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Research Article

Predicting Building Energy Consumption with a New Grey Model

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Based on the existing grey prediction model, this paper proposes a new grey prediction model (the fractional discrete grey model, FDGM (1, 1, t^α)), introduces the modeling mechanism and characteristics of the FDGM (1, 1, t^α), and uses three groups of data to verify its effectiveness compared with that of other grey models. This paper forecasts the building energy consumption in China over the next five years based on the idea of metabolism. The results show that the FDGM (1, 1, t^α) can be transformed into other grey models through parameter setting changes, so the new model has strong adaptability. The FDGM (1, 1, t^α) is more reliable and effective than the other six compared grey models. From 2018 to 2022, the total energy consumption levels of civil buildings, urban civil buildings, and civil buildings specifically in Beijing will exhibit steady upward trends, with an average annual growth rate of 2.61%, 1.92%, and 0.78%, respectively.

1. Introduction

With the development of the economy and the explosive growth of the global population, the energy consumption levels of countries all over the world are increasing each year. As an important industry in the national economy, the construction industry accounts for a very large proportion of the total energy consumption. According to the report of the International Energy Agency (IEA), in 2017, the total energy consumption of the construction industry accounted for 36% of the world's final energy consumption, making it the industry with the largest proportion of energy consumption in the world. In developed countries, this proportion is even higher. For example, construction energy consumption accounts for approximately 39% of the total energy consumption in the United States and 40% of that in Europe [1]. In addition, the construction industry is also one of the main players in global carbon emissions, and the total direct and indirect carbon dioxide emissions due to construction account for 40% of all emissions [2]. As the world's largest carbon emitter and the second-largest economy [3], China's building energy consumption has increased rapidly in recent decades. The average annual growth rate is 5.6%, which is 2.9 times the world average. It is expected that energy consumption will exceed 1089 million tons of coal equivalent (Mtce) in 2020 [1]. At present, China's building energy consumption accounts for 16.2% of the total global building energy consumption, second only to the United States and ranking second in the world. In China, building energy consumption has been juxtaposed with industrial and transportation energy consumption, which have become the three major energy consumers in China. According to the China Building Energy Efficiency Development Report (2020), from 2009 to 2017, the total energy consumption of civil buildings in China increased from 568 million tons of coal equivalent (TCE) to 882 million TCE, with an average growth rate of 5.7%. The proportion of the total energy consumed by civil buildings out of the total terminal energy consumption of the entire society increased from 17.63% to 20.18%. Among the total energy consumption of civil buildings, the proportions of urban civil building energy consumption and rural civil building energy consumption are basically unchanged, with both between 20% and 22%. The proportion of energy consumption by public buildings has increased yearly from 17.6% to 27.0%. The proportion of heating energy consumption has decreased annually from

39.3% to 29.8%. According to current forecasts, if no effective measures are taken, the energy consumption of building refrigeration alone will more than double by 2030. The main reason for the rapid growth of building energy consumption in China is the significant increase in the urbanization rate in recent decades. According to statistics, China's urbanization rate increased from 36.2% in 2000 to 58.5% in 2017. Simultaneously, the rise of large office buildings and urban housing is an important reason for the rapid increase in building energy consumption [4]. The Chinese government promises to achieve a carbon peak by 2030 and carbon neutrality by 2060. To successfully achieve this goal, it is imperative to reduce building energy consumption [5]. Therefore, accurately predicting China's building energy consumption is of great significance for energy management, coordination between building energy systems and power grids, carbon emission reduction, and so on.

Due to the complexity of building energy systems, it is an arduous task to accurately predict building energy consumption. In recent decades, relevant researchers have proposed many building energy consumption prediction methods, including engineering methods, statistical methods, and artificial intelligence methods [6]. They are briefly introduced as follows.

First, an engineering method mainly evaluates and simulates changes in internal thermal power consumption and the operation process of internal energy-consuming equipment and then analyzes the energy consumption characteristics inherent in the operation process of the examined building. In different countries and regions, according to their own architectural characteristics, a variety of different simulation software programs have been produced. Among them, Energy Plus and the Transient System Simulation Tool (TRNSYS) in the United States, Esp-r in the UK, HASP in Japan, and CHEC and DeST in China are widely used [7–9]. The above simulation programs have been commonly used in architectural design, environmental control, and so on. However, the above software has many shortcomings, such as slow and complex modeling processes, low simulation efficiency, and strict requirements regarding the amount of input information.

Second, statistical methods mainly include the multiple linear regression method, autoregressive moving average model (ARMA), and autoregressive integrated moving average model (ARIMA). When modeling with the multiple linear regression method, the influencing factors of building energy consumption should be screened first, and the influence degrees of different influencing factors on the resulting building energy consumption values should be calculated. Then, the factors with high degrees of influence should be selected as the input indices of the model [10–12]. For example, Amber et al. used a multiple linear regression model to predict the daily power consumption levels of buildings [13]. Xu et al. used multiple linear regression to study the impacts of residents' characteristic factors on residential power consumption [14]. In addition to linear regression analysis, the ARMA model and ARIMA model based on time series modeling, the matrix-based long-term prediction method, and statistical methods combined with building simulation software can also be used to predict building energy consumption. Statistical methods have good fitting effects when used for building energy consumption prediction, and these methods have been widely utilized [15, 16].

Third, with the development of computer technology, artificial intelligence methods have been widely used because of their simple modeling approaches and high prediction accuracy rates. Common artificial intelligence methods include artificial neural networks (ANNs) [17, 18], decision trees (DTs) [19, 20], clustering [21], and support vector machines (SVMs) [22, 23]. Among them, SVMs and ANNs are the most widely used and effective methods [24]. For example, Paudel et al. combined an SVM with a data selection method and applied it to predict the energy consumption levels of low-energy buildings [22]. Shao et al. studied and analyzed hotel building energy consumption with an SVM [25]. Mena et al. proposed a neural network model for short-term energy consumption prediction regarding the power demand of green buildings [26]. Biswas et al. proposed a neural network model based on the Levenberg–Marquardt and output weight optimization-Newton algorithms and applied it to building energy consumption prediction [17]. Naji et al. trained a neural network model with an extreme learning machine (ELM) and applied it to building energy consumption estimation. In recent years, hybrid models based on artificial intelligence have been widely used in the field of building energy consumption prediction [18]. For example, Chaturvedi et al. combined an adaptive genetic algorithm with an ANN to overcome the limitations of the backpropagation training method and applied this approach to short-term load forecasting for building power systems [27]. Li et al. improved the particle swarm optimization (PSO) algorithm and proposed an improved PSO- (IPSO-) based neural network model for building power consumption prediction [28]. Others have proposed methods that combine data-driven machine learning models and statistical models [29, 30]. With the rapid development of deep learning technology, deep neural networks have also been introduced into the field of building energy consumption prediction in recent years [31].

However, the above prediction methods are based on large data samples. When the input data information is incomplete, errors and uncertainties may occur [32, 33]. As an important prediction model, the grey model was first proposed by Professor Deng. A grey differential prediction model is established through a small amount of incomplete information to describe a development law of interest more accurately [34]. The grey prediction model has attracted much attention because of its convenience, simple modeling process, limited data requirement, and high accuracy [35]. Compared with machine learning and statistical prediction methods based on big data samples, the grey prediction method can realize simulation and prediction for small data; that is, only four data points are required to establish a grey prediction model. This type of model has great advantages in terms of solving uncertainty problems with small sample sizes and has been widely used in the fields of energy, environment, engineering, and social management [35–40].

In order to improve the modeling effect of the grey prediction model and build a better high-precision model, scholars have optimized the model parameters from different angles. For example, discretization of the grey model was considered to be an important way to improve the prediction accuracy of the model [41, 42]. Selecting the appropriate ash action could also improve the prediction accuracy of the grey model [43–45]. Since the fractional-order accumulation idea was introduced into the grey prediction model, the prediction accuracy of the grey model has been greatly improved [46, 47]. Other scholars have changed the form of the whitening equation in the grey model and established the grey Bernoulli model GBM (1, 1) and the nonlinear grey Bernoulli model NGBM (1, 1) [48]. On this basis, some scholars have improved the NGBM (1, 1) model from different angles. For example, Wu et al. introduced the fractional-order accumulation operator into NGBM (1, 1) model and established the FANGBM (1, 1) model [35]. Xu et al. improved the background value of the NGBM (1, 1) model and proposed an optimized grey nonlinear prediction model ONGBM (1, 1) through a simulated annealing algorithm [49].

