

# A Predictive Analysis of Clean Energy Consumption, Economic Growth and Environmental Regulation in China Using an Optimized Grey Dynamic Model

Zheng-Xin Wang

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**Abstract** To accurately predict the consumption of clean energy in China, a grey dynamic model is constructed by taking economic growth and environmental regulation as exogenous variables. The Nash equilibrium idea-based optimization method is proposed to solve the parameters of the model so as to obtain better modeling effects than that of the traditional model. The empirical results show that: (1) a spontaneous increasing mechanism of the clean energy consumption has not yet formed in China; (2) both GDP and effluent charge play a positive role in accelerating clean energy consumption in China, but effluent charge has a stronger effect than GDP; (3) clean energy consumption in China is expected to stably increase at an annual rate of 5.73 % averagely in 2012–2020. By 2020, clean energy consumption in China is expected to reach 454.55 million tons of standard coal. The study also provides some policy suggestions of promoting clean energy consumption based on the empirical analysis conclusions.

**Keywords** Clean energy consumption · Economic growth · Environmental regulation · Grey dynamic model · Optimization

## 1 Introduction

Due to increasing global warming, low-carbon economy has been a universal concern world widely. Clean energy, as a new energy which does not or seldom release

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Z.-X. Wang (✉)  
School of Economics & International Trade,  
Zhejiang University of Finance & Economics, Hangzhou 310018, China  
e-mail: zxwang@zufe.edu.cn

Z.-X. Wang  
Center for Research of Regulation & Policy,  
Zhejiang University of Finance & Economics, Hangzhou 310018, China

greenhouse gases, has been a favorite selection for developing low-carbon economy. Besides, the renewable energy contained in clean energy plays a vital part in alleviating the energy pressure in future. [Grimaud and Rougce \(2005\)](#) considered that the study on energy system and economic growth need to focus on clean renewable energies such as solar energy, biomass energy and hydropower instead of exhaustible resources including oil and coal.

As the largest developing country in the world, China has been the second power of energy consumption and greenhouse gas emission. China committed to decrease the CO<sub>2</sub> emission per GDP by 40–45 % in 2020 compared to 2005 in the World Climate Change Congress held in Copenhagen, Denmark in 2009. To realize such goal, China requires adjusting energy consumption structure and developing clean energy at large scale. So, the accurate medium-and-long-term prediction of clean energy consumption can not only guide the reasonable development of clean energy in China, but also provide a scientific decision basis for formulating economic development and energy security strategy.

The research team from the energy research institute of [National Development and Reform Commission of China \(2009\)](#) analyzed the factors influencing economical society development, energy demands and CO<sub>2</sub> emission using methods such as scenario analysis. [Wang and Mu \(2010\)](#) predicated the energy consumption structure and total energy consumption of Beijing in three scenarios in 2015–2020 by collecting the relative data in 1985–2008. And They also predicated the intensity of CO<sub>2</sub> emission per GDP in Beijing during 2025–2020 by using the CO<sub>2</sub> emission relation formula of energy structure and energy consumption. While [Liang et al. \(2004\)](#) employed input-output method and scenario analysis jointly to predict energy consumption and energy intensity. By using the model ARIMA (1,2,1) and selecting the total energy consumption during 1978–2010, [Song and Zhang \(2012\)](#) forecasted the energy consumption during the period of “the Twelfth Five-Year Plan”, and provided policy suggestions. [Xing and Zhou \(2008\)](#) utilized the principal components aided co-integration analysis and error modification model to construct the prediction model of China energy consumption. The results show that industry and population structures as well as fuel price are the factors affecting energy consumption in China. This model can well forecast the short-term energy consumption due to its high dependence to lag years; however fail to obtain the satisfied results in the application of long-term prediction. [Fu et al. \(2010\)](#) established a society development scenario in future using a genetic algorithm based medium and long term forecasting model of China energy consumption logistic. By deducing the clean energy consumption based on the target of carbon emission reduction, they conducted prediction analysis on the clean energy consumption in China in 2020. Their results are agreement with the China energy plan. Existing researches into energy consumption prediction focus on the total energy consumption and pay less attention to the clean energy consumption; Those models consider only economical factors including economic growth, industry structure and energy price etc. and show less concern on the governments’ environmental regulation.

By taking the uncertain systems whose part information is known, part information is unknown, as research object, grey systems theory ([Deng 1982, 2002; Liu et al. 2004](#)) is able to accurately describe and effectively monitor the behavior and evolution law of system operation by extracting the useful information from part known information

