Hindawi
Mathematical Problems in Engineering
Volume 2019, Article ID 4141085, 9 pages
https://doi.org/10.1155/2019/4141085

Research Article

Forecasting of Wastewater Discharge and the Energy Consumption in China Based on Grey Model

ZhenHua Li, ZhiHong Zou, and Yang Yu

School of Economics and Management, Beihang University, Beijing 100191, China

Correspondence should be addressed to ZhiHong Zou; zouzhihong@buaa.edu.cn

Received 25 December 2018; Accepted 28 February 2019; Published 18 March 2019

Academic Editor: Francesco Riganti-Fulginei

Water pollution control is currently an important development strategy for China. Analysis and forecasting of wastewater discharge and the energy consumption are critical for this strategy. In this paper, we proposed the two time series models, namely, improved GM(0,n) model (IGM(0,n)) and optimized FGM(1,1) model (OFGM(1,1)). Two numerical experiments were used to test the validity of these models. It was indicated that the forecasting ability of two models had remarkably improved, compared to traditional FGM(1,1) and GM(0,n), respectively. We applied the two models to forecast wastewater discharge and energy consumption in China. The forecasting results have shown that the current growth rate in treated wastewater could meet the planning target of the 13th Five-Year Plan. The wastewater discharge and the energy consumption would reach 77.39 billion tons and 22.75 billion kWh, respectively, in 2020.

1. Introduction

With the rapid development of the Chinese economy, wastewater discharge has increased dramatically during the past decades, and China is currently the largest sewage producer. Since 2005 to 2015 the wastewater discharge has up to 73.53 billion tons from 52.45 billion tons. A large amount of wastewater has negative effects on the environment and human health [1–3]. The government attaches great importance to water pollution. The daily wastewater treatment capacity of China increased dramatically during the past decade. The administration of water pollution control and energy conservation is a significant development strategy for China [4, 5]. As of September 30, 2016, China had built 3552 WWTPs, with a total capacity of 1.7946×108m^3/d [6]. About 72.39% of wastewater was treated. A large amount of wastewater would be treated in the future. Wastewater treatment plant (WWTP) is one of the energy-intensive industries [7, 8]. The energy demand for wastewater treatment would increase substantially. Therefore, accurate prediction of the wastewater discharge and energy consumption constitutes a vital part of water pollution control policy of China.

Several studies focused on wastewater discharge and energy demand in China. Wang et al. applied an optimized NGBM(1,1) model for predicting the qualified discharge rate of industrial wastewater in China [9]. Liu et al. employed an indicator system to forecast the amount of domestic wastewater discharge in Jiangsu Province [10]. Li et al. used stochastic gradient regression to predict wastewater discharge of Tianjin and analyze its influence factors. The results showed that the model has higher precision than the support vector machine method and adaptive regression splines method [11]. Chen et al. investigated the overall status of wastewater discharge in China to analyze its driving factors [12]. Yin et al. developed a neural network model to forecast and analyze urban water-energy demand in China [13]. Xie and Wang examined the challenge of energy consumption in wastewater treatment plants [14]. Jian et al. applied the various methods to survey the energy consumption status and its influencing factors in 1441 municipal wastewater treatment plants [15]. Currently, the efforts to improve wastewater treatment are not keeping pace with economic development. At the same time, the average electricity consumption per cubic meter for wastewater was higher than developed country [14, 15].

The present work attempted to forecast wastewater discharge and energy consumption in China. Various prediction methods including ARIMA, artificial neural network (ANN), and nonparametric regression used to predict the system's future behavior [11, 16–18]. The forecasting results of ARIMA, ANN, and nonparametric regression depend on the number of training data and the availability of data. These limitations have not yet been overcome. The advantage of grey forecasting model is that we only need small amounts of data to predict the system's future behavior [19]. It can overcome the problem that the observed data available are very small. Just a few data are sufficient to characterize the system's behavior. It is more suitable for short-term prediction than a medium-term and long-term prediction. Different grey forecasting models were suited for data sequence with different characteristics. The grey Bernoulli model was suitable for fluctuant data. Grey Verhulst model was suitable for the historical data with 'S' distributing. Grey GM(1,1) model was suitable for historical data with exponential distributing. Grey forecasting model has been widely used in economics, finance, and other fields and has achieved lots of good results [20–25]. A grey forecasting model may yield large forecasting errors. Types of research concentrated on grey forecasting models to improve the forecasting precision. Xu et al. presented an approach to the least squares to grey Verhulst model. The model achieves reliable and precise results [26]. Jin et al. proposed a new grey model to avoid the error amplification resulting from the improper choice of the initial condition [27]. Wang developed a grey dynamic model of GMC (1,n) and proposed the Nash equilibrium idea-based optimization method to solve the model parameters. The results showed that the model was with higher accuracy than traditional model [28]. Wang and Hao constructed a nonlinear optimization model of GMC (1,n) and optimized the parameters of background. The results showed that the method could minimize the modeling error [29]. Wang et al. proposed an approach called DGGM (1,1) to predict quarterly hydropower production in China. The results indicated that DGGM (1,1) has a higher prediction accuracy than traditional GM (1,1) and SARIMA models [30]. Hsu and Wang presented Bayesian grey forecast models and used the technique of Markov Chain Monte Carlo to estimate the parameters for grey differential function [31]. Chen et al. improved nonlinear grey Bernoulli model (NGBM) by the Nash equilibrium concept. They found that the prediction by the method was better than the NGBM [32]. Lee and Tong combined residual modification with genetic programming sign estimation to improve the grey forecasting model [33].