The research of the above scholars has promoted the application and development of grey model to a certain extent. However, it can be found that although the existing research optimizes the grey model from the structure or parameters, each optimization method only improves the performance of the model to a certain extent, and the accuracy is still not high enough. In addition, most of the above studies predict building energy consumption from the microperspective, and few scholars predict the future building energy consumption of a country or region at the macrolevel. Therefore, based on the existing grey prediction model, this paper intends to introduce the concept of a fractional accumulation operator, establish a new grey prediction model (the fractional discrete grey model, FDGM (1, 1, t^{α})), introduce the idea of metabolism, and predict building energy consumption in China over the next five years. The main contributions of this paper are as follows: first, based on the advantages of existing grey prediction models, a new model, FDGM (1, 1, t^{α}), is proposed. The new model can be transformed into other grey prediction models by changing its parameters. Second, the new model is used to fit three sets of data and is compared with the other six grey models, demonstrating the excellent fitting effect of the new model. Third, the FDGM (1, 1, t^{α}) model is used to predict building energy consumption in China over the next five years.

This paper is organized as follows. Section 2 introduces the basic knowledge of the FDGM (1, 1, t^{α}) model, mainly including the modeling mechanism, model characteristics, and solution method. In Section 3, the feasibility and effectiveness of the model are verified via three cases. Section 4 forecasts the building energy consumption in China over the next five years. Section 5 is the conclusion of this paper.

2. The Fractional Discrete Grey Model FDGM (1, 1, t^{α})

2.1. Construction of the FDGM (1, 1, t^{α}) Model. Referring to Wu et al. [46], the definitions of the r-th fractional-order accumulation operator (r-FOA) and the r-th inverse fractional-order accumulation operator (r-IFOA) are given as follows.

Definition 1. Assume $X^{(0)} = \{x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)\}$, $r \in R^{+}$, is the original time series, and its r-th fractional-order accumulation (FOA) sequence is $X^{(r)} = \{x^{(r)}(1), x^{(r)}(2), \ldots, x^{(r)}(n)\}$, where

$$x^{(r)}(k) = \sum_{i=1}^{k} \frac{\Gamma(r+k-i)}{\Gamma(k-i+1)\Gamma(r)} x^{(0)}(i), \quad k = 1, 2, \ldots, n$$
$$= \left[\frac{\Gamma(r+k-1)}{\Gamma(k)\Gamma(r)}, \frac{\Gamma(r+k-2)}{\Gamma(k-1)\Gamma(r)}, \ldots, \frac{\Gamma(r)}{\Gamma(1)\Gamma(r)}\right] \times \begin{bmatrix} x^{(0)}(1) \\ x^{(0)}(2) \\ \vdots \\ x^{(0)}(n) \end{bmatrix}. \quad (1)$$

When $r = 1$, the FOA is the first fractional-order accumulation operator (1-FOA), and $x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i)$.

Definition 2. Assume $X^{(0)} = \{x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)\}$, $r \in R^{+}$, is the original time series, and its inverse fractional-order accumulation (IFOA) sequence is $X^{(-r)} = \{x^{(-r)}(1), x^{(-r)}(2), \ldots, x^{(-r)}(n)\}$, where

$$x^{(-r)}(k) = \sum_{i=1}^{k-1} (-1)^{i} \frac{\Gamma(r+1)}{\Gamma(i+1)\Gamma(r-i+1)} x^{(0)}(k-i), \quad k = 1, 2, \ldots, n$$
$$= \left[\frac{\Gamma(r+1)}{\Gamma(r+1)\Gamma(1)}, \frac{\Gamma(r+2)}{\Gamma(r)\Gamma(2)}, \ldots, \frac{(-1)^{k-1}\Gamma(r+1)}{\Gamma(k)\Gamma(r-k-2)}\right] \times \begin{bmatrix} x^{(0)}(k) \\ x^{(0)}(k-1) \\ \vdots \\ x^{(0)}(1) \end{bmatrix}. \quad (2)$$

When $r=1$, the IFOA is the first inverse fractional-order accumulation operator (1-IFOA), and $x^{(-1)}(k)=x^{(0)}(k)-x^{(0)}(k-1)$.

Definition 3. Assume that $X^{(0)}=\{x^{(0)}(1),x^{(0)}(2),\ldots,x^{(0)}(n)\}$, $r\in R^{+}$, is an original sequence, the $r-$th order accumulation operator is $X^{(r)}=\{x^{(r)}(1),x^{(r)}(2),\ldots,x^{(r)}(n)\}$, and the $r-$th order inverse accumulation operator is $X^{(-r)}=\{x^{(-r)}(1),x^{(-r)}(2),\ldots,x^{(-r)}(n)\}$; then, the operators have the following relations:

$$X^{(0)}=\left(X^{(r)}\right)^{(-r)}=\left(X^{(-r)}\right)^{(r)}. \tag{3}$$

Referring to the definition of GM (1, 1, t^{α}) the whitening equation of the FDGM (1, 1, t^{α}) model is

$$\hat{x}^{(r)}(t)=a\hat{x}^{(r)}(t-1)+bt^{\alpha}+c,\quad t=2,3,\ldots,n. \tag{4}$$

Given $\hat{x}^{(r)}(1)=x^{(r)}(1)$, the solution process of equation (4) is as follows:

When $t=2$, we have

$$\hat{x}^{(r)}(2)=a\hat{x}^{(r)}(1)+2^{\alpha}b+c. \tag{5}$$

When $t=3$, we have

$$\hat{x}^{(r)}(3)=a\hat{x}^{(r)}(2)+3^{\alpha}b+c. \tag{6}$$

Combining equations (5) and (6), we can obtain

$$\hat{x}^{(r)}(3)=a^{2}\hat{x}^{(r)}(1)+a\left(2^{\alpha}b+c\right)+3^{\alpha}b+c. \tag{7}$$

By repeating the above calculation process, the following conclusions can be drawn:

$$\hat{x}^{(r)}(t)=a^{t-1}\hat{x}^{(r)}(1)+\sum_{i=0}^{t-2}a^{i}\left[b(t-i)^{\alpha}+c\right],\quad t=2,3,\ldots,n. \tag{8}$$

Based on Definition 3, $\hat{x}^{(0)}(t)$ is

$$\hat{x}^{(0)}(k)=\left(\hat{x}^{(r)}(k)\right)^{(-r)},\quad k=1,2,3,\ldots,n. \tag{9}$$

Given the original sequence $X^{(0)}=\{x^{(0)}(1),x^{(0)}(2),\ldots,x^{(0)}(n)\},r\in R^{+}$, the least-squares criterion of the FDGM (1, 1, t^{α}) model can be described as the following unconstrained optimization problem:

$$\min_{a,b,c}\sum_{t=2}^{n}\left[x^{(r)}(t)-ax^{(r)}(t-1)-bt^{\alpha}-c\right]^{2}. \tag{10}$$

The solution of this optimization problem is $[\hat{a},\hat{b},\hat{c}]^{T}=(B^{T}B)^{-1}B^{T}Y$, where

$$B=\begin{pmatrix} x^{(r)}(1) & 2^{\alpha} & 1\\ x^{(r)}(2) & 3^{\alpha} & 1\\ \vdots & \vdots & \vdots\\ x^{(r)}(n-1) & n^{\alpha} & 1\end{pmatrix},\quad Y=\begin{pmatrix} x^{(r)}(2)\\ x^{(r)}(3)\\ \vdots\\ x^{(r)}(n)\end{pmatrix}. \tag{11}$$

To minimize the error between the original data and predicted data, the optimal values of the parameters r,α must be determined:

$$\min_{r,\alpha} f(r,\alpha)=\text{MAPE}=\frac{1}{n-1}\sum_{t=2}^{n}\left|\frac{x^{(0)}(t)-\hat{x}^{(0)}(t)}{x^{(0)}(t)}\right|\times 100\%.$$

$$s.t.\begin{cases}[\hat{a},\hat{b},\hat{c}]^{T}=\left(B^{T}B\right)^{-1}B^{T}Y,\\ B=\begin{pmatrix} x^{(r)}(1) & 2^{\alpha} & 1\\ x^{(r)}(2) & 3^{\alpha} & 1\\ \vdots & \vdots & \vdots\\ x^{(r)}(n-1) & n^{\alpha} & 1\end{pmatrix},Y=\begin{pmatrix} x^{(r)}(2)\\ x^{(r)}(3)\\ \vdots\\ x^{(r)}(n)\end{pmatrix},\\ \hat{x}^{(r)}(1)=x^{(r)}(1),\hat{x}^{(r)}(t)=a^{t-1}\hat{x}^{(r)}(1)+\sum_{i=0}^{t-2}a^{i}\left[b(t-i)^{\alpha}+c\right]\\ \hat{x}^{(0)}(t)=\left(\hat{x}^{(r)}(t)\right)^{(-r)},\quad t=2,3,\ldots,n.\end{cases} \tag{12}$$

Because equation (12) is highly complex, it would have been a difficult task to develop analytic solutions for parameters r,α. Here, the grey wolf optimization (GWO) is applied to find the values of r,α. Furthermore, the flowchart of the FDGM (1, 1, t^{α}) model is shown in Figure 1.