through generation and development. Owing to the grey system modeling technology can be realized without the distribution information and large amount of historical information of variables, in recent years, the univariate grey dynamic model GM (1,1) has been widely used in the prediction of energy consumption (Kumar and Jain 2010; Lee and Tong 2011, 2012; Pao et al. 2012), and obtained better effects than traditional methods. The GM (1,n) model (Deng 2002), as the basic model of multivariable grey model method, contains a system behavior variable and  $n$ -lexogenous variables, and is usually used to analyze the influences of multi exogenous variables on the system behavior variable; in the case of known variation trend of the exogenous variable, it can be used to conduct extrapolated prediction on system behavior variable. Hsu (2009) used the background values' interpolated coefficients in genetic algorithm optimizing model GM (1,n) to predict the output value of integrated circuit industry in Taiwan. Hao et al. (2011) determined the lag period of variables using grey relational analysis, and then carried out prediction by constructing model GM (1,n). Wang (2014) used model GM (1,n) to established the grey control system of high-tech industries in China and analyzed the stability, observability and controllability and performed a quantitative prediction on system evolution. Deng (2002) pointed out that model GM (1,n) presents dynamic characteristic, however it is generally unfits for prediction due to lack of complete information. Tien (2012) found that model GM (1,n) is likely to generate large errors in prediction, and verified the point of Deng based on experimental data. Tien (2005) added a control parameter in grey action based on traditional model GM (1,n), and resolved the whitening differential equation using convolution integral technology. The improved model was named as model GMC (1,n). However owing to the discrete time response function is used to directly replace the continuous time response function in resolving process of model, the precision of modeling results is affected.

Since this research can obtain part influencing factors information of clean energy rather than all information in real modeling analysis, this search considers the clean energy consumption in China and its influencing factors as a grey system whose part information is known, part information is unknown, and attempts to propose a optimized model GMC (1,n). The model can be used to analyze the relation between clean energy consumption in China and its influencing factors to therefore forecast development trend of clean energy consumption in China.

The remainder of this paper is organized as follows. Section 2 illustrates the modeling process of grey dynamic model GMC (1,n) and proposes the parameter optimization algorithms. In Sect. 3, the research carries out the empirical analysis of clean energy consumption in China and forecast the development trend of clean energy consumption in 2012–2020. Finally, the paper concludes with some comments in Sect. 4.

## 2 Methodology

### 2.1 The Grey Dynamic Model with Convolution Integral

Suppose that pairs of observations  $X^{(0)} = (X_1^{(0)}, X_2^{(0)}, \dots, X_n^{(0)})$  are available at equispaced time intervals consisting of  $n - 1$  inputs  $X_2^{(0)}, X_3^{(0)}, \dots, X_n^{(0)}$  and an output

$X_1^{(0)}$  from some dynamic system. The existing GMC(1,  $n$ ) modeling process (Tien 2005) is carried out as follows. Consider the original predicted series:

$$X_1^{(0)} = \{X_1^{(0)}(rp + 1), X_1^{(0)}(rp + 2), \dots, X_1^{(0)}(rp + r)\} \quad (1)$$

and the original associated series:

$$X_i^{(0)} = \{X_i^{(0)}(1), X_i^{(0)}(2), \dots, X_i^{(0)}(r)\}, \quad i = 2, 3, \dots, n. \quad (2)$$

Then the 1-AGO data for  $X_1^{(0)}, X_2^{(0)}, \dots, X_n^{(0)}$  are given by Eqs. (3) and (4), respectively:

$$X_1^{(1)}(rp + t) = \sum_{j=1}^t X_1^{(0)}(rp + j), \quad t = 1, 2, \dots, r \quad (3)$$

and

$$X_i^{(1)}(t) = \sum_{j=1}^t X_i^{(0)}(j), \quad t = 1, 2, \dots, r, \quad j = 2, 3, \dots, n. \quad (4)$$

The grey forecasting model based on the predicted 1-AGO series:

$$X_1^{(1)} = \{X_1^{(1)}(rp + 1), X_1^{(1)}(rp + 2), \dots, X_1^{(1)}(rp + r)\}, \quad (5)$$

and the associated 1-AGO series:

$$X_i^{(1)} = \{X_i^{(1)}(1), X_i^{(1)}(2), \dots, X_i^{(1)}(r)\}, \quad i = 2, 3, \dots, n \quad (6)$$

is given by the differential equation:

$$\frac{dX_1^{(1)}(rp + t)}{dt} + b_1 X_1^{(1)}(rp + t) = b_2 X_2^{(1)}(t) + b_3 X_3^{(1)}(t) + \dots + b_n X_n^{(1)}(t) + u, \quad t = 1, 2, \dots \quad (7)$$

where  $b_1, b_2, \dots, b_n, u$  are parameters to be estimated and  $r$  is the data number used in model building;  $rp$  is a delay period. Eq. (7) is called the  $n$ -factor grey prediction model with convolution integral and is denoted by GMC (1,  $n$ ) (Tien 2005), the 1 representing the first-order derivative of the 1-AGO series of  $X_1^{(1)}$ , the  $n$  represents the total of  $n$  relative series introduced into the grey differential equation.

## 2.2 The Evaluation of Parameters $b_1, b_2, \dots$ , and $b_n$

The grey derivative for the first-order grey differential equation with 1-AGO is represented as:

$$\frac{dX_1^{(1)}(rp+t)}{dt} = \lim_{\Delta t \rightarrow 0} \frac{X_1^{(1)}(rp+t) - X_1^{(1)}(rp+t-\Delta t)}{\Delta t} \quad (8)$$

and when  $\Delta t \rightarrow 1$

$$\begin{aligned} \frac{dX_1^{(1)}(rp+t)}{dt} &= \frac{\Delta X_1^{(1)}(rp+t)}{\Delta t} = X_1^{(1)}(rp+t) - X_1^{(1)}(rp+t-1) \\ &= X_1^{(0)}(rp+t) \end{aligned} \quad (9)$$

The background value of the grey derivative  $dX_1^{(1)}(rp+t)/dt$  is taken as the mean of  $X_1^{(1)}(rp+t)$  and  $X_1^{(1)}(rp+t-1)$ , and those of the associated series  $X_i^{(1)}(t)$  are also taken as the mean of  $X_i^{(1)}(t)$  and  $X_i^{(1)}(t-1)$  for  $i = 2, 3, \dots, n$  respectively in the determination of model parameters by GMC (1,  $n$ ).

