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Optimization Model Based on Multivariable Grey Model and Its Application to Energy Consumption in China

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Abstract: Currently, the energy development in China is in a critical period of transformation and reform, facing unprecedented opportunities and challenges. Accurate energy consumption forecast is conducive to promoting the diversification of energy development and utilization, and ensuring the healthy and rapid development of China's economy. Based on the existing multivariable grey prediction model, a nonlinear multivariable grey prediction model with parameter optimization is established in this paper, which used the genetic algorithms to find the optimal parameters, and the modelling steps are obtained. Then, the novel model takes the oil natural gas, coal and clean energy in China as the research objects, and the results are compared with the other four grey prediction models. The novel model has higher simulation and prediction accuracy, which is better than the other four grey prediction models. Finally, the novel model is used to predict those four energy consumption forecasts in China from 2020 to 2024. The results show that various energy consumption will further increase, while the fastest growing is clean energy and natural gas, which provides effective information for the Chinese government to formulate energy economic policies.

Keywords: Grey prediction model, Energy consumption, Simulated annealing optimization, Genetic Algorithm.

1. Introduction

At present, facing the profound adjustment of the international energy supply and demand pattern a new round of energy technological transformation is under way. As a major energy producer and consumer, China must seize the opportunity, implement the new development concept, focus on supply-side structural reform, and actively promote energy consumption, supply, technology, institutional revolution and international cooperation. Also need to optimize the energy structure, strive to make up for many shortcomings in energy development, such as resource and environmental constraints, low quality and efficiency, weak infrastructure, and lack of key technologies, etc. Then, those efforts should be made to enhance the competitiveness of the energy industry, build a clean, low-carbon, safe and efficient modern energy system, and better support the sustained and stable development of Chinese economy.

According to the preliminary calculation by the National Bureau of Statistics (NBS), China's GDP in 2019 reached 99086.5 billion yuan, and its economic aggregate approached the 100 trillion yuan mark. Translated at the average annual exchange rate, it reached 14.4 trillion dollar, ranking second in the world. As of 2019, The energy production of China was generally stable. In the past decade, from the perspective of total energy production, the total energy production of China has continued to grow. Primary energy production totaled 3.97 billion tons of standard coal, up 5.1%

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year on year. Raw coal output was 3.85 billion tons, up 4% year on year. Crude oil output was 191 million tons, up 0.9% year on year. Natural gas output was 176.17 billion cubic meters, up 10% year on year. And power generation reached 7503.43 billion kilowatt-hours, up 4.7% year on year. In the middle of this period, the total energy production only decreased in 2015 and 2016, and resumed steady growth in 2017, while the total energy production reached a historical high in 2019; from the perspective of growth rate, it was as high as 9.1% in 2010, and significantly decreased in 2012, with the growth rate dropping by 5.8 percentage points and continuing decrease about 4.2% in 2016. While in 2017, the growth rate rebounded to 3.6%, and the growth rate in the past two years was stable at 5% and 5.1%, still 4 percentage points lower than the high growth rate of 9.1% in 2010.

Not only that, energy consumption is also showing a steady growth trend. The total energy consumption in 2019 was 4.86 billion tons of standard coal, an increase of 3.3% over the previous year. Coal consumption increased by 1.0%, crude oil consumption increased by 6.8%, natural gas consumption increased by 8.6%, and electricity consumption increased by 4.5%. Over the past decade, total energy consumption has continued to rise, with an increase of 1.25 billion tons of standard coal in 2019 compared with 2010. According to the data of energy consumption structure in recent years, the proportion of coal consumption showed a downward trend, falling to less than 60% in 2018. However, it is still the main energy source in China in the short term. The proportion of clean energy consumption in total energy consumption nearly doubled from 13 percent in 2011 to 23.4 percent in 2019. In general, in the energy composition of China, coal occupies the dominant position, oil and natural gas are highly dependent on foreign countries, and the proportion of clean energy consumption continues to increase.

The energy development of China is at a critical stage of transformation and transformation, facing unprecedented opportunities and challenges. An important development goal and task in the 14th Five-Year Plan is to increase efforts to strengthen the clean energy industry and lay a firm foundation for achieving the goal of 20% of non-fossil energy in primary energy consumption by 2030. During the "14th Five-Year Plan" period, China will still face a complicated international situation and domestic energy revolution, coal will still occupy a dominant position in the primary energy consumption of China for a long period of time in the future. In order to accelerate the revolution of energy consumption, improve the level of clean and efficient utilization of traditional fossil energy will become an important task for the energy development of China during the "14th Five-Year Plan" period. Energy production should not only optimize the stock, but also take promoting clean and efficient development and utilization of coal as the foothold and primary task of energy transformation and development (Zhou et al., 2017). Improve the mechanisms and policies that encourage the development of distributed energy, straighten out the energy price system, restore the attributes of energy commodities, give full play to the decisive role of the market in allocating resources and give better play to the role of the government, and build an energy market system with fair competition.

Therefore, the prediction and analysis of the energy consumption in China are very important. In this paper, the novel model is applied to four energy consumption forecasts in China, and the prediction results provide effective information for the Chinese government to formulate energy economic policies. The original data are obtained from the National Bureau of Statistics of China. Accurate energy consumption prediction helps to have a clear grasp of the future energy supply situation, help adjust and improve the energy structure of a country, and promote the diversification of energy development and utilization. On the basis of prediction data, it is also helpful to take

practical measures to allocate social resources in advance and ensure the healthy and rapid development of Chinese economy.