2.2. Special Cases of FDGM (1, 1, t^{α}) Model. When the parameters r,α of the model change, the model is transformed into other grey models.

Scenario 1. $r=1,\alpha=0$.

When $r=1,\alpha=0$, the FDGM (1, 1, t^{α}) model can be converted to the DGM (1, 1) model.

Assume that Y,B are as mentioned at the end of the current section and that $[\hat{a},\hat{b},\hat{c}]^{T}=(B^{T}B)^{-1}B^{T}Y$.

The time response function of the DGM (1, 1) model $x^{(1)}(t)=ax^{(1)}(t-1)+b$ is

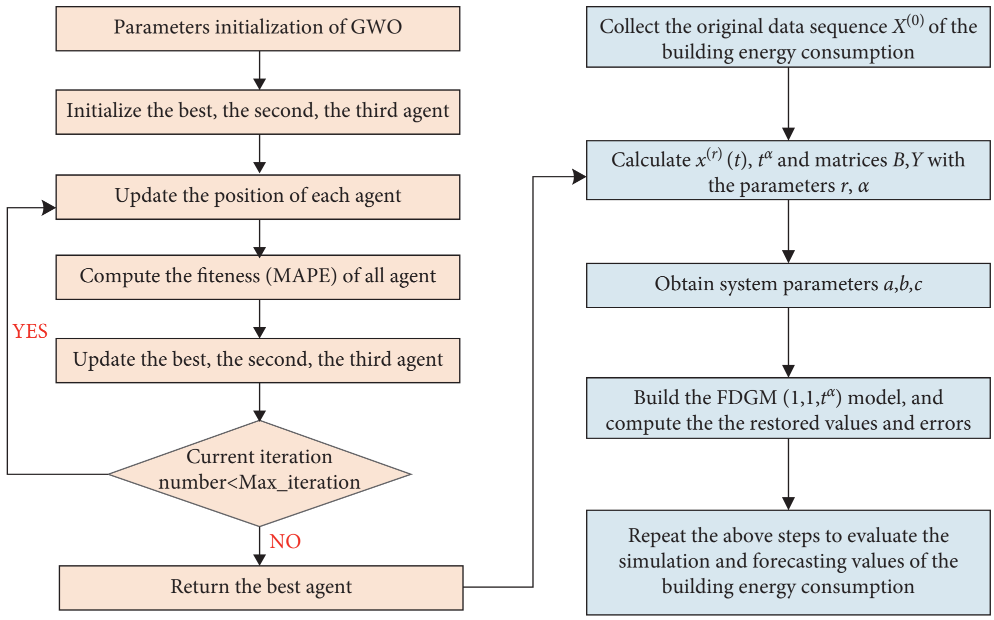

Figure 1: The flowchart of the FDGM (1, 1, t^{α}) model.

Table 1: Error metrics of the prediction model.

Name	Abbreviation	Formulation
Mean absolute percentage error	MAPE	$1/n \sum_{k=1}^{n} \lvert x^{(0)}(k) - \hat{x}^{(0)}(k)/x^{(0)}(k) \rvert \times 100$
Root mean squares percentage error	RMSPE	$\sqrt{1/n \sum_{k=1}^{n} x^{(0)}(k) - x^{(0)}(k)/x^{(0)}(k)} \times 100$
Mean absolute error	MAE	$1/n \sum_{k=1}^{n} \lvert x^{(0)}(k) - x^{(0)}(k) \rvert$
Mean squares error	MSE	$1/n \sum_{k=1}^{n} (x^{(0)}(k) - x^{(0)}(k))^2$
Index of agreement	IA	$1 - \sum_{k=1}^{n} (\hat{x}^{(0)}(k) - x^{(0)}(k))^2 / \sum_{k=1}^{n} (\lvert \hat{x}^{(0)}(k) - \overline{x} \rvert + \lvert x^{(0)}(k) - \overline{x} \rvert)^2$
Correlation coefficient	R	$R = \mathrm{cov}(\widehat{X}^{(0)}, X^{(0)}) / \sqrt{\mathrm{Var}(\widehat{X}^{(0)})} \sqrt{\mathrm{Var}(X^{(0)})}$

$$\hat{x}^{(1)}(k+1) = a^k\left(x^{(0)}(1) - \frac{b}{1-a}\right) + \frac{b}{1-a}, \quad k = 0, 1, 2, \ldots, n. \tag{13}$$

Additionally, the reduction value is

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k), \quad k = 1, 2, \ldots, n. \tag{14}$$

Scenario 2. $r = 0, \alpha = 0$.

When $r = 0, \alpha = 0$, the FDGM (1, 1, t^{α}) model can be converted to the autoregressive grey model (ARGM (1, 1)).

Assume that Y, B are as mentioned at the end of the current section and that $[\hat{a}, \hat{b}, \hat{c}]^T = (B^T B)^{-1} B^T Y$.

The time response function of the ARGM (1, 1) model $x^{(0)}(t) = a x^{(0)}(t-1) + b$ is

$$\hat{x}^{(0)}(k+1) = a^k\left(x^{(0)}(1) - \frac{b}{1-a}\right) + \frac{b}{1-a}, \quad k = 0, 1, 2, \ldots, n. \tag{15}$$

2.3. Metabolic Idea. Introducing the idea of metabolism can make the results of the grey prediction model more accurate. The metabolic mechanism is as follows:

Step 1: build a model with the original input sequence and predict the data for two periods

Step 2: delete the first two data points of the original sequence, add the two predicted periods of data, establish the model, and predict the next two periods of data

Step 3: repeat step 2 to obtain all the predicted values

2.4. Error Metric. Six error metrics are used in the paper to test the effectiveness of the proposed grey prediction model, as shown in Table 1.

3. Validation of FDGM (1, 1, t^{α})

In this section, three examples involving the total energy consumption of civil buildings, urban civil buildings, and civil buildings specifically in Beijing are used to check the reliability of the new model. The obtained results compared with the prediction results of the GM (1, 1), SIGM (1, 1), DGM (1, 1), NGM (1, 1), NDGM (1, 1), and FANDGM (1, 1) models. Among them, the original data acquired from a 2009 to 2015 time series are used to establish the prediction models, and the associated data

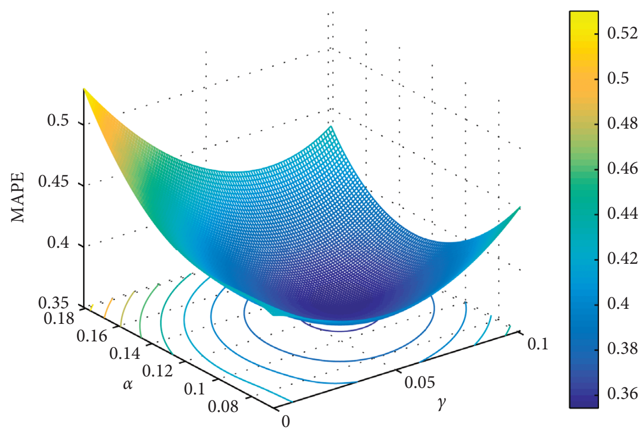

Figure 2: The relationship between MAPE and parameters.

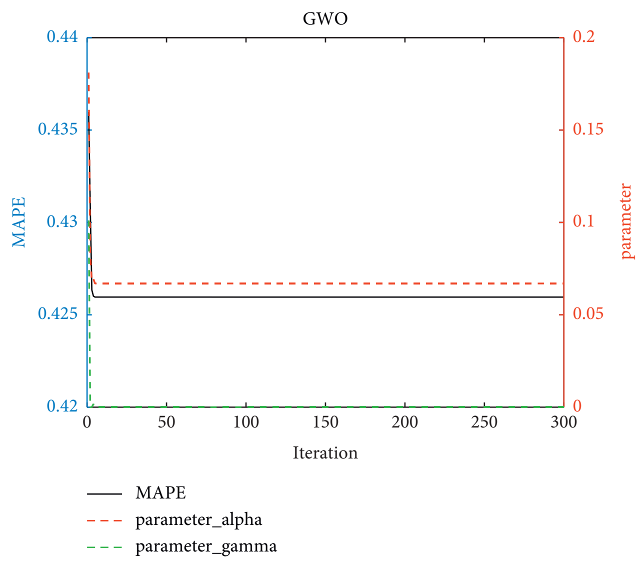

Figure 3: Iterations, MAPE, and parameters of the GWO algorithm.