The least-squares solution to the model parameters of GMC (1,  $n$ ) in Eq. (7) by  $t$  from 1 to  $r$  is:

$$(b_1, b_2, \dots, b_n, u)^T = (B^T B)^{-1} B^T Y_R, \quad (10)$$

where:

$$B = \begin{bmatrix} -\frac{X_1^{(1)}(rp+1)+X_1^{(1)}(rp+2)}{2} & \frac{X_2^{(1)}(1)+X_2^{(1)}(2)}{2} & \frac{X_3^{(1)}(1)+X_3^{(1)}(2)}{2} & \dots & \frac{X_n^{(1)}(1)+X_n^{(1)}(2)}{2} & 1 \\ -\frac{X_1^{(1)}(rp+2)+X_1^{(1)}(rp+3)}{2} & \frac{X_2^{(1)}(2)+X_2^{(1)}(3)}{2} & \frac{X_3^{(1)}(2)+X_3^{(1)}(3)}{2} & \dots & \frac{X_n^{(1)}(2)+X_n^{(1)}(3)}{2} & 1 \\ \dots & \dots & \dots & \dots & \dots & \dots \\ -\frac{X_1^{(1)}(rp+r-1)+X_1^{(1)}(rp+r)}{2} & \frac{X_2^{(1)}(r-1)+X_2^{(1)}(r)}{2} & \frac{X_3^{(1)}(r-1)+X_3^{(1)}(r)}{2} & \dots & \frac{X_n^{(1)}(r-1)+X_n^{(1)}(r)}{2} & 1 \end{bmatrix} \quad (11)$$

and

$$Y_R = \left( X_1^{(0)}(rp+2), X_1^{(0)}(rp+3), \dots, X_1^{(0)}(rp+r) \right)^T \quad (12)$$

## 2.3 The Evaluation of $\hat{X}_1^{(0)}$

The right-hand side of Eq. (7), the discrete function  $f(t)$  (Tien 2005) can be obtained as:

$$f(t) = b_2 X_2^{(1)}(t) + b_3 X_3^{(1)}(t) + \dots + b_n X_n^{(1)}(t) + u, \quad t = 1, 2, \dots \quad (13)$$

The unit impulse response function  $h(t)$  of the system characterised by Eq. (21) can be derived by Laplace transform. From Eq. (7):

$$\frac{dX_1^{(1)}(t)}{dt} + b_1 X_1^{(1)}(t) = \delta(t) \quad (14)$$

where  $\delta(t)$  is the unit impulse function to determine the corresponding unit impulse response function. Applying a Laplace transform to Eq. (14) with the initial condition  $X_1^{(1)}(1) = 0$ , gives:

$$s\bar{X}_1^{(1)}(s) + b_1\bar{X}_1^{(1)}(s) = 1 \quad (15)$$

or

$$\bar{X}_1^{(1)}(s) = \frac{1}{s + b_1}. \quad (16)$$

The inverse transform of  $\bar{X}_1^{(1)}(s)$  is:

$$X_1^{(1)}(t) = e^{-b_1 t}. \quad (17)$$

That is, the unit impulse response function  $h(t)$  of the system is:

$$h(t) = e^{-b_1 t}. \quad (18)$$

The 1-AGO modeling values of the predicted series (Tien 2005) can be derived with the initial condition  $\hat{X}_1^{(1)}(rp + 1) = X_1^{(1)}(rp + 1)$  as:

$$\hat{X}_1^{(1)}(rp + t) = X_1^{(1)}(rp + 1)e^{-b_1(t-1)} + \int_1^t e^{-b_1(t-\tau)} f(\tau) d\tau, \quad t = 1, 2, \dots \quad (19)$$

The modeling values,  $\hat{X}_1^{(1)}(rp + t)$  can be evaluated approximately by:

$$\hat{X}_1^{(1)}(rp + 1) = X_1^{(1)}(rp + 1) = X_1^{(0)}(rp + 1) \quad (20)$$

and

$$\begin{aligned} \hat{X}_1^{(1)}(rp + t) &\cong X_1^{(0)}(rp + 1)e^{-b_1(t-1)} + u(t-2) \\ &\times \left\{ \sum_{k=2}^t e^{-b_1\left(t-k+\frac{1}{2}\right)} \cdot \frac{1}{2} [f(t) + f(t-1)] \right\} \end{aligned} \quad (21)$$

where  $u(t-2)$  is the unit step function.