2. Literature review

2.1 Research progress of energy consumption prediction

Aiming at the problem of energy consumption trend prediction, abundant scholars have proposed different learning methods from different perspectives. The existing methods mainly include time series model, regression analysis model, econometric model, artificial neural network model, hybrid prediction model, etc. For example, Ruiz et al. (Ruiz et al. 2020) proposed a time series clustering method extracted from energy consumption data and applied it to the modelling and prediction of public building energy. Senatro Di Leo et al. (Di Leo et al. 2020) used regression analysis to forecast energy demand, and used data of local regions and the whole of Italy to verify the effectiveness of the model. De Albuquerque et al. (De et al. 2018) established an oil price prediction model by studying the relationship between the changes of economic parameters in the United States and the oil supply and demand in the United States. Huang (Huang et al. 2018) introduced the principle of "decomposition and integration" into the modeling method of artificial neural network and proposed a novel international energy prediction method. Barak et al. (Barak et al. 2016) used the combination of linear regression ARIMA and ANFIS hybrid algorithm to predict energy consumption.

The above models more accurately predict the energy data, but usually these models require high data volume during the establishment process. To obtain a highly accurate model, a large amount of data must be preprocessed (An et al. 2012), after data cleaning, conversion, the selection of work can be used as the input of the neural network model, so more time and effort are needed in data processing.

In recent years, great changes have taken place in the global energy structure. Therefore, some historical data has little reference value for the current energy situation or future energy development trends, this situation lead to sharply reduce energy related data, at this time, some modelling methods that require a large amount of data training to ensure the accuracy of the model are not applicable. Therefore, if there is a model that can spend a small amount of time to find the data and build the model, and at the same time obtain good prediction accuracy, such model is considered attractive (Deng et al. 2002). In this paper, the research direction is turned to the grey prediction model. Relatively speaking, the grey system prediction model has more advantages in dealing with the uncertain system with "small sample and poor data" (Wu et al. 2020), and can produce more accurate prediction results even in the case of relatively scarce data (Wang et al. 2018, Dumanc et al. 2019).

2.2 Research progress of grey prediction model in energy consumption prediction

Grey prediction model can be applied to the system with uncertainty and scarce data. Grey prediction model has also been successfully applied to the prediction of energy consumption. For example, Luo et al. (Luo et al. 2020) added nonlinear terms to the grey Riccati model, and optimized the nonlinear terms with the simulated annealing (SA) optimization algorithm, then predicted the consumption of clean energy. Ma et al. (Ma et al. 2017) proposed a novel polynomial grey prediction model, TDPGM(1,1) model, to predict natural gas consumption in China. Ye et al. (Ye et al. 2019) proposed an interval grey optimized model DGM(1,1) to predict the energy consumption. Xiao et al. (Xiao et al. 2020) used Box-Cox transformation to establish a new constrained grey Bernoulli optimization model to predict biomass energy consumption in China, the United States, Brazil and Germany. Zhao and Wu (Zhao et al. 2020) proposed a neighborhood cumulative discrete grey model

and used it to predict non-renewable energy consumption in several countries.

The above models are all researched on the basis of the univariate grey model. The univariate grey prediction model is a first-order equation with one variable (Mao et al.2020, Xiao et al.2020, Zeng et al.2020, Xiao et al.2020, Duan et al.2020, Duan et al.2020), and the modelling object is a single time series without considering the influence of relevant factors on the system, so it has the advantage of simple modeling process. However, the energy system has a complex structure and many influencing factors. The modeling process of multivariable grey prediction model (Wang et al.2018, Kong et al.2019, Yan et al.2020) fully considers the influence of relevant factors on system changes, making up for the limitations of univariate model and the deficiency of the limited simulation ability of univariate model. For example, Wang et al. (Wang et al.2016) used an optimized multivariable grey prediction model to predict the industrial energy consumption of China; Zeng et al. (Zeng et al. 2019) proposed a novel multivariable grey prediction model and applied to energy consumption prediction. Dang et al. (Dang et al. 2017) proposed a new multivariable grey prediction model TMGM(1,N) to predict the total electricity consumption in Jiangsu Province, China; Wu et al. (Wu et al. 2018)proposed a multivariable grey prediction model that considers the change of the total population, which was used to predict the electricity consumption in Shandong Province, China, and achieved good results.

The above multivariable gray prediction models have achieved good results in predicting energy consumption problems, but most of the models are linear models. This article is based on the classic GMC(1,N) model (Tien et al.2005), this paper obtains a non-linear multivariate grey prediction model by adding non-linear terms, and the optimized model used the genetic algorithm to optimize the non-linear terms. Then the novel model is applied to the four major energy consumption in China, and the fossil energy consumption of coal, oil and natural gas, and clean energy consumption are forecast for the next five years.

2.3 Contribution and organization

1) A nonlinear multivariable grey prediction model is proposed, which can have better results for the nonlinear data of energy structure;

2) Genetic algorithm is used to optimize the nonlinear terms and improve the accuracy of the model. The novel model takes the oil, natural gas, coal and clean energy consumption in China as research objects, and its results are better than those of the other four gray prediction models;

3) The new model effectively predicts the consumption of three kinds of fossil energy and clean energy of China in the next five years, and the results show that the consumption has not reached the peak of consumption within five years. Meanwhile, the clean energy and natural gas are growing fastest.

The other sections of this article are arranged as follows. Section 3 proposes the GOMC(1,N) model and obtains the optimal modelling steps of the model; Section 4 uses the three kinds of fossil energy and clean energy in China as the empirical analysis of the model, and predict the consumption of the four kinds of energy in China in the next five years; Section 5 is a summary and prospect.

3. GOMC(1,N) model

This section first introduces the definition and related conclusions of the traditional GMC(1,N) model, then establishes the nonlinear GOMC(1,N) model, and optimizes the nonlinear terms of the model by using genetic algorithm.