In this paper, we presented two grey forecasting models an optimized FGM(1,1) (OFGM(1,1)) model and improved GM(0,n) (IGM(0,n)) to forecast wastewater discharge and energy consumption in China. The GM(0,n) model was a special form of GM(1,n) model with no derivatives [34, 35]. A new method was used to improve the accuracy of the traditional GM(0,n) model. The empirical results showed that IGM(0,n) model has a better performance than the traditional model. Tien proposed the FGM(1,1) model and showed that the model had higher prediction accuracy than GM(1,1) model [36]. To improve the forecasting accuracy of FGM(1,1) model, an optimized FGM(1,1) model was proposed. The particle swarm optimization algorithm was used to optimize the generating coefficient of the model. FGM(1,1) model and GM(1,1) were employed to compare the effectiveness of OFGM(1,1) model. The mean absolute percentage error (MAPE) was chosen to minimize the error between actual values and forecasting values [37, 38]. The results demonstrate that OFGM(1,1) model had higher forecasting accuracy than the other forecasting model. So, the paper adopted IGM(0,n) model and OFGM(1,1) model to forecast the wastewater discharge and energy consumption in China. It would provide a profitable reference for the economic and environmental benefits of sewage treatment.

2. Methodology and Data

2.1. The OFGM(1,1) Model. GM(1,1) model is a single-variable grey forecasting model. To improve its performance, Tien put forward a new prediction model FGM(1,1) model. For the GM(1,1) model, the forecasting values of this model are independent of the first data of time series. So an arbitrary number could be inserted in front of the time series [34]. By doing so, it only requires three data values to forecast the system's future behavior. Empirical results show that this model has a higher prediction accuracy than GM(1,1) model. The existing model FGM(1,1) has several defects. It is inaccurate to set generating coefficient as a constant. The constant could affect the prediction accuracy of the model. To improve its performance, the article introduces an unknown interpolation coefficient γ to calculate the generating coefficient of FGM(1,1).

The procedures of the new method can be concluded as follows.

An arbitrary number would be inserted in front of series $X^0 = (x^0(1), x^0(2), \ldots, x^0(n))$. The new series is

$$\widehat{X}^0 = \left(x^0(0), x^0(1), x^0(2), \ldots, x^0(n)\right) \tag{1}$$

where $x^0(0)$ is arbitrary number; to keep life simple, we assume $x^0(0) = 0$. Consequently, the 1-GAO of $\widehat{X}^0$ is given by

$$x^1(k) = \sum_{i=0}^{k} x^0(k) \tag{2}$$

The new series is written as

$$\widehat{X}^1 = \left(x^1(0), x^1(1), x^1(2), \ldots, x^1(n)\right) \tag{3}$$

Hence, grey model FGM(1,1) based on series $\widehat{X}^1$ can be written as

$$x^0(k) + az^1(k) = b \tag{4}$$

where $z^1(k) = 0.5x^1(k) + 0.5x^1(k-1)$ $(k = 1, 2, 3, \ldots, n)$.

The grey differential equation of Eq. (4) is

$$\frac{dx^1}{dt} + ax^1 = b \tag{5}$$

where a and b are the interim parameters. The parameters are

$$\begin{bmatrix} a \\ b \end{bmatrix} = \left(B^T B\right)^{-1} B^T Y \tag{6}$$

where

$$B=\begin{bmatrix} -\left(\gamma x^{1}(0)+(1-\gamma)x^{1}(1)\right) & 1\\ -\left(\gamma x^{1}(1)+(1-\gamma)x^{1}(2)\right) & 1\\ \vdots & \vdots\\ -\left(\gamma x^{1}(n-1)+(1-\gamma)x^{10}(n)\right) & 1\end{bmatrix},$$
$$Y=\begin{bmatrix} x^{0}(1)\\ x^{0}(2)\\ \vdots\\ x^{0}(n)\end{bmatrix} \quad (7)$$

If $\gamma=0.5$, the model is transformed into FGM(1,1) model.

The time response function is

$$\widehat{x}^{1}(k)=\left(x^{0}(1)-\frac{b}{a}\right)e^{k-1}-\frac{b}{a}\quad (k=1,2,3,\ldots,n) \quad (8)$$

Applying the 1-GAOto Eq. (8), we have the modeling value $x^{0}(k)$ as forecasts

$$\widehat{x}^{0}(k)=\left(x^{0}(1)-\frac{b}{a}\right)\left(1-e^{a}\right)e^{-a(k-1)} \quad (k=1,2,3,\ldots,n) \quad (9)$$

2.2. The Improved Grey Multivariable Model IGM(0,n). The GM(0,n) is a multivariable grey forecasting model, which is a particular case of the GM(1,n) model [29]. To improve the modeling and forecasting precision of the system, we used the secondary approximation model to enhance the adaptability of IGM(0,n) on real data. The procedures of IGM(0,n) could be indicated as follows.

Suppose the set of a primitive data sequence is

$$X_{1}^{(0)},X_{2}^{(0)},\ldots,X_{n}^{(0)} \quad (10)$$

where $X_{k}^{(0)}=(x_{k}^{(0)}(1),x_{k}^{(0)}(2),\ldots,x_{k}^{(0)}(m))$ and $X_{j}^{(0)}(i)$ is the jth value of $X_{j}^{(0)}$ at equispaced interval of i time. $X_{1}^{(0)}$ is the feature sequence of system, and the others are the influence factors sequences of system.

