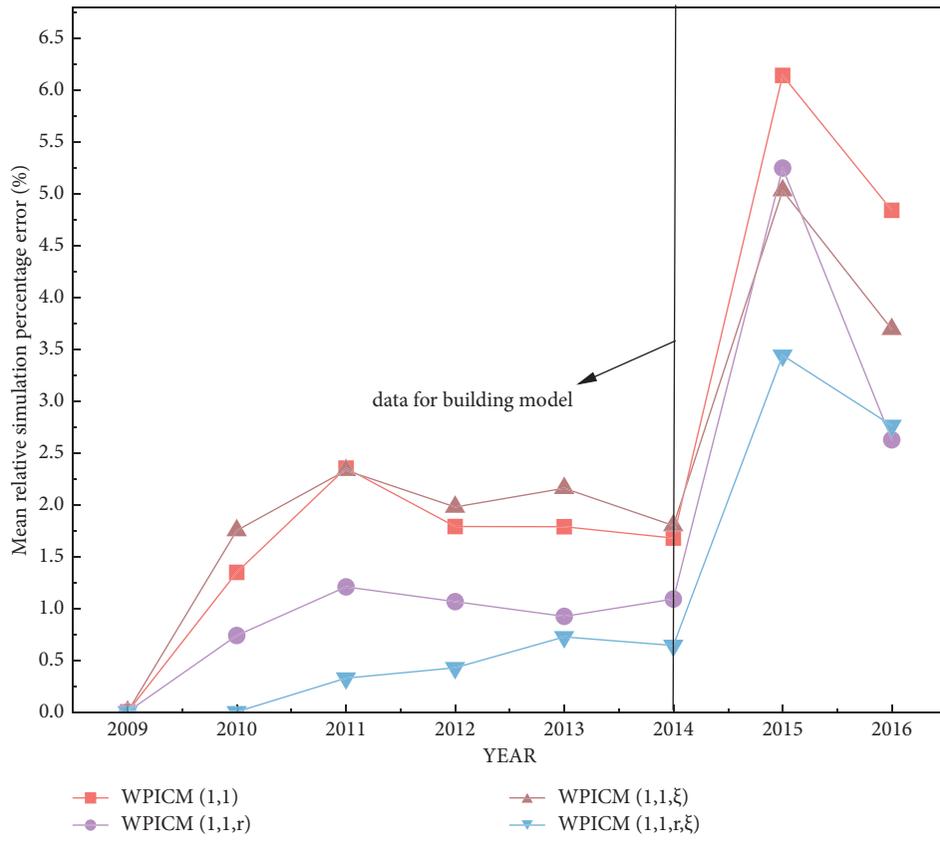


FIGURE 6: MRPE of model's performance.

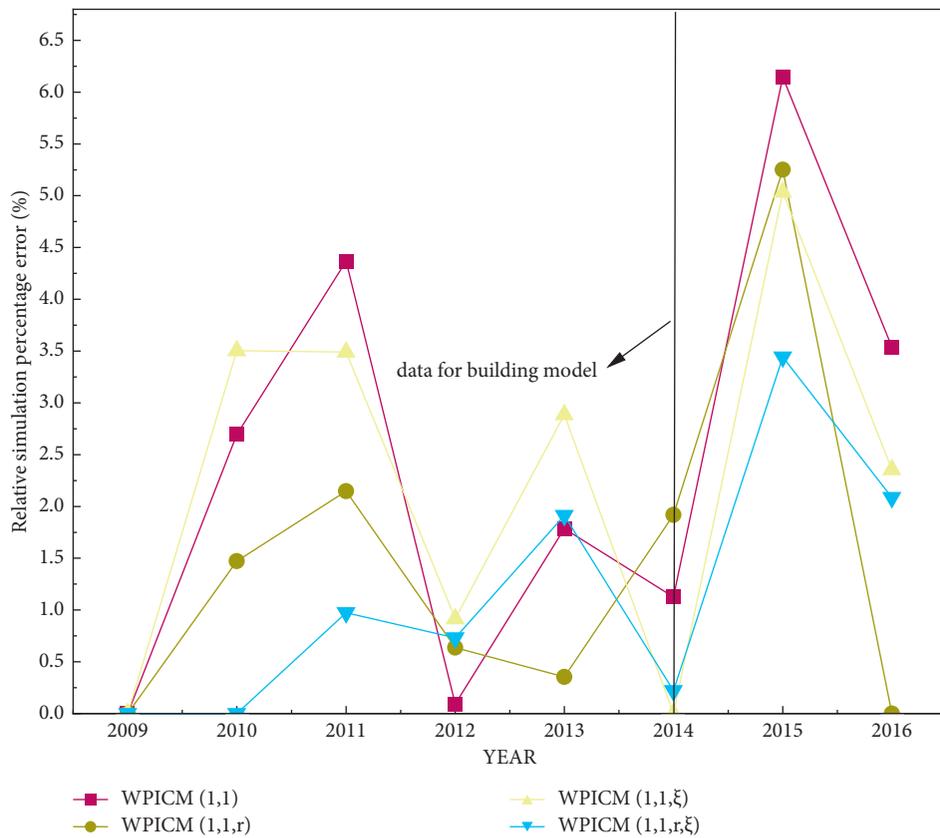


FIGURE 7: RSPE of model's performance.

TABLE 5: Error test.

Testing method	Average relative error test	Absolute grey correlation test
Testing results	$\bar{\Delta}_g = 0.77\% < 1\%$	$\epsilon^{ji} = 0.9878 > 0.9$

TABLE 6: Prediction data of WPIC of China during 2018–2024 (ten thousand of kW).

Year	2018	2019	2020	2021	2022	2023	2024
WPIC(K)	259,392.73	318,300.48	390,578.90	479,263.68	588,079.56	721,596.80	885,423.10

These suggestions can contribute to the advance of the low carbon economy and achieve rapid development of clean energy production.

## 5. Conclusion

Wind power is fluctuant and intermittent, which has an impact on the power grid. Large-scale wind power is a serious threat to the stability and security of the power system. Accurate prediction of wind power installed capacity is significant to the safety of the power system.

In this paper, a new parameter combination optimization model WPICM(1, 1,  $r$ ,  $\xi$ ) is proposed. Compared with the model that performs parameter optimization alone, the result shows the comprehensive performance of the proposed model WPICM(1, 1,  $r$ ,  $\xi$ ). The MRPE is 1.34%, and the overall performance of the model is better than that of the conventional grey prediction model. By optimizing the performance parameters of the traditional grey model, improving the forecasting level of wind power installed capacity has important practical significance for the wind power industry.

The combination optimization model has some shortcomings, and there is a future study to be completed. For instance, the lack of processing methods for individual abnormal points in the data resulted in the abnormal points still affecting the prediction results. Other parameters may choose to be optimized, such as initial value. The data processing process needs to be improved. In the selecting variables process, correlation analysis focuses on wind power installed capacity. Future studies might involve other influencing factors.

## Data Availability

The data that support the findings of this study are openly available in CWEA (Chinese Wind Energy Association) ([https://www.cwea.org.cn/industry\\_data.html](https://www.cwea.org.cn/industry_data.html)) and GWEC (Global Wind Energy Council) (<https://gwec.net/green-recovery-data-analysis/>).

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

## Acknowledgments

This work was supported by the Chongqing Natural Science Foundation of China (Grant Nos. cstc2019jcyj-msxmX0003

and cstc2019jcyj-msxmX0767) and Key Project of Scientific and Technological Research of Chongqing Education Commission (Grant No. KJZD-K202000804).

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