3.1 Definition and properties of GMC(1,N) model

Definition 1. Set the raw data is $X^{(0)} = \{X^{(0)}(1), X^{(0)}(2), \dots, X^{(0)}(n)\}$, after an accumulation, the sequence is recorded as $X^{(1)} = \{X^{(1)}(1), X^{(1)}(2), \dots, X^{(1)}(n)\}$, where

$$X^{(1)}(k) = \sum_{j=1}^k X^{(0)}(j), k = 1, 2, 3, \dots, n$$

Definition 2. GMC(1,N) model is defined as follows:

$$X_1^{(0)}(rp+t) + b_1 Z_1^{(1)}(rp+t) = b_2 Z_2^{(1)}(t) + b_3 Z_3^{(1)}(t) + \dots + b_n Z_n^{(1)}(t) + u \quad (1)$$

where, r is the number of data points used for modelling, rp is the time delay coefficient, rf is the number of points used to predict, $b_1, b_2, \dots, b_n$ and u are the parameters to be estimated. And the differential equation

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

is called the whitening equation of the GMC(1,N) model, and

$$X_1^{(1)}(rp+t) = \sum_{k=rp+1}^{rp+t} X_1^{(0)}(k), t = 1, 2, \dots, r+rf$$

$$Z_1^{(1)}(rp+t) = \frac{X_1^{(1)}(rp+t) + X_1^{(1)}(rp+t-1)}{2}$$

Theorem 1. Least square estimation formula of GMC(1,N) model parameters

$$[b_1, b_2, \dots, b_n, u]^T = (B^T B)^{-1} B^T Y_n$$

where

$$B = \begin{bmatrix} -Z_1^{(1)}(rp+2) & Z_2^{(1)}(2) & \dots & Z_n^{(1)}(2) & 1 \\ -Z_1^{(1)}(rp+3) & Z_2^{(1)}(3) & \dots & Z_n^{(1)}(3) & 1 \\ \dots & \dots & \dots & \dots & \dots \\ -Z_1^{(1)}(rp+n) & Z_2^{(1)}(n) & \dots & Z_n^{(1)}(n) & 1 \end{bmatrix}, Y = \begin{bmatrix} X^{(0)}(2) \\ X^{(0)}(3) \\ \dots \\ X^{(0)}(n) \end{bmatrix}$$

Theorem 2. Let Eq. (2) as

$$f(t) = \sum_{j=2}^n b_j X_j^{(1)}(t) + u$$

and the solution of Eq. (2) is:

$$X_1^{(1)}(rp+t) = X_1^{(1)}(rp+1)e^{-b_1(t-1)} + \int_1^t e^{-b_1(t-\tau)} f(\tau) d\tau \quad (3)$$

where, $\int_1^t e^{-b_1(t-\tau)} f(\tau) d\tau = u(t-2) \times \sum_{\tau=2}^t \frac{1}{2} [e^{-b_1(t-\tau)} f(\tau) + e^{-b_1(t-\tau+1)} f(\tau-1)]$, and $u(t-2)$ is

the unit step function, defined as

$$\begin{cases} u(t-2) = 0, t < 2 \\ u(t-2) = 1, t \geq 2 \end{cases}$$

Then the reduction formula is

$$\hat{X}_1^{(0)}(rp+t) = \hat{X}_1^{(1)}(rp+t) - \hat{X}_1^{(1)}(rp+t-1)$$

3.2 Establishment of GOMC(1,N) model

In this section, the grey GOMC(1,N) model is established firstly, then the parameter estimation formula and the time response formula of the model are obtained, and the nonlinear terms of the model are optimized by using genetic algorithm. Because the traditional GMC(1,N) model is still a linear model in nature and sometimes has low efficiency in predicting complex nonlinear time series, which limits its applicability. Therefore, this section first establishes a nonlinear model, as follows:

Definition 3. Set $X^{(0)}, X^{(1)}, Z^{(1)}$ are defined as **Definition 1**, then the model can be built as

$$X_1^{(0)}(rp+t) + b_1 Z_1^{(1)}(rp+t) = b_2 Z_2^{(1)}(t) + b_3 Z_3^{(1)}(t) + L + b_n Z_n^{(1)}(t) + c(k-1)^r + u \quad (4)$$

This model is called the nonlinear GMC(1,N) optimization model, abbreviated as GOMC(1,N) model. The following whitening equation can be obtained from Eq. (4):

$$\frac{dX_1^{(1)}(rp+t)}{dt} + b_1 X_1^{(1)}(t) = b_2 X_2^{(1)}(t) + b_3 X_3^{(1)}(t) + L + b_n X_n^{(1)}(t) + c(k-1)^r + u \quad (5)$$

where, $c(k-1)^r$ and u are respectively as the nonlinear correction terms, r is the number of data points used for modelling, rp is the time delay coefficient, rf is the number of points used to predict, b_1, b_2, L, b_n, c and u are the parameters to be estimated. By the least square method, the parameter estimation of the **Theorem 3** can be obtained.

Theorem 3. Set parameter list is $P = (b_1, b_2, L, b_n, c, u)^T$ and

where

$$B = \begin{pmatrix} -Z_1^{(1)}(rp+2) & Z_2^{(1)}(2) & L & Z_n^{(1)}(2) & 1 & 1 \\ -Z_1^{(1)}(rp+3) & Z_2^{(1)}(3) & L & Z_n^{(1)}(3) & 4 & 1 \\ \mathbf{M} & \mathbf{M} & \mathbf{M} & \mathbf{M} & \mathbf{M} & \mathbf{M} \\ -Z_1^{(1)}(rp+n) & Z_2^{(1)}(n) & L & Z_n^{(1)}(n) & (n-1)^r & 1 \end{pmatrix}$$

$$P = \begin{pmatrix} b_1 \\ b_2 \\ \mathbf{M} \\ b_n \\ c \\ u \end{pmatrix}, Y_R = \begin{pmatrix} X_1^{(0)}(rp+2) \\ X_1^{(0)}(rp+3) \\ \mathbf{M} \\ X_1^{(0)}(rp+n) \end{pmatrix}$$