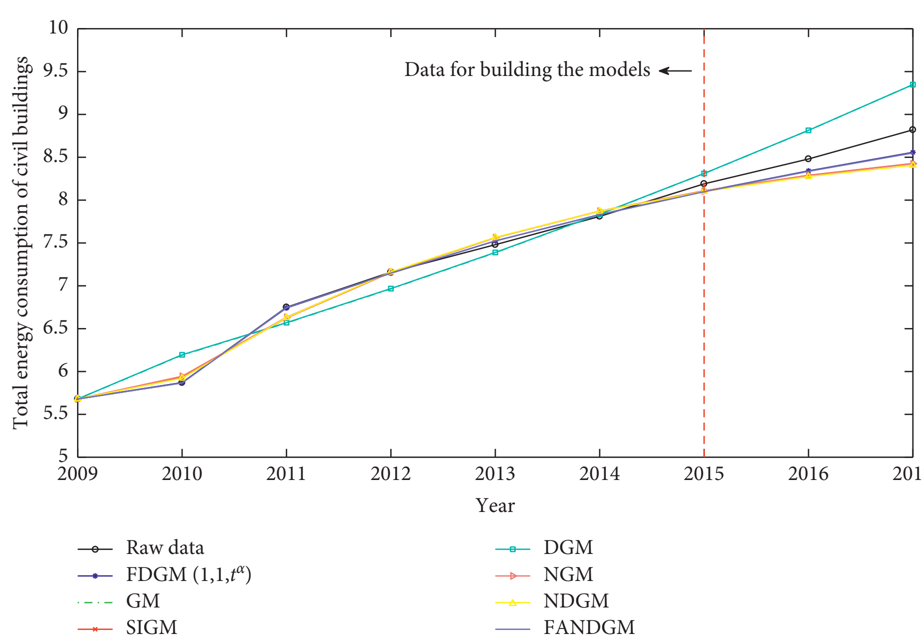

Figure 4: Results of total energy consumption of civil buildings.

Table 2: Fitting results and prediction results of total energy consumption of civil buildings.

Year	Data	GM	SIGM	DGM	NGM	NDGM	FANDGM	FDGM
2009	5.68	5.6800	5.6800	5.6800	5.6800	5.6800	5.6800	5.6800
2010	5.87	6.1914	5.9298	6.1952	5.9452	5.9226	5.8661	5.8700
2011	6.75	6.5667	6.6255	6.5701	6.6336	6.6294	6.7459	6.7421
2012	7.16	6.9648	7.1567	6.9678	7.1602	7.1633	7.1496	7.1471
2013	7.48	7.3871	7.5625	7.3895	7.5630	7.5665	7.5246	7.5239
2014	7.81	7.8349	7.8723	7.8368	7.8711	7.8711	7.8303	7.8318
2015	8.19	8.3099	8.1089	8.3111	8.1068	8.1011	8.0983	8.1018
2016	8.48	8.8137	8.2896	8.8142	8.2870	8.2749	8.3358	8.3414
2017	8.82	9.3481	8.4276	9.3477	8.4249	8.4061	8.5501	8.5577

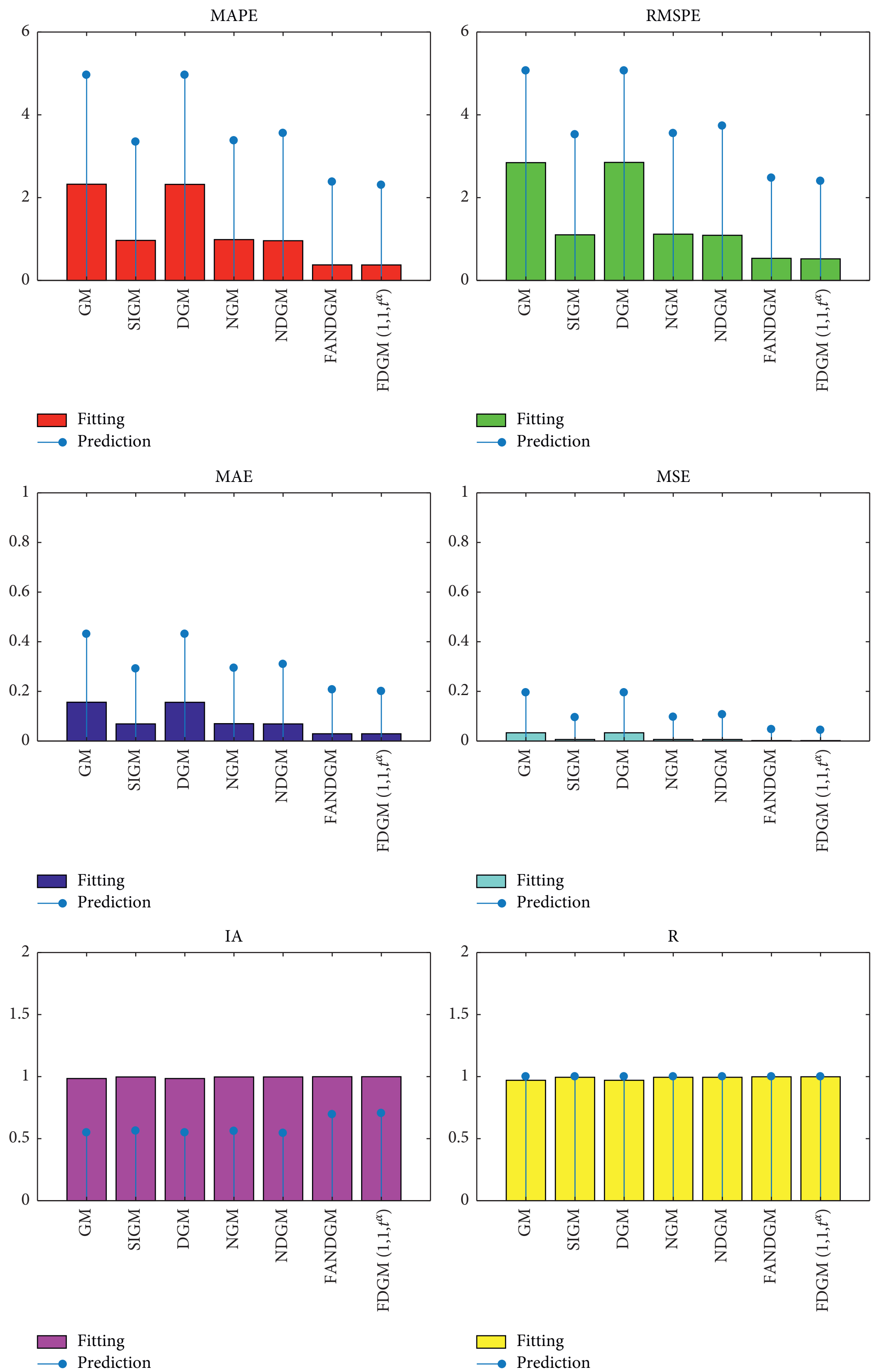

Figure 5: Error metrics of total energy consumption of civil buildings.

Table 3: Error metrics of total energy consumption of civil buildings.

	GM	SIGM	DGM	NGM	NDGM	FANDGM	FDGM
Fitting							
MAPE	2.3236	0.9665	2.3200	0.9860	0.9587	0.3746	0.3731
RMSPE	2.8450	1.1011	2.8507	1.1173	1.0896	0.5332	0.5207
MAE	0.1563	0.0689	0.1559	0.0699	0.0688	0.0292	0.0291
MSE	0.0331	0.0061	0.0331	0.0061	0.0061	0.0018	0.0017
IA	0.9846	0.9973	0.9846	0.9973	0.9973	0.9992	0.9992
R	0.9704	0.9946	0.9704	0.9946	0.9946	0.9985	0.9986
Prediction							
MAPE	4.9614	3.3467	4.9619	3.3776	3.5560	2.3802	2.3038
RMSPE	5.0663	3.5235	5.0658	3.5528	3.7332	2.4754	2.3991
MAE	0.4309	0.2914	0.4309	0.2940	0.3095	0.2070	0.2004
MSE	0.1951	0.0951	0.1951	0.0967	0.1067	0.0468	0.0440
IA	0.5488	0.5630	0.5487	0.5608	0.5445	0.6953	0.7046
R	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

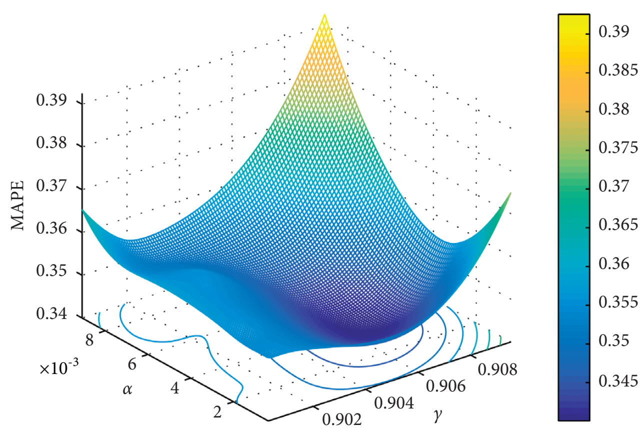

Figure 6: The relationship between MAPE and parameters.