Applying 1-IAGO to Eq. (21) yields the following modelled values together with the forecasts:

$$\hat{X}_1^{(1)}(rp+1) = X_1^{(1)}(rp+1) = X_1^{(0)}(rp+1) \quad (22)$$

and

$$\hat{X}_1^{(0)}(rp+t) = \hat{X}_1^{(1)}(rp+t) - \hat{X}_1^{(1)}(rp+t-1), \quad t = 2, 3, \dots \quad (23)$$

Assume the system parameters in Eq. (7) to be constants in the post-sampling period and then, by using the post-sampling data, combined with the given data for the corresponding associated series, as a new input series, the corresponding forecasts or values of indirect measurement for the predicted series can be derived.

It is obvious that when the number of associated series is zero, that is, when  $n = 1$ , Eq. (7) reduces to the grey single variable forecasting model GM (1, 1).

## 2.4 Parameters Optimization

To reduce the error yielded in approximate substitution of using Eq. (19) with Eq. (21), the correction parameter of boundary value and the weight generated by the mean of discrete function  $f(t)$  were introduced into Eq. (21).

$$\begin{aligned} \hat{X}_1^{(1)}(rp+t) \cong & \left( X_1^{(0)}(rp+1) + c \right) e^{-b_1(t-1)} + u(t-2) \\ & \times \left\{ \sum_{k=2}^t e^{-b_1\left(t-k+\frac{1}{2}\right)} \cdot [\lambda f(t) + (1-\lambda)f(t-1)] \right\} \end{aligned} \quad (24)$$

Where,  $c$  is the correction parameter of boundary value;  $\lambda$  is the the weight generated by the mean of discrete function  $\lambda \in [0, 1]$ ; when  $c = 0$  and  $\lambda = 0.5$ , Eq. (24) is equivalent to Eq. (21)

We determine the constant  $c$  by minimizing

$$g(c) = \sum_{t=1}^r \left[ \hat{X}_1^{(1)}(rp+t) - X_1^{(1)}(rp+t) \right]^2. \quad (25)$$

By setting  $\frac{dg(c)}{dc} = 0$ , then we have

$$\begin{aligned} \sum_{t=1}^r \left\{ \left( X_1^{(0)}(rp+1) + c \right) e^{-b_1(t-1)} + u(t-2) \right. \\ \left. \times \left\{ \sum_{k=2}^t e^{-b_1\left(t-k+\frac{1}{2}\right)} \cdot [\lambda f(t) + (1-\lambda)f(t-1)] \right\} - X_1^{(1)}(rp+t) \right\} e^{-b_1(t-1)} = 0 \end{aligned} \quad (26)$$

with the result that

$$c = \frac{\sum_{t=1}^r \left\{ X_1^{(1)}(rp+t) - u(t-2) \times \left[ \sum_{k=2}^t e^{-b_1(t-k+\frac{1}{2})} \cdot [\lambda f(t) + (1-\lambda)f(t-1)] \right] \right\} e^{-b_1(t-1)} - \sum_{t=1}^r X_1^{(0)}(rp+1) e^{-2b_1(t-1)}}{\sum_{t=1}^r e^{-2b_1(t-1)}} \quad (27)$$

The Nash equilibrium concept in Economics can be used to solve the optimal parameters  $c$  and  $\lambda$ , under the condition of giving the raw data sequence  $X_i^{(0)}$ ,  $i = 1, 2, \dots, n$ . This optimization way has been proved to be able to effectively solve the Nash nonlinear grey Bernoulli model (Chen et al. 2010) containing two unknown parameters and further improve the simulation and prediction accuracy. Consider the following optimal problem:

$$\text{MinMAPE}(\lambda, c | X_i^{(0)}) = \text{Min}_{\lambda, c} \left\{ \frac{1}{r-1} \sum_{t=rp+2}^{rp+r} \left| \frac{X_1^{(0)}(t) - \hat{X}_1^{(0)}(t)}{X_1^{(0)}(t)} \right| \right\} \quad (28)$$

Based on Eq. (28) and assisted by the operations research software, LINGO, the optimal Nash solution  $c_N^*$  and  $\lambda_N^*$  can be reached. The optimization process is as follows:

$$\begin{aligned} c_0^* &= \text{Arg}_{(c)} \text{MinMAPE} \left\{ c | X_i^{(0)}, \lambda_0 = 0.5, i = 1, 2, \dots, n \right\}, \\ \lambda_1^* &= \text{Arg}_{(\lambda)} \text{MinMAPE} \left\{ \lambda | X_i^{(0)}, c = c_0^*, i = 1, 2, \dots, n \right\}, \\ &\vdots \\ c_i^* &= \text{Arg}_{(c)} \text{MinMAPE} \left\{ c | X_i^{(0)}, \lambda = \lambda_i^*, i = 1, 2, \dots, n \right\}, \\ \lambda_{i+1}^* &= \text{Arg}_{(\lambda)} \text{MinMAPE} \left\{ \lambda | X_i^{(0)}, c = c_i^*, i = 1, 2, \dots, n \right\}, \\ &\vdots \\ c_N^* &= \text{Arg}_{(c)} \text{MinMAPE} \left\{ c | X_i^{(0)}, \lambda = \lambda_N^*, i = 1, 2, \dots, n \right\}, \\ \lambda_N^* &= \text{Arg}_{(\lambda)} \text{MinMAPE} \left\{ \lambda | X_i^{(0)}, c = c_N^*, i = 1, 2, \dots, n \right\}. \end{aligned} \quad (29)$$

By substituting the optimal parameter values of  $c_N^*$  and  $\lambda_N^*$  into Eq. (24) and conducting first-order regressive reduction according to Eq. (23), the optimized prediction value is gettable. The effectiveness of this method and the superiority of this method to traditional method are explained in the following empirical analysis section.