Then parameter $P = (b_1, b_2, L, b_n, c, u)^T$ satisfies:

$$P = (b_1, b_2, \dots, b_n, c, u)^T = (B^T B)^{-1} B^T Y \quad (6)$$

Proof. Substituting non negative raw data $X^{(0)} = (x^{(0)}(1), x^{(0)}(2), x^{(0)}(3), \dots, x^{(0)}(n))$ into Eq. (4), so

$$\begin{cases} x^{(0)}(rp+2) + b_1 z^{(1)}(rp+2) = \sum_{i=2}^n b_i [z^{(1)}(2)]^2 + c + d \\ x^{(0)}(rp+3) + b_1 z^{(1)}(rp+3) = \sum_{i=2}^n b_i [z^{(1)}(3)]^2 + c \cdot 2^\tau + d \\ \vdots \\ x^{(0)}(rp+n) + b_1 z^{(1)}(rp+n) = \sum_{i=2}^n b_i [z^{(1)}(n)]^2 + c(n-1)^\tau + d \end{cases} \quad (7)$$

that is $Y = B\hat{P}$. then replacing $x^{(0)}(k), k = 2, 3, \dots, n$ with $-az^{(1)}(k) + b[z^{(1)}(k)]^2 + c(k-1)^\tau + d$, so

$$\varepsilon = Y - B\hat{P}$$

Set

$$s = \varepsilon^T \varepsilon = (Y - B\hat{P})^T (Y - B\hat{P}) = \sum_{k=2}^n \{x^{(0)}(rp+k) + b_1 z^{(1)}(rp+k) - \sum_{i=2}^n b_i [z^{(1)}(k)]^2 - c(k-1)^\tau - d\}^2$$

and the $b_1, b_2, \dots, b_n, c, u$ that makes s the smallest should satisfy:

$$\begin{cases} \frac{\partial s}{\partial b_1} = 2z^{(1)}(rp+k) \sum_{k=2}^n x^{(0)}(rp+k) + b_1 z^{(1)}(rp+k) - \sum_{i=2}^n b_i [z^{(1)}(k)]^2 - c(k-1)^\tau - d \\ \frac{\partial s}{\partial c} = 2(k-1)^\tau \sum_{k=2}^n x^{(0)}(rp+k) + b_1 z^{(1)}(rp+k) - \sum_{i=2}^n b_i [z^{(1)}(k)]^2 - c(k-1)^\tau - d \\ \frac{\partial s}{\partial u} = 2 \sum_{k=2}^n x^{(0)}(rp+k) + b_1 z^{(1)}(rp+k) - \sum_{i=2}^n b_i [z^{(1)}(k)]^2 - c(k-1)^\tau - d \end{cases} \quad (8)$$

230

231 According to the above equations, the following equation can be got:

$$B^T \varepsilon = 0 \Rightarrow B^T (Y - B\hat{P}) = 0 \Rightarrow B^T Y - B^T B\hat{P} = 0 \Rightarrow \hat{P} = (B^T B)^{-1} B^T Y$$

232 that is **Definition 3** is proved.

233 From **Theorem 2**, the following theorem can be obtained:

234 **Theorem 3.**

$$f(t) = \sum_{j=2}^n b_j X_j^{(1)}(t) + c(k-1)^\tau + u$$

235 The solution of Eq. (5) is:

$$X_1^{(1)}(rp+t) = X_1^{(1)}(rp+1)e^{-b_1(t-1)} + u(t-2) \times \sum_{\tau=2}^t \frac{1}{2} [e^{-b_1(t-\tau)} f(\tau) + e^{-b_1(t-\tau+1)} f(\tau-1)] \quad (9)$$

236 where, $u(t-2)$ is the unit step function, and defined as

$$\begin{cases} u(t-2) = 0, t < 2 \\ u(t-2) = 1, t \geq 2 \end{cases}$$

240 And the reduction formula is:

$$\hat{X}_1^{(0)}(rp+t) = \hat{X}_1^{(1)}(rp+t) - \hat{X}_1^{(1)}(rp+t-1) \quad (10)$$

3.3 Optimization of nonlinear correction term in GMC(1,N) model

As can be seen from Section 3.2, the parameters $P=(b_1, b_2, L, b_n, c, u)^T$ of the model can be obtained by determining the order r , which is the nonlinear quantity. In this section, the genetic algorithm is used to search this order, and the average absolute percentage error MAPE is taken as the objective function, which is defined as:

$$MAPE = \frac{1}{n-1} \left(\sum_{i=1}^n \left| \frac{x^{(0)}(i) - \hat{x}^{(0)}(i)}{x^{(0)}(i)} \right| \right) \times 100\% \quad (11)$$

The optimization of nonlinear terms is mainly aimed at the order r in Eq. (4). This model uses the genetic algorithm proposed by Holland et al. (Holland et al. 1992) to search the order. It applies the evolutionary principle of survival of the fittest and elimination of the unfit in the biological world to optimize the selection of encoded parameter individuals. Select the appropriate fitness function, and calculate the fitness value of all individuals, after selection, mutation and crossover, make the overall fitness level of the population continuously improve, which not only inherited the good information of the previous generation, but also better than the previous generation. Then the cycle repeats until the desired conditions are met, the calculation steps are shown in Table 1.

Table 1

Algorithm: The algorithm of GA to find the optimal r

Set the objective function

Input: The original series and the number of modeling data

Output: The best order

for $r \in [0.1, n]$ do

Substitute r to $\hat{P} = (B^T B)^{-1} B^T Y$ and obtain parameters $P = (b_1, b_2, L, b_n, c, u)^T$

Substitute parameters to discrete equation Eq. (6) and compute the simulation value to get $\hat{x}^{(1)}(k)$

Compute $\hat{x}^{(0)}(k)$ in Eq. (9,10)

Compute MAPE in Eq. (11)

End

Update the minimum value MAPE

Return the best r by using GA.