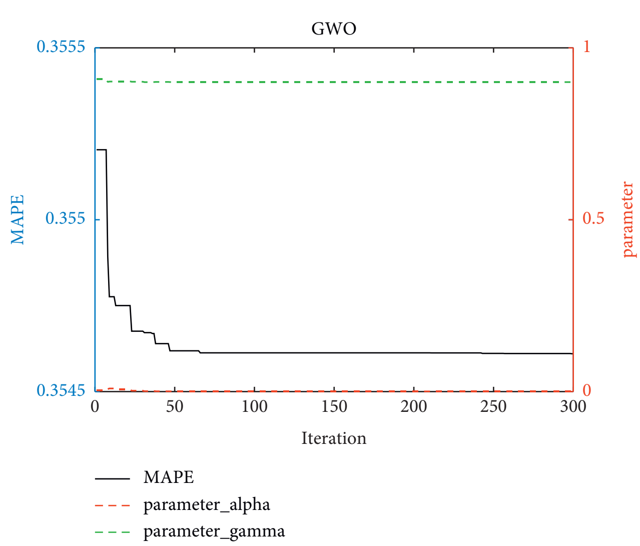

Figure 7: Iterations, MAPE, and parameters of the GWO algorithm.

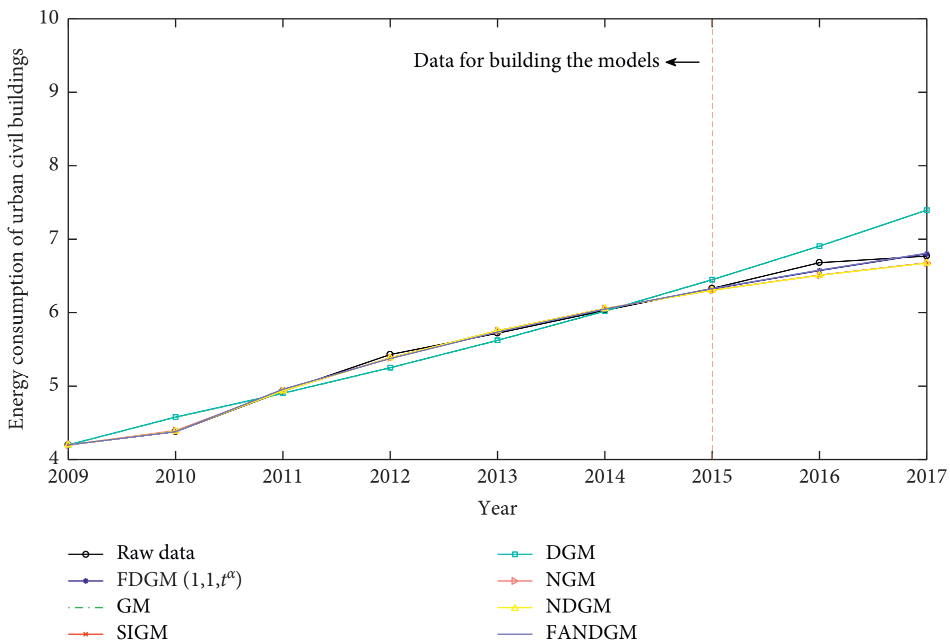

FIGURE 8: Results of energy consumption of urban civil buildings.

TABLE 4: Fitting results and prediction results of energy consumption of urban civil buildings.

Year	Data	GM	SIGM	DGM	NGM	NDGM	FANDGM	FDGM
2009	4.2	4.2000	4.2000	4.2000	4.2000	4.2000	4.2000	4.2000
2010	4.38	4.5764	4.3864	4.5795	4.3953	4.3854	4.3800	4.3800
2011	4.93	4.9011	4.9341	4.9041	4.9399	4.9346	4.9573	4.9530
2012	5.43	5.2488	5.3839	5.2517	5.3873	5.3847	5.3745	5.3814
2013	5.72	5.6213	5.7532	5.6240	5.7549	5.7538	5.7361	5.7373
2014	6.03	6.0201	6.0564	6.0226	6.0570	6.0564	6.0490	6.0466
2015	6.33	6.4472	6.3055	6.4494	6.3052	6.3044	6.3276	6.3222
2016	6.68	6.9046	6.5100	6.9066	6.5091	6.5078	6.5793	6.5718
2017	6.77	7.3945	6.6779	7.3961	6.6767	6.6745	6.8098	6.8008

from 2016 to 2017 are used to check the reliability of the prediction models.

3.1. Total Energy Consumption of Civil Buildings. According to the data of the China Building Energy Efficiency Development Report, in 2017, the total energy consumption of civil buildings in China reached 882 million TCE, accounting for 20.18% of the total terminal energy consumption of the entire society. From 2009 to 2017, the average annual GDP growth rate was 7.9%, and the average annual growth rate of energy consumption by civil buildings was 5.6%. The growth trend of the energy consumption of civil buildings is basically consistent with that of the GDP in China, reflecting the correlation between building energy consumption and the level of economic development. Therefore, this section takes the total energy consumption of civil buildings as an example to test the accuracy of the proposed model and other grey prediction models. The relationships between the parameters and the mean absolute precision error (MAPE) of the FDGM (1, 1, t^{α}) model calculated via the GWO algorithm are shown in Figure 2, and Figure 3 shows the relationships between the number of iterations, the model parameters, and the MAPE. The fitting and prediction results of each model are shown in Figure 4 and Table 2, and the error metrics of each model are shown in Figure 5 and Table 3. The predicted value of the FDGM (1, 1, t^{α}) model is nearest to the actual value. From the prediction values and fitting values, the six error metrics of the FDGM (1, 1, t^{α}) model are the best among those of the seven prediction models. This also shows that the FDGM (1, 1, t^{α}) model has higher accuracy than other grey prediction models in predicting the total energy consumption of civil buildings.

3.2. Energy Consumption of Urban Civil Buildings. According to the data of the China Building Energy Efficiency Development Report, in 2017, the energy consumption of urban civil buildings in China reached 667 million TCE, accounting for 15.26% of the total terminal energy consumption of the entire society. From 2009 to 2017, the average annual growth rate of energy consumption by urban civil buildings was 6%, which was slightly higher than the growth rate of the total energy consumption of civil buildings. The energy consumption intensity of urban civil buildings increased from 7.06 kgce/m^2 to 8.13 kgce/m^2 with a stable growth rate, which is the embodiment of urban