### 3 Empirical Analysis

In this section, the model proposed in this study and traditional model were used to model China's clean energy consumption and the real data of related variables.



By comparing the modeling results, the model with higher accuracy was used to predict the development trend in 2012–2020. In addition, corresponding policy recommendations were proposed.

### 3.1 Variables and Data

Clean energy is also known as the energy without pollutant emission. It mainly includes hydro-energy, nuclear energy, wind energy, solar energy and other renewable energies. Most of the clean energy is convertible into electricity for use. A number of available researches suggest that economic growth acts one of the main factors driving the energy consumption. Since clean energy is a kind of energy, this paper employed the GDP as the variable influencing the clean energy consumption. In the consumption process of petrochemical energies such as coal, oil, and natural gas etc., a large amount of pollutants are discharged into the atmosphere, water, and soil. As the main policy tool for environmental regulation, effluent charge plays a positive role in promoting clean energy consumption. The collection of effluent charge can inhibit the usage of traditional fossil energy to some extent and promote production sectors to use clean energy. Therefore, effluent charge is also used a variable for clean energy consumption. In the subsequent modeling and prediction in this study, clean energy consumption, GDP, and effluent charge are represented by  $X_1$ ,  $X_2$ , and  $X_3$  respectively.

The data of clean energy consumption and GDP were collected from China Statistical Yearbook (1996–2012) released by National Bureau of Statistics; the data of effluent charge were sourced from China's environmental statistical bulletin issued by Chinese Ministry of Environmental Protection (1996–2012). To eliminate the effect of price changes on GDP and effluent charge, the GDP and effluent charge calculated at current prices were deflated with 1995 as the base period. Table 1 shows the data of clean energy consumption, real GDP, and effluent charge of China in 1995–2011. In this table, the clean energy includes hydropower, nuclear power, and wind power.

### 3.2 The Dynamic Equation of the Chinese Clean Energy Consumption

To avoid the ill-conditioned data matrix in parameter identification, original data should be pretreated before establishing a multi-variable grey model (Deng 2002). In the present research, the time sequence data in Table 1 are pre-processed using the initialization transformation technology. The specific treatment method is indicated as follows: with the data of 1995 as the initial point of system evaluation, the data of 1995–2011 are divided by the data in 1995. In this way, the time series data with consistent magnitude orders and dimensions can be obtained to more effectively identify model parameters (Table 2).

Applying the GMC (1, 3) model given by Eqs. (7)–(16), the values of the parameters  $n$ ,  $r$  and  $rp$  in Eq. (7), and the estimates of the model parameters  $b_1$ ,  $b_2$ ,  $b_3$  and  $u$  in Eq. (10) can be obtained (Table 3). The resulting GMC (1, 3) model from Eq. (7) has the form

**Table 1** The data of clean energy consumption, real GDP, and effluent charge of China in 1995–2011

Year	Clean energy consumption (million tons of standard coal)	Real GDP (billion Yuan)	Effluent charge (10 thousand Yuan)
1995	8,002	60,794	371,000
1996	8,112	66,878	378,158
1997	8,698	73,096	408,070
1998	8,852	78,822	443,615
1999	8,294	84,828	509,223
2000	9,314	91,980	530,060
2001	11,280	99,615	564,924
2002	11,638	108,662	617,095
2003	11,946	119,555	661,349
2004	14,302	131,613	820,272
2005	16,048	146,498	1,053,838
2006	17,331	165,069	1,214,295
2007	19,075	188,447	1,395,904
2008	22,441	206,603	1,406,552
2009	23,918	225,640	1,320,088
2010	27,945	249,212	1,393,259
2011	27,840	272,389	1,333,976

**Table 2** The initialized data of clean energy consumption, real GDP, and effluent charge of China in 1995–2011

Year	Clean energy consumption	Real GDP	Effluent charge
1995	1.0000	1.0000	1.0000
1996	1.0137	1.1001	1.0193
1997	1.0870	1.2024	1.0999
1998	1.1063	1.2965	1.1957
1999	1.0365	1.3953	1.3726
2000	1.1640	1.5130	1.4287
2001	1.4098	1.6386	1.5227
2002	1.4545	1.7874	1.6633
2003	1.4930	1.9666	1.7826
2004	1.7873	2.1649	2.2110
2005	2.0055	2.4098	2.8405
2006	2.1659	2.7152	3.2730
2007	2.3838	3.0998	3.7625
2008	2.8046	3.3984	3.7912
2009	2.9892	3.7116	3.5582
2010	3.4923	4.0993	3.7554
2011	3.4793	4.4805	3.5956

**Table 3** The parameters and the MAPE for GMC (1,3)

Parameter	Value	Parameter	Value
$n$	3	$b_3$	0.14562
$r$	17	$u$	0.88602
$rp$	0	$c$	0.06554
$b_1$	0.15938	$\lambda$	0.52248
$b_2$	0.05566	MAPE (%)	3.86068