Based on the definition of GOMC(1,N) model and the genetic algorithm, the whole prediction process of this model is proposed as follows:

Step 1: Input the original series $x(0)$.

Step 2: Compute the 1-AGO series $x^{(1)}$ of $x^{(0)}$, and the mean sequence $z^{(1)}$ of 1-AGO series.

Step 3: Substitute the data of step 1 into Eq. (6) and initial nonlinear order to obtain parameters

b_1, b_2, L, b_n, c, u

Step 4: Substitute the coefficients obtained in the previous step into the time response equation, then

computing the restored value $\hat{x}^{(0)}(k)$.

Step 5: Substitute the data of above three steps into Eq. (11) to construct the GOMC model and compute the MAPE

Step 6: Using GA algorithm to optimize nonlinear term and computing the lowest value MAPE.

Step 7: Substituting the optimal r to reconstruct GOMC model and computing the simulated data $\hat{x}^{(0)}(k)$ and MAPE.

4. Application of GOMC(1,N) model in the energy consumption of China

4.1 Analyzing the validity of the novel model of energy consumption in China

China as the largest developing country in world, its formulation and implementation of energy measures have attracted global attention. Therefore, this article applies the novel model to four energy consumption prediction in China, and uses the prediction results to provide effective information for the Chinese government to make energy economy policies. The original data comes from the National Bureau of Statistics of China, as shown in Table 2. In this section, the trend change diagram of each factor is made. In the Fig. 1, GDP, oil, natural gas and clean energy show an obvious linear upward trend, while coal shows an unsaturated S-shaped change trend, population shows a stable trend, and the growth rate slows down. Among them, population and GDP are the main influencing factors of the four types of energy. The models used in the comparative experiment are traditional GM(1,N), GMC(1,N), NGM(1,N) and OBGm(1,N). The first three examples are fossil energy consumption projections, and the last one is clean energy consumption projections.

Table 2

Year	Total oil consumption	Total coal consumption	Total gas consumption	Total clean energy consumption	Total Population	GDP
2010	62752.75	249568.42	14425.92	33900.91	134091	412119.3
2011	65023.22	271704.19	17803.98	32511.61	134735	487940.2
2012	68363.46	275464.53	19302.62	39007.39	135404	538580
2013	71292.12	280999.36	22096.39	42525.13	136072	592963.2
2014	74090.24	279328.74	24270.94	48116.08	136782	643563.1
2015	78672.62	273849.48	25364.4	52018.5	137462	688858.2
2016	80626.51	270207.78	27020.78	57963.93	138271	746395.1
2017	84323.45	270911.52	31397.03	61897	139008	832035.9
2018	87696	273760	36192	66352	139538	919281.1
2019	91854	280422	39366	74358	140005	990865.1

Fig. 1 Comparison of trends for different factors

In the first case, the coal consumption was selected as the research object. Data from 2010 to 2015 were used to build the model, and data from 2016 to 2019 were used for model testing. The results of each models are shown in Table 3, where the optimal r in GOMC(1,N) is 2.3900, and the optimal background value coefficient of OBGM(1,N) is 0.2324. According to the calculation results, the data trend chart is made, as shown in Fig. 2.

Table 3

Raw data	GM (1,N)	APE (%)	NGM (1,N)	APE (%)	OBGM (1,N)	APE (%)	GMC (1,N)	APE (%)	GOMC (1,N)	APE (%)
249568.4200	249568.4200	0.0000	2.4957E+05	0.0000	249568.4200	0.0000	2.4957E+05	0.0000	249568.4200	0.0000
271704.19	242601.8406	-10.7110	2.7170E+05	0.0000	275738.4520	1.4848	1.2330E+06	-3.5381E+02	229402.6578	15.5690
275464.53	314050.0992	14.0075	-5.0176E+06	-1.9215E+03	264832.7171	-3.8596	2.7693E+07	-9.9532E+03	265096.9649	3.7637
280999.36	294533.3046	4.8164	1.5297E+07	5.3439E+03	319210.3160	13.5982	7.1947E+08	-2.5594E+05	284084.5453	-1.0979
279328.74	285391.2008	2.1704	-6.2632E+07	-2.2522E+04	155177.6660	-44.4462	1.8807E+10	-6.7329E+06	290230.6448	-3.9029
MAPE _{sim} (%)		7.9263		7.4469E+03		15.8472		1.7498E+06		6.0834
273849.48	283575.4284	3.5516	2.3640E+08	8.6225E+04	623149.3350	127.5518	4.9175E+11	1.7957E+08	283036.6024	3.3548
270207.78	284559.7033	5.3114	-9.1096E+08	-3.3723E+05	-1.1292E+06	-5.1790E+02	1.2858E+13	4.7585E+09	269930.4942	-0.1026
270911.52	286204.6379	5.6451	3.4915E+09	1.2887E+06	5.0347E+06	1.7584E+03	3.3619E+14	1.2410E+11	267480.8647	-1.2663
273760	287607.9110	5.0584	-1.3401E+10	-4.8952E+06	-1.5434E+07	-5.7378E+03	8.7904E+15	3.2110E+12	276741.8309	1.0892
280422	288856.0498	3.0076	5.1415E+10	1.8335E+07	5.2659E+07	1.8679E+04	2.2984E+17	8.1963E+13	280324.5790	-0.0347
MAPE _{pre} (%)		4.5148		2.4942E+07		5364.0675		1.7061E+13		1.1695