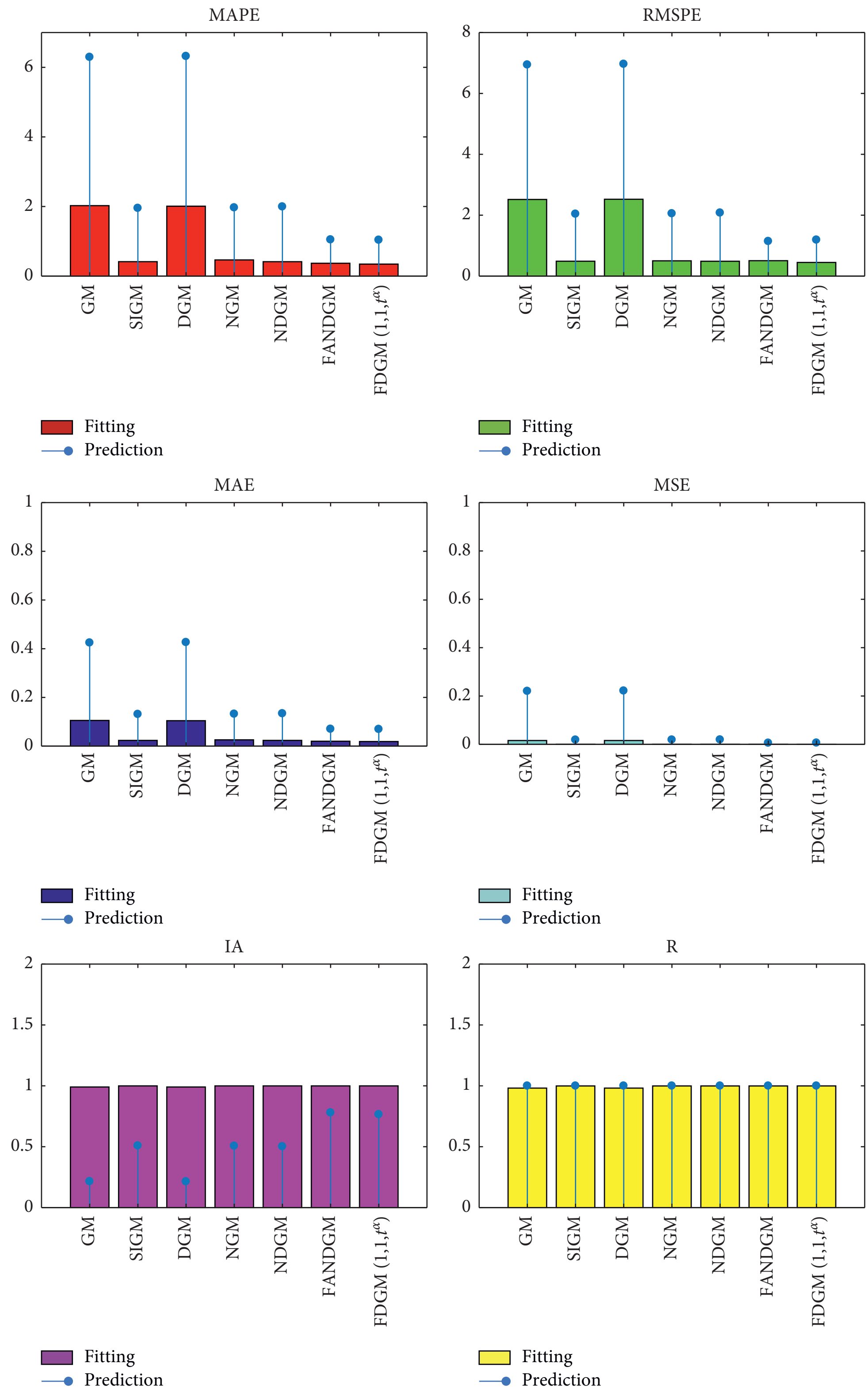

Figure 9: Error metrics of energy consumption of urban civil buildings.

Table 5: Error metrics of energy consumption of urban civil buildings.

	GM	SIGM	DGM	NGM	NDGM	FANDGM	FDGM
Fitting							
MAPE	2.0248	0.4143	2.0088	0.4645	0.4138	0.3685	0.3441
RMSPE	2.5172	0.4881	2.5233	0.5013	0.4869	0.5051	0.4476
MAE	0.1054	0.0235	0.1044	0.0258	0.0235	0.0201	0.0189
MSE	0.0160	0.0008	0.0160	0.0008	0.0008	0.0007	0.0006
IA	0.9904	0.9996	0.9904	0.9995	0.9996	0.9996	0.9997
R	0.9814	0.9991	0.9814	0.9991	0.9991	0.9991	0.9993
Prediction							
MAPE	6.2936	1.9532	6.3197	1.9682	1.9945	1.0474	1.0375
RMSPE	6.9426	2.0411	6.9651	2.0547	2.0782	1.1437	1.1897
MAE	0.4246	0.1311	0.4263	0.1321	0.1339	0.0702	0.0695
MSE	0.2202	0.0187	0.2217	0.0190	0.0194	0.0059	0.0063
IA	0.2148	0.5086	0.2141	0.5062	0.5020	0.7798	0.7651
R	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

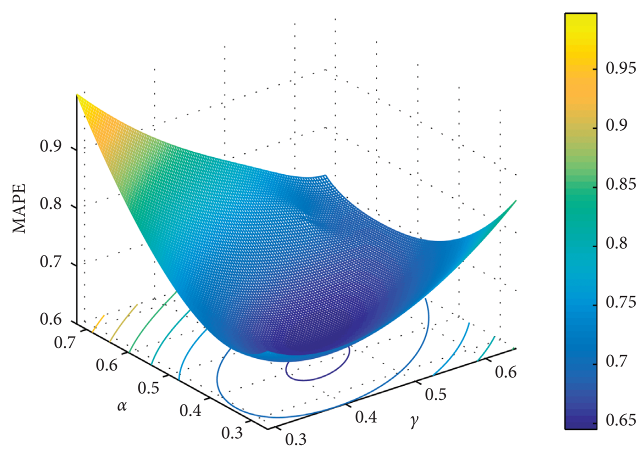

Figure 10: The relationship between MAPE and parameters.

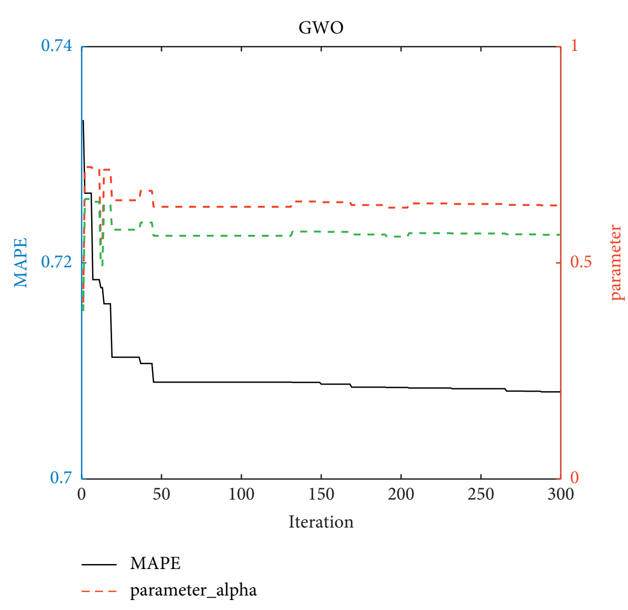

Figure 11: Iterations, MAPE, and parameters of the GWO algorithm.

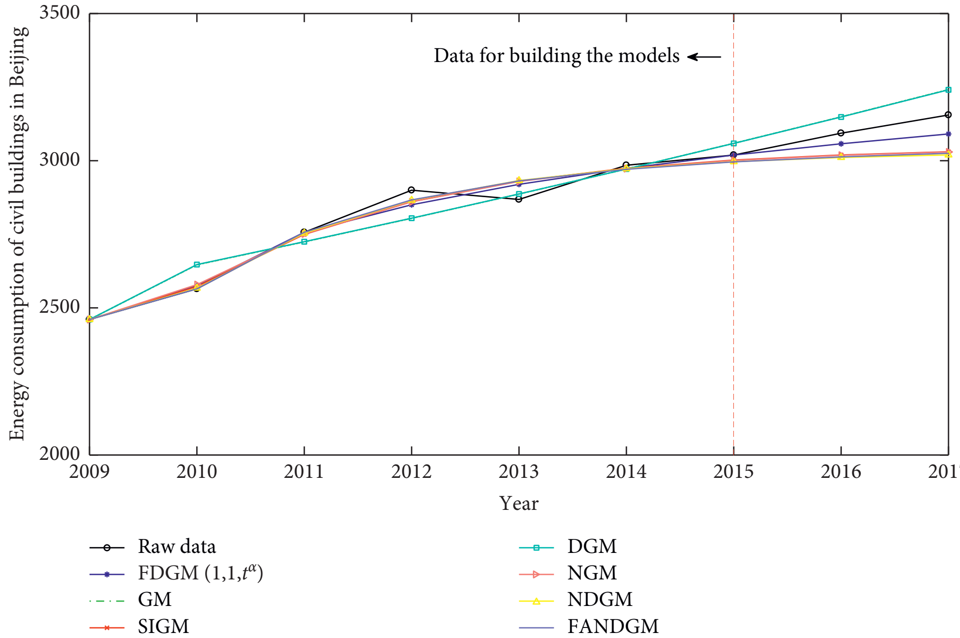

FIGURE 12: Results of energy consumption of civil building in Beijing.

TABLE 6: Fitting results and prediction results of energy consumption of civil building in Beijing.