The first order accumulation generation operator (1-GAO) for $X_{i}^{(0)}$ is given as

$$X_{1}^{(1)},X_{2}^{(1)},\ldots,X_{n}^{(1)} \quad (11)$$

where $X_{k}^{(1)}=(x_{k}^{(1)}(1),x_{k}^{(1)}(2),\ldots,x_{k}^{(1)}(m))$ and $x_{k}^{(1)}(i)=\sum_{j=1}^{i}x_{k}^{(0)}(j)$, $i=1,2,\ldots,m$.

Then, the GM(0,n) model is written as

$$x_{1}^{(1)}(k)=a+b_{2}x_{2}^{(1)}(k)+b_{3}x_{3}^{(1)}(k)+\cdots+b_{n}x_{n}^{(1)}(k)\quad k=2,\cdots,m \quad (12)$$

The least-squares solution of the parameters of GM(0,n) is

$$\widehat{b}=\left(B^{T}B\right)^{-1}B^{T}Y \quad (13)$$

where $\widehat{b}=(a,b_{2},\ldots,b_{n})^{T}$, $\mathrm{Y}=(x_{k}^{(1)}(2),\ldots,x_{k}^{(1)}(m))^{T}$, and

$$B=\begin{bmatrix}1 & x_{2}^{(1)}(2) & \ldots & x_{n-1}^{(1)}(2) & x_{n}^{(1)}(2)\\ 1 & x_{2}^{(1)}(3) & \ldots & x_{n-1}^{(1)}(3) & x_{n}^{(1)}(3)\\ \vdots & \vdots & \ddots & \vdots & \vdots\\ 1 & x_{2}^{(1)}(m) & \ldots & x_{n-1}^{(1)}(m) & x_{n}^{(1)}(m)\end{bmatrix}. \quad (14)$$

The time response of Eq. (12) is

$$\widehat{x}_{1}^{(1)}(k)=a+b_{2}x_{2}^{(1)}(k)+b_{3}x_{3}^{(1)}(k)+\cdots+b_{n}x_{n}^{(1)}(k) \quad (15)$$

After inversely accumulating generation operation from Eq. (11), the grey forecasting model of the original sequence is defined as

$$\widehat{x}_{1}^{(0)}(k)=\widehat{x}_{1}^{(1)}(k)-\widehat{x}_{1}^{(1)}(k-1)\quad k=2,3,\ldots,n. \quad (16)$$

To improve the modelling and prediction precision of the GM(0,n), this paper inputs quadratic polynomials of the influence factors sequence in GM(0,n). On this basis, the improved GM(0,n) (IGM(0,n)) is defined as

$$x_{1}^{(1)}(k)=a+b_{2}x_{2}^{(1)}(k)+b_{2}^{1}\left(x_{2}^{(1)}(k)\right)^{2}+\cdots+b_{n}x_{n}^{(1)}(k)+b_{n}^{1}\left(x_{n}^{(1)}(k)\right)^{2} \quad (17)$$

The least-squares solution of the parameters of IGM(0,n) is

$$\widetilde{b}=\left(\widetilde{B}^{T}\widetilde{B}\right)^{T}Y \quad (18)$$

where $\widetilde{b}=(a,b_{2},b_{2}^{1},\ldots,b_{n},b_{n}^{1})^{T}$, $\mathrm{Y}=(x_{k}^{(1)}(2),\ldots,x_{k}^{(1)}(m))^{T}$, and

$$\widetilde{B}=\begin{bmatrix}1 & x_{2}^{(1)}(2) & x_{2}^{(1)}(2)^{2} & \cdots & x_{n}^{(1)}(2) & x_{n}^{(1)}(2)^{2}\\ 1 & x_{2}^{(1)}(3) & x_{2}^{(1)}(3)^{2} & \cdots & x_{n}^{(1)}(3) & x_{n}^{(1)}(3)^{2}\\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots\\ 1 & x_{2}^{(1)}(m) & x_{2}^{(1)}(m)^{2} & \cdots & x_{n}^{(1)}(m) & x_{n}^{(1)}(m)^{2}\end{bmatrix}. \quad (19)$$

The time response of Eq. (17) is

$$\widetilde{x}_{1}^{(1)}(k)=a+b_{2}x_{2}^{(1)}(k)+b_{2}^{1}\left(x_{2}^{(1)}(k)\right)^{2}+\cdots+b_{n}x_{n}^{(1)}(k)+b_{n}^{1}\left(x_{n}^{(1)}(k)\right)^{2} \quad (20)$$

By performing the inverse accumulation generation operator from Eq. (10), the grey forecasting model of the primitive data sequences is finally obtained as

$$\widetilde{x}_{1}^{(0)}(k)=\widetilde{x}_{1}^{(1)}(k)-\widetilde{x}_{1}^{(1)}(k-1)\quad k=2,3,\ldots,n. \quad (21)$$

2.3. Particle Swarm Optimization (PSO) Algorithm. PSO algorithm was proposed by Kennedy and Eberhart [39]. As one of the intelligent optimization algorithms, the method was simple implementation [40, 41]. It had better efficiency than other evolutionary computations to obtain the optimal solution. To solve the generating coefficient problem, PSO was employed to calculate the generating coefficient of FGM(1,1).