**Table 4** The discrete function  $f(t)$  for GMC (1, 3) in Eq. (11)

$t$	$f(t)$	$t$	$f(t)$
1	1.08729	10	3.80623
2	1.29695	11	4.35399
3	1.52404	12	4.98172
4	1.77032	13	5.70215
5	2.04785	14	6.44337
6	2.34011	15	7.16809
7	2.65305	16	7.94310
8	2.99474	17	8.71607
9	3.36378		

$$\frac{dX_1^{(1)}(t)}{dt} + 0.15938X_1^{(1)}(t) = 0.05566X_2^{(1)}(t) + 0.14562X_3^{(1)}(t) + 0.88602.$$

To sum up the right-hand side of Eq. (7), the discrete function  $f(t)$  in Eq. (11) for the GMC (1, 3) model is obtained and tabulated (Table 4). The optimal parameters  $c$  and  $\lambda$ , and the mean absolute percentage error (MAPE) are also listed in Table 3.

### 3.3 Empirical Results

The dynamic equation of China's clean energy consumption reveals that the development coefficient of the system behavior variable is 0.15938, which is more than 0. The value of development coefficient in a grey model reflects the self-growth characteristics of the system behavior variable. When the value is negative, it means a spontaneous growth mechanism. When the value is positive means a negative growth mechanism. This outcome proves that China's clean energy consumption has not yet formed the spontaneous growth mechanism and the growth momentum derives from the grey action, that is, the right part of the equation.

In the grey action, GDP and effluent charge show the action coefficient of 0.05566 and 0.14562 separately on clean energy consumption, suggesting that the two variables exerts positive promoting role on clean energy consumption. In addition, the effect of effluent charge is significantly higher than that of GDP due to China's energy consumption structure. It is known that GDP growth has a direct pulling effect on the consumption demand on total energy. However, the data released by Chinese Bureau of Statistics suggested that clean energy consumption merely accounts for 6–8 % of

**Table 5** The modeling results obtained using the GM (1, 3), and GMC (1, 3) models

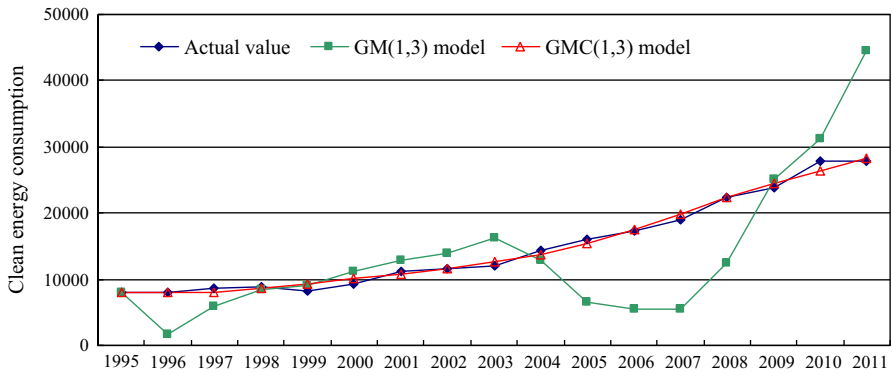
Year	Actual value	GM (1, 3)		GMC (1, 3)	
		Modeling value	Relative error (%)	Modeling value	Relative error (%)
1995	8,002	8,002	0	8,002	0
1996	8,112	1,752	78.406	8,112	0.000
1997	8,698	5,804	33.270	8,086	7.041
1998	8,852	8,458	4.446	8,647	2.320
1999	8,294	9,070	9.358	9,313	12.293
2000	9,314	11,185	20.084	10,049	7.887
2001	11,280	12,776	13.254	10,807	4.193
2002	11,638	13,938	19.760	11,638	0.000
2003	11,946	16,139	35.098	12,554	5.086
2004	14,302	12,846	10.175	13,715	4.103
2005	16,048	6,557	59.143	15,370	4.224
2006	17,331	5,536	68.058	17,462	0.752
2007	19,075	5,460	71.373	19,885	4.250
2008	22,441	12,443	44.553	22,359	0.368
2009	23,918	25,168	5.226	24,478	2.340
2010	27,945	31,271	11.904	26,421	5.453
2011	27,840	44,416	59.540	28,247	1.461
MAPE (%)			33.978		3.861

the total energy consumption in China in 1995–2011, although the value is still in an upward trend. The collection of effluent charge directly affects the energy choices of industrial enterprises. In case of neglecting the influences of prices, industrial enterprises may reduce traditional petrochemical energy consumption and increase clean energy consumption.