Year	Data	GM	SIGM	DGM	NGM	NDGM	FANDGM	FDGM
2009	2460.39	2460.3900	2460.3900	2460.3900	2460.3900	2460.3900	2460.3900	2460.3900
2010	2564.6	2646.4536	2572.3236	2647.1152	2578.9504	2566.9588	2564.8337	2575.0330
2011	2756.76	2724.2529	2749.5114	2724.7572	2751.2447	2753.7262	2756.7600	2756.7646
2012	2899.75	2804.3393	2860.8200	2804.6764	2860.3700	2865.5442	2866.8027	2850.2345
2013	2868.38	2886.7801	2930.7435	2886.9398	2929.4862	2932.4898	2931.4577	2919.5983
2014	2984.54	2971.6444	2974.6692	2971.6160	2973.2621	2972.5703	2970.8287	2974.1532
2015	3019.16	3059.0035	3002.2632	3058.7758	3000.9882	2996.5666	2995.9603	3019.1671
2016	3093.43	3148.9308	3019.5976	3148.4921	3018.5490	3010.9332	3012.9464	3057.4776
2017	3155.3	3241.5017	3030.4870	3240.8398	3029.6714	3019.5345	3025.1708	3090.8232

living standard improvement. The energy consumption intensity of public buildings decreased from 19.19 kgce/m^2 to 18.63 kgce/m^2. This reflects that national energy-saving measures for public buildings have been effectively promoted, and the effect of these policies is obvious. Therefore, this section takes the energy consumption of urban civil buildings as an example to test the accuracy of the proposed model and other grey prediction models. The relationships between the parameters and MAPE of the FDGM (1, 1, t^α) model calculated via the GWO algorithm are shown in Figure 6, and Figure 7 shows the relationships between the number of iterations, the model parameters, and the MAPE. The fitting and prediction results of each model are shown in Figure 8 and Table 4, and the error metrics of each model are shown in Figure 9 and Table 5. The predicted value of the FDGM (1, 1, t^α) model is nearest to the actual value. From the prediction values and fitting values, the six error metrics of the FDGM (1, 1, t^α) model are the best among those of the seven prediction models. This also shows that the FDGM (1, 1, t^α) model has higher accuracy than other grey prediction models in terms of predicting the energy consumption of civil buildings.

3.3. Energy Consumption of Civil Buildings in Beijing. This paper collects the energy consumption data of civil buildings in Beijing based on provided energy balance table data. From 2009 to 2017, the energy consumption of civil buildings in Beijing increased from 24.6039 million TCE to 31.553 million TCE, showing an upward and slowing trend, which may be due to rapid economic development and population control. Therefore, this section takes the energy consumption of civil buildings in Beijing as an example to test the accuracy of the proposed model and other grey prediction models. The relationships between the parameters and MAPE of the FDGM (1, 1, t^α) model calculated via the GWO algorithm are shown in Figure 10, and Figure 11 shows the relationships between the number of iterations, the model parameters, and the MAPE of the FDGM (1, 1, t^α). The fitting and prediction results of each model are shown in Figure 12 and Table 6, and the error metrics of each model are shown in Figure 13 and Table 7. The predicted value of the FDGM (1, 1, t^α) model is nearest to the actual value. From the prediction values and fitting values, the six error metrics of the FDGM (1, 1, t^α) model are the best among those of the seven prediction models. This also shows that

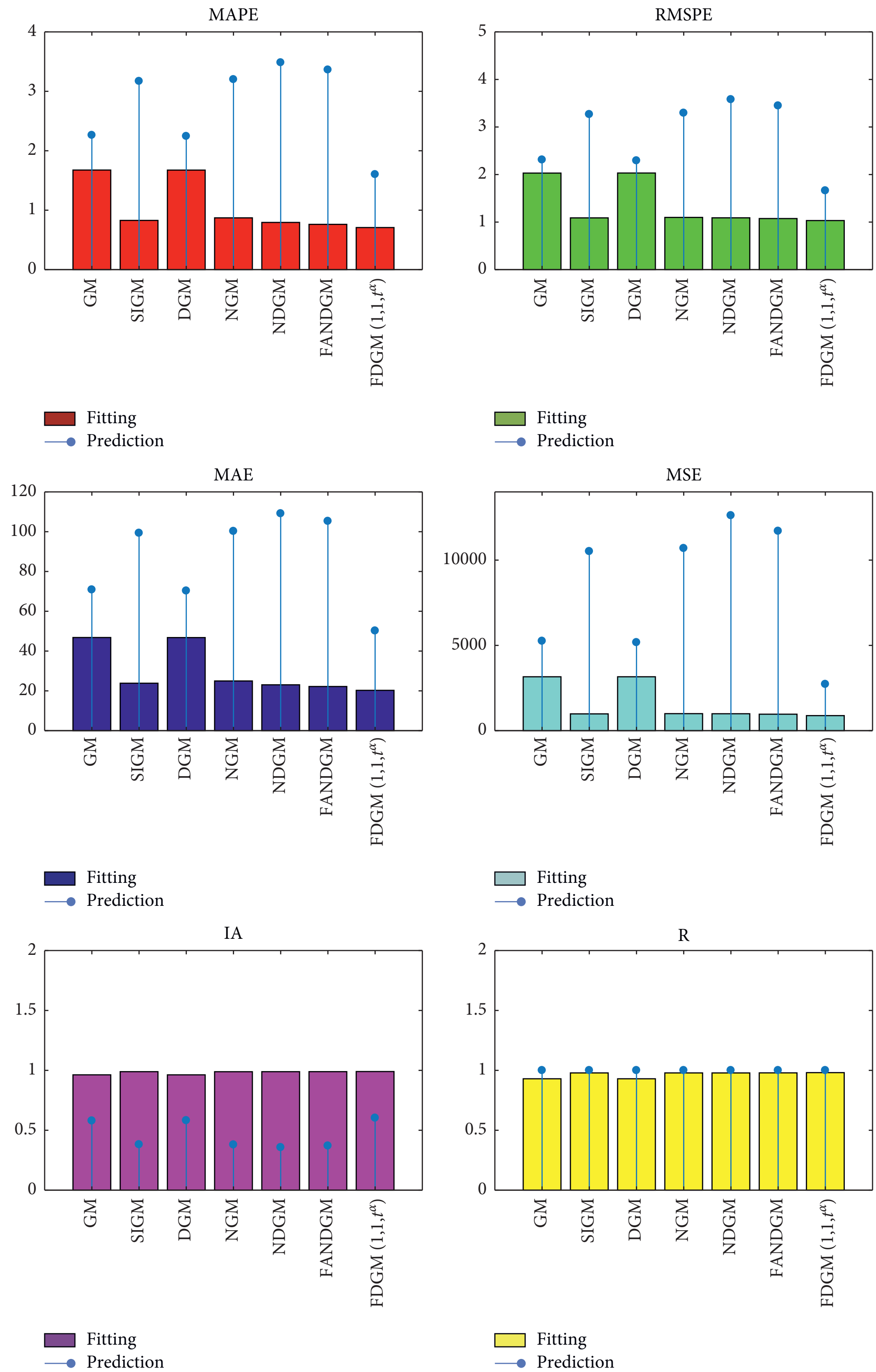

FIGURE 13: Error metrics of energy consumption of civil building in Beijing.

Table 7: Error metrics of energy consumption of civil building in Beijing.

	GM	SIGM	DGM	NGM	NDGM	FANDGM	FDGM
Fitting							
MAPE	1.6757	0.8285	1.6749	0.8713	0.7943	0.7620	0.7081
RMSPE	2.0307	1.0887	2.0321	1.0985	1.0900	1.0746	1.0321
MAE	46.8184	23.8389	46.7819	24.9669	23.0452	22.1949	20.2609
MSE	3158.7145	983.3152	3158.8055	996.4190	991.4353	965.1000	881.9719
IA	0.9627	0.9890	0.9626	0.9887	0.9890	0.9893	0.9902
R	0.9297	0.9787	0.9297	0.9786	0.9785	0.9791	0.9809
Prediction							
MAPE	2.2631	3.1712	2.2455	3.2011	3.4848	3.3630	1.6028
RMSPE	2.3111	3.2668	2.2932	3.2948	3.5795	3.4480	1.6623
MAE	70.8512	99.3227	70.3009	100.2548	109.1311	105.3064	50.2146
MSE	5255.5344	10514.7588	5174.4429	10694.8474	12618.9893	11705.6125	2724.9169
IA	0.5797	0.3814	0.5821	0.3797	0.3574	0.3706	0.6030
R	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

Table 8: Predictions for building energy consumption over the next 5 years.