In this article, the velocity and particle iteration followed the equations

$$v_{ij}^{k+1} = \omega v_{ij}^{k} + c_1 r_1 \left(p_{ij}^{k} - x_{ij}^{k}\right) + c_2 r_2 \left(g_{ij}^{k} - x_{ij}^{k}\right) \quad (22)$$

$$x_{ij}^{k+1} = x_{ij}^{k} + v_{ij}^{k} \quad (j = 1, 2, \cdots, 40) \quad (23)$$

where inertia weight ω was 1; c_1 and c_2 were acceleration factors that were 0.85; r_1 and r_2 were random numbers in the interval between 0 and 1; maximum number of iterations was 200; population was $D = 40$.

2.4. Assessment of the Modelling and Forecasting Precision. Mean absolute percentage error (MAPE), mean absolute error (MAE), and mean square error (MSE) were used to test the accuracy of the forecast models. Generally, the lower deviation indexes meant higher accuracy. The calculation formulas were defined as

$$MAPE = \frac{1}{k}\sum_{i=1}^{k}\left|\frac{\hat{x}^1(i) - x^0(i)}{x^0(i)}\right| \times 100\% \quad (24)$$

$$MAE = \frac{1}{k}\sum_{i=1}^{k}\left|\hat{x}^1(i) - x^0(i)\right| \quad (25)$$

$$MSE = \frac{1}{k}\sum_{i=1}^{k}\left(\hat{x}^1(i) - x^0(i)\right)^2 \quad (26)$$

The fitness function was defined as

$$\min \quad MAPE = \frac{1}{k}\sum_{i=1}^{k}\left|\frac{\hat{x}^1(i) - x^0(i)}{x^0(i)}\right| \times 100\% \quad (27)$$

where $x^0(i)$ and $\hat{x}^1(i)$ were the ith actual value and prediction value, respectively, and k was the number of predictions.

2.5. Validation of the OFGM(1, 1) Model and IGM(0,n) Model

2.5.1. OFGM(1, 1) Model. In this section, data sequence A was used to verify the performance of OFGM(1,1) model [39]. For this data sequence, the first five data were used for training data, while the other data were used to evaluate the forecasting performance. The evolution of fitness of the OFGM(1,1) model was shown in Figure 1. It can be seen in Figure 1 that the fitness value converges very fast to the stagnation point. This algorithm is very effective in solving the parameter optimization problem.

The actual and forecast values of data sequence A using FGM(1,1) and OFGM(1,1) were shown in Table 1 and Figure 2. There deviation indexes were shown in Tables 2 and 3. It can be seen from Table 2 that the training accuracies of FGM(1,1) and OFGM(1,1) were 2.42% and 1.92%, respectively. The other deviation indexes also showed that he optimized FGM(1,1) had higher training accuracy than FGM(1,1). According to Table 3, deviation indexes of OFGM(1,1) were the smallest. Results showed that OFGM(1,1) model had a better performance than FGM(1,1) model. The OFGM(1,1) model would be used to predict the energy consumption in China.

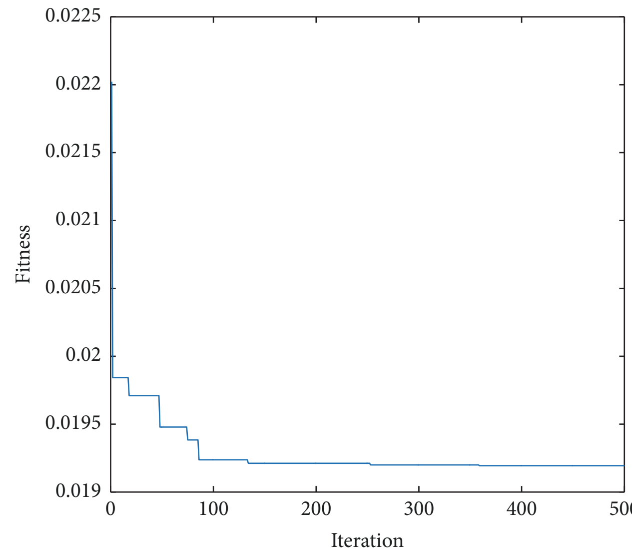

FIGURE 1: Evolution of fitness of OFGM(1,1) model.

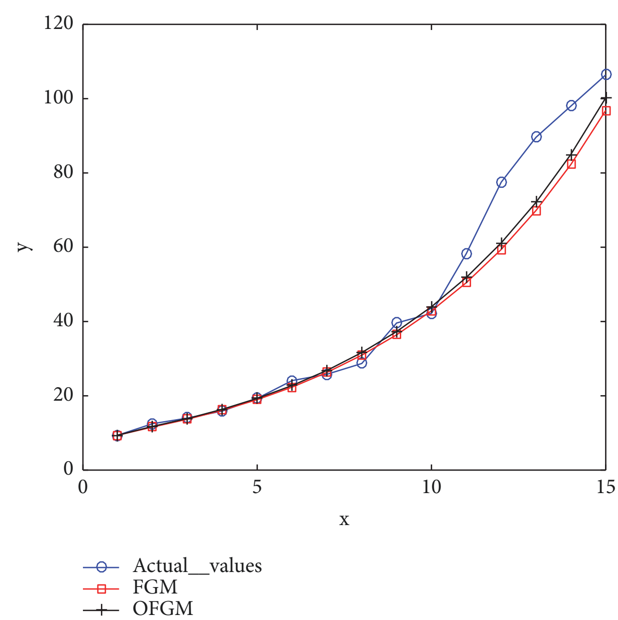

FIGURE 2: Forecasting values by FGM(1,1) and of OFGM(1,1).