According to the results in the Table 3, it can be seen that NGM(1,N), GMC(1,N) and OBGM(1,N) have large errors in the two stages, indicating that these three models are not suitable for the prediction of coal consumption in China. GM(1,N) and GOMC(1,N) have small errors in the two stages, and GOMC(1,N) has the smallest errors. Meanwhile, the error of the optimized model has significantly improved, indicating that GOMC(1,N) is more suitable for the prediction of coal consumption than other models. In order to see the result more intuitively, the results of the Table 3 are converted into a trend comparison chart. Because the errors of NGM, GMC and OBGM models are too large, which will affect the comparison effect of other models, so they are not shown in the trend comparison chart. The results of GM(1,N) model basically overestimates the actual trend, and the trend of GOMC(1,N) model is the closest to the actual trend line. In Fig. 3, the APE value of

GOMC(1,N) was basically the lowest except 2011, and it was close to 0 in three years. All the above information indicates that the GOMC model has effectively predicted the coal consumption in China.

Fig. 2 Trend comparison diagram of the model data in Case 1

Fig. 3 APE comparison of the model in Case 1

Case 2: Forecast the oil consumption in China

The object of the second case study is the oil consumption in China, which is the same as the previous case. The data of the first five years is used to build the model, and the data of the next five years is used for model testing. The calculation results of each models are shown in Table 4, where the optimal parameter of GOMC(1,N) is $r = 1.3979$ and the optimal background value parameter of OBGM(1,N) is 0.6652. The data trend chart is also made, as shown in Fig. 4.

Table 4

Raw data	GM (1,N)	APE (%)	NGM (1,N)	APE (%)	OBGM (1,N)	APE (%)	GMC (1,N)	APE (%)	GOMC (1,N)	APE (%)
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62752.75	62752.7500	0.0000	62752.7500	0.0000	62752.7500	0.0000	62752.7500	0.0000	62752.7500	0.0000
65023.22	55991.9966	-13.8892	65023.2200	0.0000	66857.3905	2.8208	57348.8656	11.802	64044.8368	1.5047
68363.46	74421.1583	8.8610	-86286.6955	-226.2176	69849.5486	2.1738	63546.6930	7.0458	68138.6580	0.3288
71292.12	73053.8363	2.4711	108401.5624	52.0527	72995.3786	2.3891	67460.8386	5.3741	71396.7926	-0.1468
74090.24	74414.7815	0.4380	-126574.0415	-270.8377	75890.5112	2.4298	70550.6162	4.7774	74337.2781	-0.3334
MAPE _{SIM} (%)		6.4149		137.2770		2.4534		7.2500		0.5784
78672.62	76614.8923	-2.6156	170466.3184	116.6781	85309.7110	8.4363	73210.3920	-6.9430	77028.7039	-2.0896
80626.51	79718.5786	-1.1261	-190542.8696	-336.3278	81968.0400	1.6639	75825.4665	-5.9547	79745.7842	-1.0924
84323.45	84268.3456	-0.0653	268757.8325	218.7225	87024.1350	3.2028	79017.7160	-6.2921	83193.7840	-1.3397
87696	88844.2261	1.3093	-288500.3173	-428.9777	91789.2220	4.6675	82823.1312	-5.5565	87627.2664	-0.0784
91854	92609.4143	0.8224	412477.1341	349.0573	95593.7830	4.0714	86618.3787	-5.6999	92485.1557	0.6871
MAPE _{PRE} (%)		1.1877		1449.7635		4.4084		6.0893		1.0574

The results in the Table 4 show that the NGM(1,N) model has the largest errors in the two stages. The modelling errors of the GM(1,N) and GMC(1,N) model are similar, while the GOMC(1,N) has the highest accuracy, the MAPE_{SIM} is 7 percentage points lower than the unoptimized model, and the MAPE_{PRE} is improved 5 percentage points. It shows that the GOMC(1,N) model is more suitable for the oil consumption prediction in China than other models. In Fig. 4, the results of the GM(1,N) and OBGM(1,N) model are basically overestimated the actual trend, GMC(1,N) model overestimated the actual trend in the modeling stage, and underestimated the actual value in the forecasting stage, while the GOMC(1,N) model was close to the actual trend. Meanwhile, in the APE comparison in Fig. 5, the APE value of the GOMC(1,N) model is the lowest in every year, which indicates that the GOMC(1,N) model can effectively predict the oil consumption in China.

Fig. 4 Trend comparison diagram of the model data in Case 2

Fig. 5 APE comparison of the model in Case 2

Case 3: Forecast the natural gas consumption in China

The third object is the third largest energy source in the energy structure of China, which is also the energy source with great development in recent years. In this case, the data of 2010-2018 are used to build the model, and the data of the last year are used to test the model. The results of the five models are shown in Table 5, where the optimal parameter of GOMC(1,N) is $r = 5.1988$ and the optimal background value parameter of OBGM(1,N) is 0.0015. Then, according to the obtained data, the data trend comparison chart is made, as shown in Fig. 6.