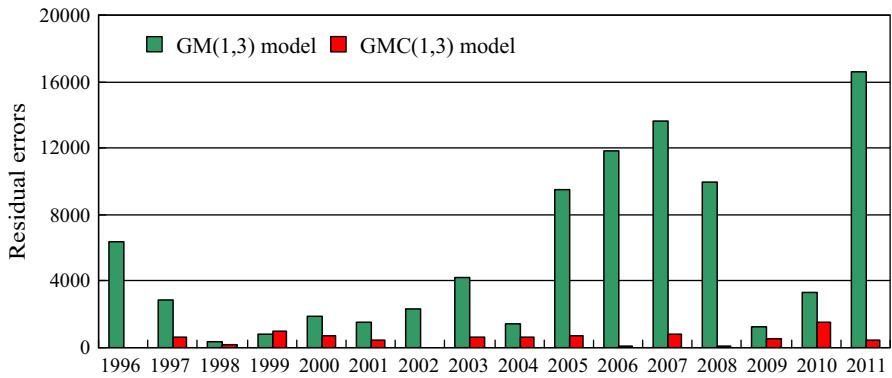
By substituting the parameter estimation results in Table 3 and the discrete function value in Table 4 into Eqs. (22), (23), and (24) and inversely transforming the initialization transformation, the simulation results of GMC (1,3) model on China's clean energy consumption are available (as shown in Table 5). To reflect the improving effect of this modeling method, the modeling results of traditional multivariable grey model GM (1,3) are also listed in Table 5.

Table 5 reveals that the optimization model GMC (1,3) proposed in this study achieves lower relative simulation error than traditional model in the two sample intervals, namely, 1995–1998 and 2000–2011. In the whole modeling sampling interval, the MAPE of GMC (1,3) is 3.861 %, which is far lower than the 33.978 % of traditional model. Since the grey action of traditional model does not contain constant terms and the time response function has low accuracy, traditional model yields unacceptable error in simulating the clean energy consumption in several years; however, the optimization model propose in this study effectively solves these problems and significantly improves the modeling accuracy.

Figure 1 demonstrates the degree of closeness between the modeling results of the models and the real values of the clean energy consumption in China. Clearly, the



**Fig. 1** The actual value and the modeling curves obtained using the GM (1, 3), and GMC (1, 3) models.



**Fig. 2** The residual errors occurring in the GM (1, 3), and GMC (1, 3) models.

proposed model GMC (1, 3) is closer to the actual data than the traditional one. Moreover, as can be seen from a histogram of the modeling residual errors (Fig. 2), the residual error from the GMC (1, 3) model is notably smaller than that of the GM (1, 3). The reason for this lies in the fact that through optimization of the parameters, the modeling ability of the GMC (1, 3) model can be further improved in the GM (1, 3) model.

### 3.4 Prediction on Clean Energy Consumption

The discussion above proved that the GMC (1,3) model proposed in this study can more effectively describe the relationships of China's clean energy consumption with GDP and effluent charge and show higher modeling accuracy than traditional ones. Since the MAPE of the GMC (1,3) is less than 5 %, this model is effectively applicable to middle-to-long term prediction according to the conclusions by Liu et al. (2004). Therefore, GMC (1,3) is used to predict China's clean energy consumption in 2012–2020.

In the GMC (1,3) model, clean energy consumption serves as the behavioral variable in the grey system, namely, endogenous variables, while real GDP and effluent charge

are exogenous variables of the system. The prediction on endogenous variable can only be achieved by valuing exogenous variables in advance. In this study, the real GDP and effluent charge in 2012–2020 were firstly predicted using the single variable grey model GM (1,1) (Liu et al. 2004). The prediction results obtained were then substituted into grey action of GMC (1,3) model to finally realize the prediction on China's clean energy consumption. Since the larger the sample amount, the more strict the class ratio conditions of GM (1,1), the real GDP and effluent charge data in 2005–2011 were used to built the GM (1,1) model.

The initialized actual GDP sequence was used to estimate the parameters of GM (1,1). The development coefficient  $a = -0.09664$ ; grey action  $b = 0.86403$  thus the time response function is expressed as follows:

$$\begin{cases} \hat{X}_2^{(1)}(k+1) = 27.34480e^{0.09664k} - 24.93504 \\ \hat{X}_2^{(0)}(k+1) = \hat{X}_2^{(1)}(k+1) - \hat{X}_2^{(1)}(k) \end{cases}, \quad k = 1, 2, 3, \dots$$

By calculation, the MAPE of the GM (1,1) model is 0.90 %. Therefore, this model is applicable for middle-to-long term prediction. Table 6 shows the actual GDP prediction results in 2012–2020.

In similar way, the effluent charge sequence GM (1,1) model gets a development coefficient of  $a = -0.01043$ , grey action of  $b = 3.48088$ , and the time response function is expressed as follows:

$$\begin{cases} \hat{X}_3^{(1)}(k+1) = 336.58854e^{0.01043k} - 333.74801 \\ \hat{X}_3^{(0)}(k+1) = \hat{X}_3^{(1)}(k+1) - \hat{X}_3^{(1)}(k) \end{cases}, \quad k = 1, 2, 3, \dots$$

The MAPE of the GM (1,1) model for effluent charge is 4.29 %. Therefore, this model is applicable for middle-to-long term prediction. Table 6 shows the effluent charge prediction results in 2012–2020.