2.5.2. IGM(0,n) Model. In this section, the data sequences $X_1^{(0)}$ and $X_2^{(0)}$ [30] were used to evaluate the performance of improved IGM(0,2) model. The simulation results of these data sequences using GM(0,2) model and IGM(0,2) model

Table 1: Actual and forecast values of data sequence A.

Sequence X^1	FGM(1,1) model		OFGM(1, 1) model	
	Model value	Relative error (%)	Model value	Relative error (%)
9.4	9.4	0	9.4	0
12.5	11.6	6.9	11.77	5.80
14.0	13.70	2.16	13.88	0.84
15.9	16.12	1.39	16.37	2.95
19.3	18.97	1.68	19.30	0
24.1	22.33	7.33	22.76	5.57
25.8	26.29	1.89	26.83	4.00
28.7	30.94	7.81	31.64	10.23
39.6	36.42	8.03	37.30	5.80
42.2	42.87	15.82	43.98	4.22
58.3	50.46	13.45	51.86	11.05
77.5	59.39	23.37	61.15	21.10
89.6	69.90	21.98	72.09	19.54
98.0	82.28	16.04	85.01	13.26
106.4	96.84	8.99	100.23	5.80

Table 2: Deviation indexes of simulation results for different forecasting methods.

Method	MAPE(%)	MAE	MSE
FGM(1,1) model	2.42	0.3500	0.2115
OFGM(1, 1) model	1.92	0.2640	0.1536

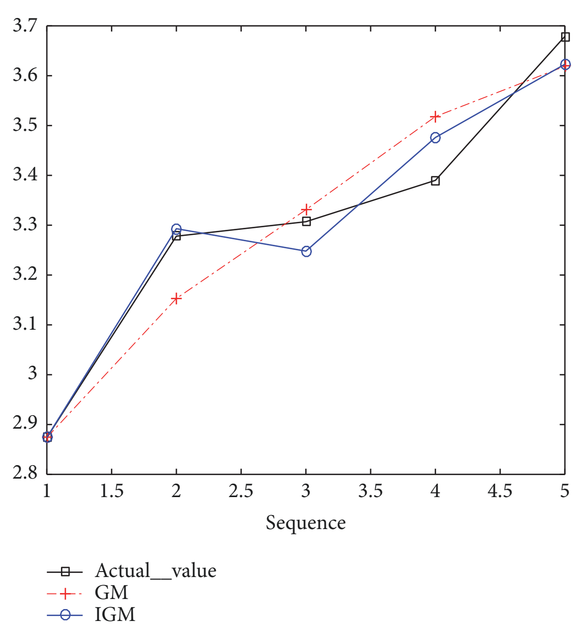

Figure 3: Forecasting values by GM(0,2) and IGM(0,2).

were depicted in Table 4 and Figure 3. To show the superiority of IGM(0,2) model, the deviation indexes of GM(0,2) and IGM(0,2) model were compared in Table 5. As can be seen in Tables 4 and 5, the relative errors of GM(0,2) were ranging from 0.7% to 3.8%. The relative errors of IGM(0,2) were ranging from 0.4% to 2.5%. The MAPEs for GM(0,2) and IGM(0,2) were 2.48% and 1.53%, respectively. Meanwhile, the MAE and MSE of IGM(0,2) model were smaller than the GM(0,2) model. The performance comparisons showed that the IGM(0,2) had the best fitting effect with minimum deviation indexes. The IGM(0,2) model would be used to forecast the wastewater discharge of China.

2.6. Data Sources. This article collected annual data on wastewater discharged and the energy consumption in China for 2005-2015. The IGM(0,2) was used to predict wastewater discharge. The OFGM(1,1) method was employed to forecast energy consumption. The data sequences of wastewater discharge and real GDP were feature sequence and influence factor sequence of a system, respectively.

Water pollution and energy shortage would become tumbling block of China's economic growth. With the accelerated industrialization and urbanization, wastewater discharge would continue to increase in the future. From 2005 to 2015, real GDP had risen from 18.7319 trillion yuan to 68.9052 yuan. Based on economic development target, the country's per capita GDP will probably reach 20 thousand yuan in 2020, assuming that China's average annual economic growth rate is 7% in 2016-2020 [42]. Treated wastewater had up to 72.39% from 60.8% since 2012 to 2015. Energy demand for sewer had increased remarkably. So far, the average electricity consumption per cubic meter for wastewater was 0.2927kWh/m^3 in China [14, 15] and would not be changed in the short term. It means that the energy consumption of

Table 3: Deviation indexes of forecasting results for different forecasting methods.

Method	MAPE(%)	MAE	MSE
FGM(1,1) model	11.05	7.928	113.49
OFGM(1, 1) model	10.58	6.8850	84.2164

Table 4: Forecasting values by GM(0,2) and IGM(0,2).