Table 5

Raw data	GM (1,N)	APE (%)	NGM (1,N)	APE (%)	OBGM (1,N)	APE (%)	GMC (1,N)	APE (%)	GOMC (1,N)	APE (%)
14425.92	14425.9200	0.0000	14425.9200	0.0000	14425.9200	0.0000	14425.9200	0.0000	14425.9200	0.0000
17803.98	15276.8872	-14.1940	17620.1443	-1.0326	17590.2932	-1.2002	16462.5122	7.5347	17519.0397	1.6004
19302.62	21171.6507	9.6828	23253.2793	20.4670	19793.5381	2.5433	16073.7801	16.7275	19931.6832	-3.2590
22096.39	22215.6182	0.5396	26834.4179	21.4425	22007.1709	-0.4038	12180.2480	44.8768	21909.7717	0.8446
24270.94	23874.6923	-1.6326	29283.2525	20.6515	23877.5633	-1.6208	-1316.0736	105.4224	23514.3931	3.1171
25364.4	25617.8193	0.9991	31061.3799	22.4605	25411.3072	0.1849	-40881.3146	261.1760	24994.3520	1.4589
27020.78	27921.8743	3.3348	32958.7027	21.9754	27302.3937	1.0422	-152065.8967	662.7739	26693.8961	1.2097
31397.03	31379.2043	-0.0568	36785.0569	17.1609	31227.6285	-0.5395	-460581.5030	1566.9588	29001.4840	7.6298
36192	34907.2492	-3.5498	42021.6636	16.1076	36265.2771	0.2025	-1310608.0677	3721.2646	32711.8281	9.6159
MAPE _{SIM} (%)		4.2487		17.6623		0.9671		798.3418		3.5919
39366	37801.7127	-3.9737	47036.3672	19.4848	40770.5790	3.5680	-3644070.9031	-9356.8991	39365.9236	-0.0002
MAPE _{PRE} (%)		3.9737		19.4848		3.5680		9356.8991		0.0002

The results in the Table 5 show that the errors of NGM(1,N) model and GMC(1,N) model are large in the two stages, and the modelling error of OBGM(1,N) model is the smallest, while the modelling error of GOMC(1,N) model is only inferior to OBGM(1,N) model. The prediction error of GOMC(1,N) model is the best, which is close to 0, and significantly improves the error of the model before optimization, which shows that GOMC is more suitable for natural gas consumption

prediction than other models. In the Fig. 6, the NGM(1,N), GM(1,N) and OBGM(1,N) model are basically overestimate the actual consumption trend, while only the GOMC(1,N) model is close to the actual trend. In the comparison chart of APE value in Fig. 7, OBGM(1,N) model has the lowest APE value in the model establishment stage, while in the prediction stage, the APE value of GOMC(1,N) model is close to 0. In conclusion, the GOMC(1,N) model can effectively predict the natural gas consumption in China.

Fig. 6 Trend comparison diagram of the model data in Case 3

Fig. 7 APE comparison of the model in Case 3

Case 4: Forecast the clean energy consumption in China

The fourth case is about the clean energy consumption in China. Data from 2011-2018 are used to build the model, and the last year data is used to test the model. The results of the five models are as shown in Table 6, in which the optimal parameter of GOMC(1,N) is $r = 2.1658$, and the optimal parameter of OBGM(1,N) is 0.5373. The data trend chart is also made, as shown in Fig. 8.

Table 6

Raw data	GM (1,N)	APE (%)	NGM (1,N)	APE (%)	OBGM (1,N)	APE (%)	GMC (1,N)	APE (%)	GOMC (1,N)	APE (%)
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32511.61	32511.6100	0.0000	32511.6100	0.0000	32511.6100	0.0000	32511.6100	0.0000	32511.6100	0.0000
39007.39	34854.6739	-10.6460	38831.2834	-0.4515	38785.4883	-0.5689	38302.1086	1.8081	37978.8253	2.6368
42525.13	52621.5661	23.7423	49892.5793	17.3249	43081.2339	1.3077	42576.5220	-0.1209	42474.1683	0.1198
48116.08	54480.6354	13.2275	58893.5454	22.3989	47557.6525	-1.1606	46900.6772	2.5260	47203.9893	1.8956
52018.5	55361.7119	6.4270	66520.7619	27.8790	52438.7812	0.8079	51415.2635	1.1597	52309.9309	-0.5602
57963.93	58190.4972	0.3909	73550.4612	26.8901	57523.3229	-0.7601	56092.6959	3.2283	57849.5310	0.1974
61897	63714.1787	2.9358	79589.7359	28.5842	62180.0577	0.4573	60440.6844	2.3528	63527.1486	-2.6336
66352	69674.7350	5.0077	84248.5743	26.9722	66263.5893	-0.1332	63937.0457	3.6396	69026.3623	-4.0306
MAPE _{SIM} (%)		8.9110		21.5001		0.7423		2.1193		1.7249
74358	74660.7059	0.4071	87990.3594	18.3334	69923.3210	-5.9640	66478.6898	-10.5965	74388.7946	0.0414
MAPE _{PRE} (%)		0.4071		18.3334		5.9640		10.5965		0.0414

The results in the Table 6 show that the NGM(1,N) model has the largest error in the two stages, and the OBGM(1,N) model has the smallest MAPE_{SIM}, and the MAPE_{SIM} of the GOMC(1,N) model is second only to OBGM(1,N) model, with an error less than 2%, but the GOMC(1,N) model has the best MAPE_{PRE}, which is close to 0, and the error effect of the model before optimization is significantly improved. Through the data comparison, it can be seen that the error in the modelling stage is reduced by 0.4%, and the error effect in the prediction stage is increased by 10%, indicating that GOMC(1,N) is more suitable for the clean energy consumption prediction than other models. In Fig. 8, the NGM(1,N), GM(1,N) and OBGM(1,N) model are basically overestimate the actual consumption trend, and only the GOMC(1,N) model is close to the actual trend. In the APE comparison chart in Fig. 9, the APE values of the OBGM(1,N) and GOMC(1,N) model are relatively low in the modelling stage, but the APE values of GOMC(1,N) model are close to 0 point in the prediction stage. In summary, it shows that the GOMC(1,N) model can effectively predict the clean energy consumption in China.

Fig. 8 Trend comparison diagram of the model data in Case 4

Fig. 9 APE comparison of the model in Case 4

The validity of the novel model proposed in this paper is verified through the above four cases, and it can be seen that the GOMC(1,N) model always shows a high precision in the process of model comparison. As described in the introduction, energy consumption is affected by various factors. Therefore, the energy consumption trend and various related factors are considered to comprehensively model, and the nonlinear term is optimized by the genetic algorithm, which can make the overall performance of the model better than other models, which also explains the rationality of the novel model.