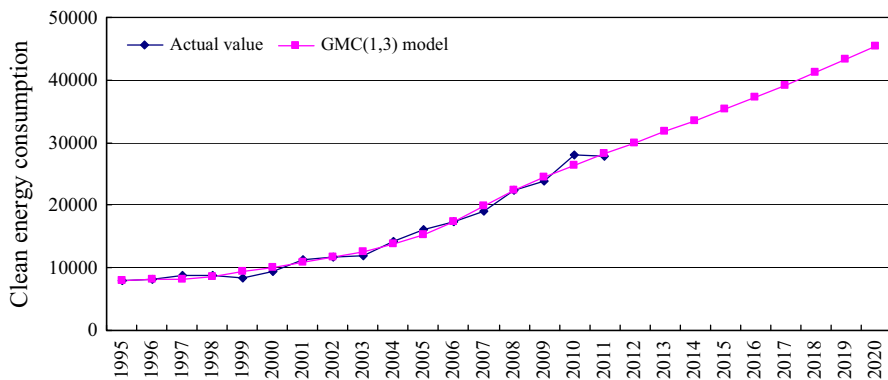
By substituting the prediction results of  $X_2^{(1)}$  and  $X_3^{(1)}$  into the time response function of GMC (1,3), that is, using Eq. (24), the prediction value of  $X_1^{(1)}$  can be obtained. Through the first-order regressive reduction on  $X_1^{(1)}$ , the prediction results of China's clean energy consumption in 2012–2020 are available, as shown in Table 6. The prediction results signify that China's clean energy consumption grows at an average speed of 5.73 % steadily in 2012–2020. To 2020, it will reach 454.55 million tons of standard coal, which is 1.63 times that in 2011. Figure 3 shows that GMC (1,3) favorably fits the historical data of China's clean energy consumption in 1995–2011 and presents the steady growth trend in 2012–2020.

### 3.5 Policy Suggestions

For a long time, fossil energy occupies a leading position in China energy consumption, while the fossil energy consumption acts as the main source of the carbon emissions in China. Therefore, to ensure that carbon emission is reduced into the planning

**Table 6** The forecasts of clean energy consumption, real GDP, and effluent charge of China in 2012–2020

Year	Real GDP (billion Yuan)	Effluent charge (10 thousand Yuan)	Clean energy consumption (million tons of standard coal)
2012	301,232	1,393,759	29,989
2013	331,798	1,408,371	31,781
2014	365,465	1,423,137	33,569
2015	402,548	1,438,058	35,377
2016	443,395	1,453,134	37,226
2017	488,385	1,468,370	39,137
2018	537,942	1,483,764	41,132
2019	592,526	1,499,320	43,231
2020	652,649	1,515,040	45,455

**Fig. 3** The actual value and the forecasting curves obtained using the GMC (1,3) model.

objectives, China should reduce fossil energy consumption and increase clean energy consumption. According to the conclusions of empirical analysis in this study, the following policy recommendations are proposed:

- (1) Government is suggested to improve the support policies to promote the formation of the spontaneous mechanism of clean energy consumption. Clean energy development cannot do without the support of the government. Chinese government can improve the corresponding policies as soon as possible to stimulate the technological innovation of clean energy production enterprises. Technology innovation can reduce the production cost and price of clean energy and thus increase the market demand for clean energy. As for some innovation funds for key technology, government should give low interest loans to help clean energy production enterprises to break through the bottleneck of fund.
- (2) Environmental regulation should be enhanced to reduce the proportion of traditional fossil energy in total energy consumption. The harmful gases produced in the combustion of fossil energy fuels seriously pollute environment and lead to many ecological problems such as global warming and decrease of species diver-

sity etc.. In addition, they greatly influence the sustainable development of economy and society and threaten the survival of mankind. Government can internalize the environmental external costs through tax policy. For example, governments collect tax on traditional fossil energy to increase the usage cost of traditional fossil energy and thus restrain the consumption of the traditional polluting energy and increase the consumption of clean energy.

- (3) Government should help consumers to convert the concept and encourage consumers consciously choose clean energy. On one hand, education is needed to guide the consumers to develop a ecology-protecting and energy-saving-oriented green consumption concept and choose clean energy consciously. On the other hand, government can take the lead of using clean energy and plays the positive demonstration role on consumers in the promotions of clean energy consumption.

## 4 Conclusions and Future Work

Due to the influences of the uncertain factors including economy, technology and policy etc, it is usually difficult to predicating clean energy consumption. Developing a highly precise model of predicting clean energy consumption is essential. In this research, the Nash equilibrium based optimization method was proposed and could highly improve the modeling precision. The fitting relative error of samples was merely 3.861 % using the model in prediction of clean energy consumption in China, and the precision is as high as 96.139 %. The model can be used in medium-and-long-term prediction. The results revealed that China will witness a stable increase of clean energy consumption. The clean energy consumption is expected to reach 454.55 million tons of standard coal by 2020. Meanwhile, the estimated results of the model parameters indicated that due to insufficient growth driving force, the China government requires to stipulate reasonable support policies to increase the consumption of clean energy so as to fulfill the commitment made in the congress in Copenhagen, 2009.

The modeling method proposed in this study cannot effectively describe the nonlinear relationship between variables in actual systems. Compared to linear correlation, nonlinear correlation is even more pervasive in economic systems. Therefore, in future work, the problem of how to establish nonlinear grey dynamic models for simulating and forecasting evolution of economic systems needs to be taken into account.

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