Sequence number	Actual value	GM(0,2) model		IGM(0, 2) model	
		Model value	Relative error (%)	Model value	Relative error (%)
2	3.278	3.153	3.8	3.293	0.4
3	3.307	3.331	0.7	3.248	1.7
4	3.390	3.518	3.8	3.476	2.5
5	3.679	3.619	1.6	3.623	1.5

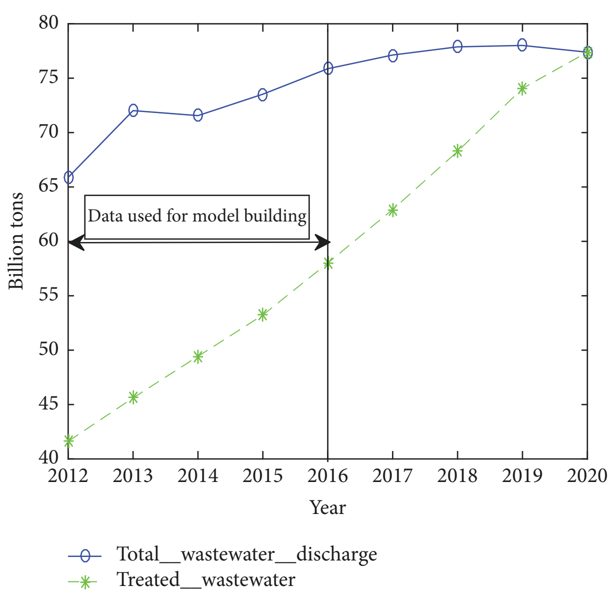

Figure 4: Simulation and forecasting of treated wastewater and wastewater discharge in China (2012 to 2020).

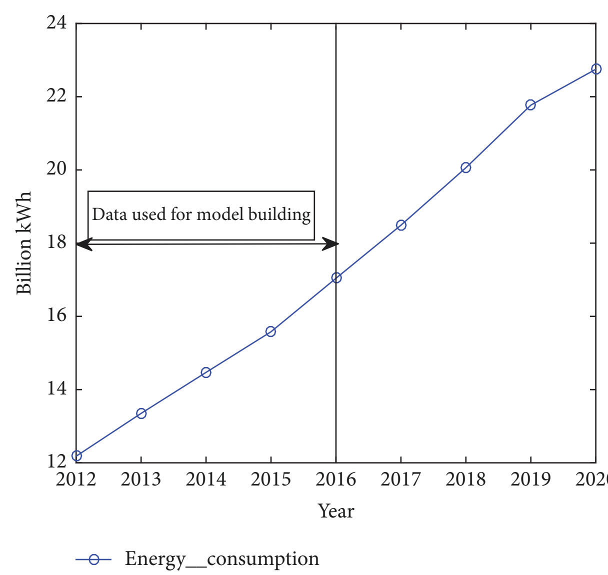

Figure 5: Simulation and forecasting energy demand in China.

wastewater treatment system had up to 15.58 billion kWh in 2015. Energy demand for wastewater in the recent year was listed in Table 6 (2012 to 2015).

3. Results and Discussion

Wastewater discharge and energy consumption in China were chosen as the goals of this study. As the trend of each series may be changing quickly over time, the data from 2011 to 2015 were applied for in-sample simulation, while data from 2016 to 2020 were utilized for out-of-sample prediction. The data were collected from the published documents and the Ministry of Environmental Protection of the People's Republic of China.

3.1. Forecasting Energy Consumption for Wastewater Treatment. The forecasting results of wastewater discharge using OFGM(1,1) were depicted in Table 7 and Figure 4. According to Table 7, the wastewater discharge in China would increase to 78.02 billion tons in 2019, before decreasing to 77.39 in 2020. All the wastewater would be treated in 2020. According to the planning target of the Chinese waste-water treatment industry in the period of the 13th Five-Year Plan, more than 95% wastewater would be treated by the end of 2020. These results showed that the current growth rate in wastewater treatment could meet the planning target. The government should formulate more effective incentive and policies for water efficiency to reduce sewage discharge.

The forecasting results of energy consumption using IGM(0,2) were depicted in Table 7 and Figure 5. According to Table 7, the energy consumption for wastewater treatment is expected to increase to 22.75 billion kWh in 2020. Currently, low energy efficiency is one of the significant issues faced by most WWTPs in China. The energy efficiency measure and treatment process modification could significantly reduce energy consumption. In addition, energy recovery from wastewater treatment could offset the electricity consumption for the wastewater treatment. Therefore, the government

Table 5: Deviation indexes of forecasting results for different forecasting methods.

Method	MAPE(%)	MAE	MSE
GM(0,2) model	2.48	0.0842	0.0540
IGM(0, 2) model	1.53	0.0090	0.0036

Table 6: The wastewater discharge and energy consumption in China (2012 to 2015).

Year	2012	2013	2014	2015
Wastewater discharge (billion tons)	68.43	69.49	71.56	73.53
Treated wastewater (billion tons)	41.62	45.61	49.43	53.23
Energy consumption (billion kWh)	12.18	13.35	14.47	15.58

Table 7: Forecasting of wastewater discharge, treated wastewater, and energy consumption in China.

Year	2016	2017	2018	2019	2020
Total wastewater discharge (billion tons)	75.87	77.13	77.89	78.02	77.39
Treated wastewater (billion tons)	58.01	62.93	68.27	74.06	77.39
Power consumption (billion kWh)	17.04	18.49	20.06	21.77	22.75

should increase investment into energy efficiency measure to reduce the energy consumption in the coming year.