Year	Total energy consumption of civil buildings	Energy consumption of urban civil buildings	Energy consumption of civil buildings in Beijing
2018	8.75507	7.01286	3120.341
2019	8.93712	7.21081	3146.826
2020	9.10622	7.39672	3170.844
2021	9.26427	7.57222	3192.816
2022	9.41280	7.73864	3213.066

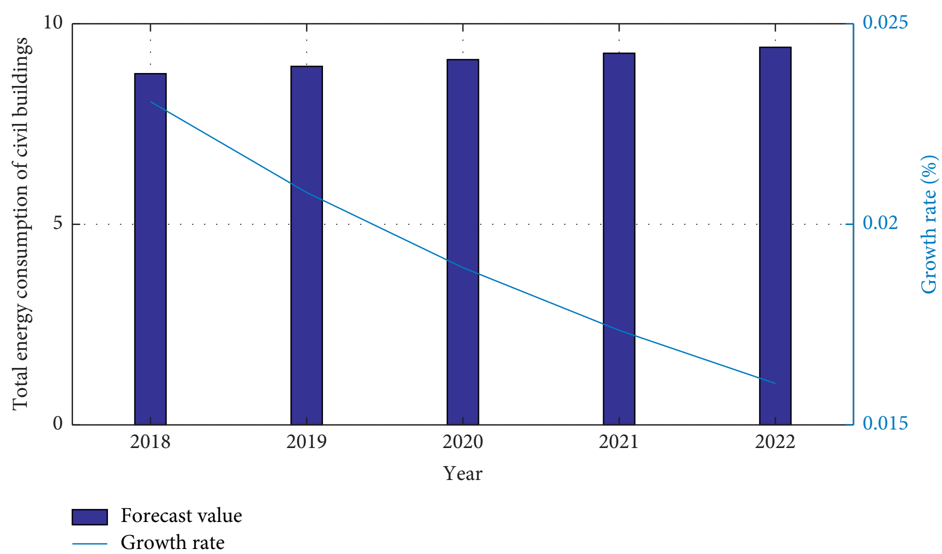

Figure 14: Total energy consumption of civil buildings and growth rate over the next 5 years.

the FDGM (1, 1, t^{α}) model has higher accuracy than other grey prediction models in terms of predicting the energy consumption of civil buildings in Beijing.

4. Forecasting Building Energy Consumption over the Next Five Years

In this section, the FDGM (1, 1, t^{α}) model, including the new metabolism mechanism, is used to forecast the total energy consumption of civil buildings, urban civil buildings, and civil buildings specifically in Beijing over the next 5 years (2018–2022). The prediction results are shown in Table 8 and Figures 14–16. The three types of building energy consumption exhibit steady upward trends. The growth rate of the energy consumption of urban civil buildings is the fastest, with an average annual growth rate of 2.61%. The growth rate of the total energy consumption of civil buildings is second, with an average annual growth rate of 1.92%. The growth rate of building energy consumption in Beijing is the slowest, at approximately 0.78%.

Based on the above prediction results, it can be found that an important reason for the high accuracy of the new

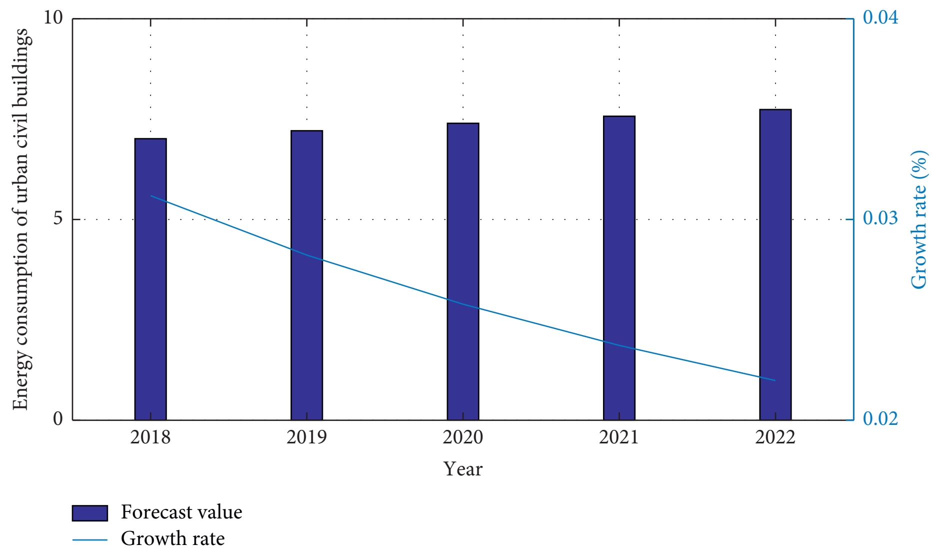

Figure 15: Energy consumption of urban civil buildings and growth rate over the next 5 years.

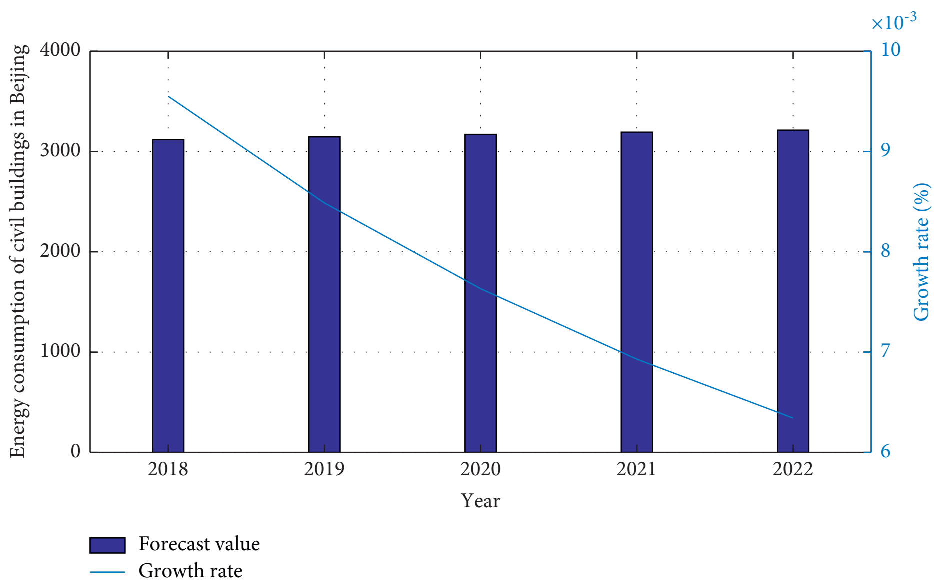

Figure 16: Energy consumption of civil buildings in Beijing over the next 5 years.

model proposed in this paper is to use the GWO algorithm to find the optimal parameters. In addition to the GWO algorithm, particle swarm optimization (PSO) and quantum genetic optimization (QGA) algorithms are also widely used to solve grey model parameters to improve the accuracy of the model. With the development of optimization algorithms, more advanced algorithms can also be used to find the optimal parameter values of the grey model, such as the chaotic cloud quantum bats algorithm (CCQBA) proposed by Li et al. [50]. In addition, the support vector regression (SVR) model can handle the nonlinear data, and the variational mode decomposition (VMD) method can reduce the nonlinearity and nonstationarity of data. Therefore, in future research, we can learn from Zhang and Hong and combine the above two methods with the GWO algorithm to build a new grey model to predict energy consumption [51].

5. Conclusions

In this paper, the FOA is combined with the discrete grey prediction model, and the FDGM (1, 1, t^{α}) model is proposed to predict the total energy consumption of civil buildings, urban civil buildings, and civil buildings specifically in Beijing. The introduction of the FOA improves the adaptability and prediction ability of the FDGM (1, 1, t^{α}) model. The results obtained from fitting and forecasting building energy consumption data show that the FDGM (1, 1, t^{α}) model is more effective and accurate than the existing GM (1, 1), SIGM (1, 1), DGM (1, 1), NGM (1, 1), NDGM (1, 1), and FANDGM (1, 1) models. In addition, this paper predicts building energy consumption over the next 5 years based on a metabolism mechanism. The forecasting results show that from 2018 to 2022, the three types of building energy consumption will exhibit steady upward trends. The growth rate of the energy consumption of urban civil buildings is the fastest.

It can be seen that building energy consumption will continue to increase in the future. Therefore, the development of building energy conservation policies and green buildings should be further promoted, and mandatory standards for energy conservation should be fully implemented in new urban buildings. The energy efficiency of new urban buildings should be improved through a three-step energy consumption improvement route involving ultralow energy-consuming buildings, near-zero energy-consuming buildings, and zero energy-consuming buildings. The energy-saving transformation of existing residential buildings should be continued to form a pattern of comprehensive transformation and improvements in energy conservation, livability, and functionality. We will strengthen the energy-saving supervision and transformation approaches for public buildings and promote the development of green buildings.

Data Availability

All data generated or used during the study are available within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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