4.2 Energy consumption forecast for the next five years

The population and GDP factors are predicted by the GM(1,1) model, which used the data from 2010-2019, and the other four energy sources are predicted by the GOMC(1,N) model. The parameters, errors and prediction results of the forecast process are shown in the Table 7. In order to directly represent the consumption trends of the four types of energy in the next five years, the trend charts of different energy data are shown in Fig. 10. Combined with the chart, it can be seen that the consumption of all kinds of energy in China will continue to rise and will not reach its peak within five years, at the same time, the consumption of the clean energy and natural gas are growing fastest, which is good news for China.

Table 7

Year	Total oil consumption	Total coal consumption	Total gas consumption	Total clean energy consumption	Total Population	GDP
2020	95485.2687	281916.0645	43240.82098	80200.3039	140908.1869	1082005.8543
2021	99712.74	310261.6585	48375.21607	87128.7653	141607.3693	1181600.8567
2022	104243.7873	358071.6489	54155.85906	94740.7841	142310.0210	1290363.2443
2023	109116.0718	431797.9703	60601.08776	103120.5235	143016.1593	1409136.8442
2024	114369.0846	538954.9428	67750.11433	112356.2007	143725.8013	1538843.1547
r	0.9209	2.2781	1.3675	2.2971	-	-
MAPE	0.3392%	2.8280%	2.2018%	1.1312%	0.0511%	0.8824%

Fig. 10 Forecast data comparison of four energy sources

According to Table 7 and Figure 10, it can be observed that the energy consumption in the future will still be dominated by coal, while the consumption of natural gas and other clean energy will show an upward trend. The national energy structure has changed. The national energy structure has changed, and the natural gas as a kind of low-carbon and clean energy, which was clearly proposed by the Chinese management in 2004 to vigorously develop natural gas and increase the proportion of natural gas in primary energy. The promotion and use of natural gas play a beneficial role in environmental governance. At the same time, the "Natural Gas Utilization Policy" promulgated by the Chinese government also reflects the emphasis of Chinese government on the use of natural gas and the attitude of giving priority to the development of urban natural gas. With the support and promotion of the country, the utilization rate of other clean energy will also show an upward trend. Therefore, it is an inevitable trend that the usage rate of natural gas and other clean energy will gradually increase under the current policy circumstances.

5. Conclusion

Based on the complexity of the energy consumption system, this paper adds nonlinear terms to the classic GMC(1,N) model, and uses the genetic algorithms to optimize the nonlinear terms, therefore, a nonlinear grey multivariate prediction model GOMC(1,N) was proposed. Through the case analysis, it can be seen that the GOMC(1,N) model has better effect than GM(1,N), NGM(1,N), OBGM(1,N) and GMC(1,N) models, which proves that the GOMC(1,N) model obtained by adding nonlinear terms and optimizing the nonlinear terms can effectively predict the energy consumption. In addition, by predicting several energy consumption in the next five years, the predicted trend is consistent with the actual situation according to the characteristics of the energy structure in China. Therefore, the novel model proposed in this paper can effectively predict the energy consumption.

Based on the data trends of different energy sources predicted by the model in the next five years, the following policy recommendations are made:

1. The trend of continued growth in the oil consumption of China in the future will give us more inspiration. Since the reform and opening up, the rapid economic growth has made China as the second largest economy in the world. China should grasp the current development situation and accelerate the process of oil industry internationalization and marketization to ensure the safety of oil. China can encourage the opening of the market so that oil and gas development companies can compete with each other, meanwhile, it could continue to step up efforts to open up the oil and gas licenses, and encourage investment in shale oil and gas.

2. In the future, the consumption of natural gas and clean energy will be on an upward trend,

which will also affect the consumption of oil and coal. This phenomenon has a restraining effect on the consumption of oil and coal, indicating that China can appropriately increase the use of natural gas and clean energy to reduce the consumption of oil and coal, and avoid excessive consumption of coal and oil. Efforts should be made to find suitable alternative energy, transform the utilization technology of fossil energy, further tap the energy saving potential, reduce the level of primary energy consumption, reduce energy waste and environmental pollution caused by energy consumption.

3. Increase investment in clean energy industries, upgrade the technology for the development and use of clean energy, and encourage relevant companies to compete. To replace fossil fuels with new sources of energy that are cheaper to develop and less polluting in some industries. Increase energy conservation and emission reduction publicity, vigorously promote green travel, and encourage urban residents to adopt public transportation or low-carbon travel modes. Meanwhile, allow the transportation department to formulate stricter number limit measures, promote a lifestyle of less coal and more gas for rural residents, reduce the use of domestic coal, through these measures, reduce the emission of pollutants due to the energy consumption.

As mentioned in this article, the irrational use of coal will cause serious pollution, which will restrict the healthy development of the energy economy. Reasonable prediction of carbon emissions will bring benefits to energy trade. China as a major coal consumer and carbon dioxide emitter in the world, it is of certain significance to predict coal consumption. Predict and formulate corresponding policy measures to save energy and reduce emissions. In the future, according to the characteristics of structural development and changes, we will establish relevant and suitable prediction models. This is also what we will do further in the future.

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Figures

Figure 1

Comparison of trends for different factors

Figure 2

Trend comparison diagram of the model data in Case 1

Figure 3

APE comparison of the model in Case 1

Figure 4

Trend comparison diagram of the model data in Case 2

Figure 5

APE comparison of the model in Case 2

Figure 6

Trend comparison diagram of the model data in Case 3

Figure 7

APE comparison of the model in Case 3

Figure 8

Trend comparison diagram of the model data in Case 4

Figure 9

APE comparison of the model in Case 4

Figure 10

Forecast data comparison of four energy sources