4. Conclusions

In this article, we attempted to model and predict wastewater discharge and energy consumption in China based on the grey model. Using the historical data, the OFGM(1,1) model obtained excellent results regarding MAPE, when compared with FGM(1,1) and GM(1,1). The MAPEs of the OFGM(1,1) for training data and test predictions are 1.92% and 10.58%. Actual examples clearly show that the new forecasting model has the higher forecasting precision than traditional grey forecasting model FGM(1,1). The model was used to forecast the energy consumption in wastewater treatment. On the other hand, IGM(0,n) model was employed to forecast the wastewater discharge in China. The numerical experiment indicates that the model has a higher accuracy than GM(0,n) model. The MAPEs of this model are 1.85%. Performance assessment results clearly indicate that IGM(0,n) model can be employed for future projection of the wastewater discharge. The results show that China's wastewater discharge will increase 78.02 billion tons in 2019, before decreasing to 77.39 in 2020. The energy consumption for wastewater treatment is expected to increase to 22.75 billion kWh in 2020. These results show that the current growth rate in treated wastewater could meet the target of the Chinese wastewater treatment industry in the period of the 13th Five-Year Plan.

However, with the strict effluent limitations, wastewater treatment plants are likely to become more energy-intensive. Energy demand for WWTPs will increase significantly in the future. The government should provide more support in finance and credit policies for improving the processing and general techniques in wastewater treatment and encourage technological innovations to recover energy from the WWTPs. The appropriate use of electricity production from sludge incineration and anaerobic digester could transform from considering wastewater as an issue to considering it as a renewable energy resource. The results shown here could offer references to policy makers in setting energy strategies and protecting water resource.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflicts of interest.

Authors' Contributions

Work presented here was conceived, carried out, and analyzed by Zhenhua Li, Zhihong Zou, and Yang Yu.

Acknowledgments

This work was supported by the National Natural Science Foundation of China (No. 51478025).

References

[1] L. Yi, W. Jiao, X. Chen, and W. Chen, "An overview of reclaimed water reuse in China," *Journal of Environmental Sciences*, vol. 23, no. 10, pp. 1585–1593, 2011.

[2] Y. Song, R. Liu, Y. Sun, K. Lei, and O. Kolditz, "Waste water treatment and pollution control in the Liao River Basin," *Environmental Earth Sciences*, vol. 73, no. 9, pp. 4875–4880, 2015.

[3] Y. Zhang, Y. Liu, Z. Niu, and S. Jin, "Ecological risk assessment of toxic organic pollutant and heavy metals in water and sediment from a landscape lake in Tianjin City, China," *Environmental Science and Pollution Research*, vol. 24, no. 13, pp. 12301–12311, 2017.

[4] The State Council of the People's Republic of China, *The Action Plan for Prevention and Control of Water Pollution*, 2015, http://www.gov.cn/zhengce/content/2015–04/16/content_9613.htm.

[5] The State Council, "The 13th five-year plan of facility construction for wastewater treatment and recycle," Tech. Rep., 2016 (Arabic).

[6] K. Smith and S. Liu, "Energy for conventional water supply and wastewater treatment in urban China: a review," *Global Challenges*, pp. 1–6, 2017.

[7] D. Panepinto, S. Fiore, M. Zappone, G. Genon, and L. Meucci, "Evaluation of the energy efficiency of a large wastewater treatment plant in Italy," *Applied Energy*, vol. 161, pp. 404–411, 2016.

[8] A. K. Plappally and J. H. Lienhard V, "Energy requirements for water production, treatment, end use, reclamation, and disposal," *Renewable & Sustainable Energy Reviews*, vol. 16, no. 7, pp. 4818–4848, 2012.

[9] Z.-X. Wang, K. W. Hipel, Q. Wang, and S.-W. He, "An optimized NGBM(1,1) model for forecasting the qualified discharge rate of industrial wastewater in China," *Applied Mathematical Modelling*, vol. 35, no. 12, pp. 5524–5532, 2011.

[10] L. Li, X. Liu, and X. Huang, "Prediction of domestic wastewater discharge volume in China," *Manufacture Engineering and Environment Engineering*, vol. 84, pp. 453–461, 2014.

[11] H. Y. Li, H. L. Wang, G. M. Li, and S. M. Li, "Study on urban wastewater discharge forecasting and influence factors analysis based on stochastic gradient regression," *Computer Society*, vol. 143, pp. 484–486, 2009.

[12] K. Chen, X. Liu, L. Ding, G. Huang, and Z. Li, "Spatial characteristics and driving factors of provincial wastewater discharge in China," *International Journal of Environmental Research and Public Health*, vol. 13, pp. 1–19, 2016.

[13] Z. Yin, B. Jia, S. Wu, J. Dai, and D. Tang, "Comprehensive forecast of urban water-energy demand based on a neural network model," *Water*, vol. 10, pp. 1–16, 2018.

[14] T. Xie and C. W. Wang, "Energy consumption in wastewater treatment plants in China," in *Proceedings of the World Congress on water, Climate and Energy*, pp. 1–6, 2012.

[15] Y. Jian, W. Fu, L. H. Mao et al., "Influence factors analysis of urban sewage treatment plant on energy consumption," *Journal of Beijing Jiaotong University*, vol. 38, pp. 33–37, 2014.

[16] N. Bowden and J. E. Payne, "Short term forecasting of electricity prices for MISO hubs: Evidence from ARIMA-EGARCH models," *Energy Economics*, vol. 30, no. 6, pp. 3186–3197, 2008.

[17] H.-T. Pao, "Forecasting electricity market pricing using artificial neural networks," *Energy Conversion and Management*, vol. 48, no. 3, pp. 907–912, 2007.

[18] B. Sivaneasan, C. Y. Yu, and K. P. Goh, "Solar forecasting using ANN with fuzzy logic pre-processing," *Energy Procedia*, vol. 143, pp. 727–732, 2017.

[19] R.-C. Tsaur, "The development of an interval grey regression model for limited time series forecasting," *Expert Systems with Applications*, vol. 37, no. 2, pp. 1200–1206, 2010.

[20] W.-Y. Wu and S.-P. Chen, "A prediction method using the grey model GMC(1, n) combined with the grey relational analysis: a case study on Internet access population forecast," *Applied Mathematics and Computation*, vol. 169, no. 1, pp. 198–217, 2005.

[21] Z.-X. Wang and D.-J. Ye, "Forecasting Chinese carbon emissions from fossil energy consumption using non-linear grey multivariable models," *Journal of Cleaner Production*, vol. 142, pp. 600–612, 2017.

[22] Y. Jiang, Y. Yao, S. Deng, and Z. Ma, "Applying grey forecasting to predicting the operating energy performance of air cooled water chillers," *International Journal of Refrigeration*, vol. 27, no. 4, pp. 385–392, 2004.

[23] L.-C. Hsu, "Applying the grey prediction model to the global integrated circuit industry," *Technological Forecasting & Social Change*, vol. 70, no. 6, pp. 563–574, 2003.

[24] C.-H. Chiao and W. Y. Wang, "Reliability improvement of fluorescent lamp using grey forecasting model," *Microelectronics Reliability*, vol. 42, no. 1, pp. 127–134, 2002.

[25] H. Zhao and S. Guo, "An optimized grey model for annual power load forecasting," *Energy*, vol. 107, pp. 272–286, 2016.

[26] J. Xu, T. Tan, M. Tu, and L. Qi, "Improvement of grey model by least squares," *Technological Forecasting & Social Change*, vol. 38, pp. 13961-12966, 2011.

[27] M. Jin, X. Zhou, Z. M. Zhang, and M. M. Tentzeris, "Short-term power load forecasting using grey correlation contest modeling," *Expert Systems with Applications*, vol. 39, no. 1, pp. 773–779, 2012.

[28] Z.-X. Wang, "A predictive analysis of clean energy consumption, economic growth and environmental regulation in china using an optimized grey dynamic model," *Computational Economics*, vol. 46, no. 3, pp. 437–453, 2015.

[29] Z.-X. Wang and P. Hao, "An improved grey multivariable model for predicting industrial energy consumption in China," *Applied Mathematical Modelling*, vol. 40, no. 11-12, pp. 5745–5758, 2016.

[30] Z.-X. Wang, Q. Li, and L.-L. Pei, "Grey forecasting method of quarterly hydropower production in China based on a data grouping approach," *Applied Mathematical Modelling*, vol. 51, pp. 302–316, 2017.

[31] L.-C. Hsu and C.-H. Wang, "Forecasting the output of integrated circuit industry using a grey model improved by the Bayesian analysis," *Technological Forecasting & Social Change*, vol. 74, no. 6, pp. 843–853, 2007.

[32] C.-I. Chen, P.-H. Hsin, and C.-S. Wu, "Forecasting Taiwan's major stock indices by the Nash nonlinear grey Bernoulli model," *Expert Systems with Applications*, vol. 37, no. 12, pp. 7557–7562, 2010.

[33] Y.-S. Lee and L.-I. Tong, "Forecasting energy consumption using a grey model improved by incorporating genetic programming," *Energy Conversion and Management*, vol. 52, no. 1, pp. 147–152, 2011.

[34] Y.-T. Lee, "Structure activity relationship analysis of phenolic acid phenethyl esters on oral and human breast cancers: the grey GM(0, N) approach," *Computers in Biology and Medicine*, vol. 41, no. 7, pp. 506–511, 2011.

[35] F. Li and Z. D. Wang, "A new method of estimating the model parameters of GM(0,N)," *Journal of Wuhan University of Technology*, vol. 26, pp. 625–627, 2002.

[36] T.-L. Tien, "A new grey prediction model FGM(1, 1)," *Mathematical and Computer Modelling*, vol. 49, no. 7-8, pp. 1416–1426, 2009.

[37] J. P. Angeline, "Evolutionary optimization versus particle swarm optimization: philosophy and performance differences," in *Proceedings of the International Conference On Evolutionary Programming*, pp. 601–610, 1998.

[38] C.-H. Wang and L.-C. Hsu, "Using genetic algorithms grey theory to forecast high technology industrial output," *Applied Mathematics and Computation*, vol. 195, no. 1, pp. 256–263, 2008.

[39] J. Kennedy and R. Eberhart, "Particle swarm optimization," in *Proceedings of the IEEE International Conference on Neural Networks (ICNN '95)*, vol. 4, pp. 1942–1948, 1995.

[40] T. Cheng, M. Chen, P. J. Fleming, Z. Yang, and S. Gan, "A novel hybrid teaching learning based multi-objective particle swarm optimization," *Neurocomputing*, vol. 222, pp. 11–25, 2017.

[41] R. Kundu, S. Das, R. Mukherjee, and S. Debchoudhury, "An improved particle swarm optimizer with difference mean based perturbation," *Neurocomputing*, vol. 129, pp. 315–333, 2014.

[42] Y. Xuan and Q. Yue, "Forecast of steel demand and the availability of depreciated steel scrap in China," *Resources, Conservation & Recycling*, vol. 109, pp. 1–12, 2016.