Expert Systems With Applications 252 (2024) 124130

Contents lists available at ScienceDirect

Expert Systems With Applications

journal homepage: www.elsevier.com/locate/eswa

An innovative information accumulation multivariable grey model and its application in China's renewable energy generation forecasting

Youyang Ren [a,1], Yuhong Wang [a,*,2], Lin Xia [a,3], Dongdong Wu [b,4]

[a] School of Business, Jiangnan University, Wuxi, Jiangsu Province 214122, PR China
[b] College of Tourism and Service Management, Nankai University, Tianjin 300350, PR China

A R T I C L E I N F O

Keywords:
Multivariate grey model
Data information accumulation
Model parameter optimization
Renewable energy generation

A B S T R A C T

Reducing greenhouse gas emissions is urgent for the global community with rising climates. Considering the importance of renewable energy in mitigating climate warming, forecasting renewable energy generation is vital for the Chinese government's future low-carbon and green development plan. This paper proposes a novel multivariable grey model based on historical data on China's renewable energy generation and three industries. A novel information accumulation mechanism with two adaptive factors is designed to improve the traditional multivariable grey modeling defect. Based on the proposed mechanism, this paper optimizes the initial and background values and nonlinear model structure with the whale optimization algorithm. The forecasting results show that the fitting MAPE is 1.13%, comprehensive MAPE is 2.60%, MSE is 50.86, and RMSE is 7.13, which significantly improve the forecasting accuracy of traditional GM(1,N) and are better than other compared models. The forecasting results show that China's renewable energy generation will gradually increase to 5834.02 TWh. The Chinese government should keep the previous Five-Year Plans rising trend of the three industries in the future Five-Year Plans to support renewable energy industries. In China's future energy system, it is necessary to promote incentive policies and capital investment for actively accelerated development to make renewable energy the leading force.

1. Introduction

The greenhouse and frequent extreme climate events have increased global warming and environmental degradation. The melting glaciers, soil erosion, and rising sea levels make human society face severe challenges from global ecological imbalance. Countries worldwide should urgently reach an agreement and adopt practical solutions to mitigate the environmental crisis and climate catastrophe. With the recognition of the low-carbon economy, different countries' governments have taken clean and environmentally friendly energy transformation as their responsibility and transferred to a green and efficient energy structure. China, the world's largest developing country, rapidly developed as the world's second-largest economy in 2010. Under the scientific guidance and economic development scale of the 12th and 13th Five-Year Plans, China's economic aggregate has firmly ranked second globally. However, China's fossil fuel consumption accounted for 82.5 % of the total energy consumption in 2022, which reflects that China's development still needs traditional energy support. China still has a long way to go to achieve its Carbon Peak and Carbon Neutrality goals. The national contributions promising to tackle global warming make it imperative for the Chinese government to intensify efforts to develop renewable energy and accelerate China's transition to green and low-carbon energy (Xing et al., 2023).

People's production applies renewable energy through power generation. Large-scale development of renewable energy can ensure power supply. It contributes to replacing high-carbon energy sources to reduce carbon emissions and achieve ecological protection. The most valuable reason is that renewable energy has strong sustainability and can satisfy

* Corresponding author.
E-mail addresses: 7220912008@stu.jiangnan.edu.cn (Y. Ren), wyh2003@gmail.com (Y. Wang), 7220912010@stu.jiangnan.edu.cn (L. Xia), dwu@mail.nankai.edu.cn (D. Wu).
[1] 0000-0002-7988-4843.
[2] 0000-0002-8549-7495.
[3] 0000-0002-3199-8614.
[4] 0000-0002-9784-401X.

https://doi.org/10.1016/j.eswa.2024.124130
Received 27 January 2024; Received in revised form 18 April 2024; Accepted 28 April 2024

the energy needs for human development in the long term. Therefore, considering the current development situation, environmental pollution, and traditional energy scarcity, developing renewable energy is crucial for the Chinese government to achieve sustainable environmental, economic, and social development (Rasool et al., 2022).

Therefore, forecasting renewable energy generation is the basis for sustainable energy development planning under the Chinese government's planned economy and is crucial to formulating the Chinese government's core renewable energy policies (Xu et al., 2020). Establishing effective forecasting models that suit China's power generation characteristics has important forward-looking significance in promoting China's decision-making on sustainable renewable energy development. However, China's renewable energy industry started late, with few historical statistics for reference. Meanwhile, renewable energy generation is affected by seasons, climate, and technology, which makes the samples with small statistical units uncertain and missing.

Considering the small sample size of the annual statistical data, the multivariable grey forecasting model is believed as an ideal technology to measure China's future renewable energy generation (Wang et al., 2022). However, the existing multivariable grey models have several drawbacks that may hinder accurate forecasting. In the information accumulation process, the existing models fail to actively introduce the effects of new and old information from the related factors on the system. The traditional simplified modeling makes the related factors-driven structure vague and needs further optimization. Also, the existing models do not comprehensively improve the model accuracy from the unified optimization perspective of modeling parameters and model structure. Therefore, this paper aims to propose a new multivariable grey model based on a novel information accumulation mechanism with comprehensive improvement from the modeling parameters and structure. The proposed grey model forecasts China's future renewable energy generation in the 14th and 15th Five-Year Plan to research and judge the future development form of China's renewable energy.

For innovation contribution, the proposed multivariable grey model modeling method forms a novel information accumulation mechanism instead of the traditional mechanism for the related factors. The novel mechanism improves the adaptability between the system and related factor sequences. It comprehensively improves the multivariable grey model's forecasting ability and expands its application by enhancing the accuracy and robustness of the forecasting effect. For practical contribution, this paper makes a scientific forecasting assessment of the future development trend of China's renewable energy generation based on the development of China's three major industries. It applies the proposed model to calculate China's future clean energy generation and carbon emissions reduction under different development scenarios. Based on the forecasting results, this paper provides foresight suggestions and references for the policy formulation of China's renewable energy development in the 14th and 15th Five-Year Plans.

The second section summarizes the research literature review and the ideas for solving the existing research problems. The third section introduces the designed model and the innovation improvement idea adopted in this paper. The fourth section is an empirical study. The fifth section discusses the subsequent forecasting measure result, and the sixth section reveals the conclusion.

2. Literature review

Renewable energy has great potential for the sustainable development of future power systems. Scholars have conducted many prediction studies based on relevant data and information about renewable energy generation (Goncalves et al., 2021; Yang et al., 2022). In the forecasting field, scholars explore open problems for application scenarios, energy transition, and development paths involved in renewable energy in the future. Aslam et al. (2021) predicted the demand for renewable energy based on the power grid's long-term operation from the microgrid intelligence perspective. Liang et al. (2022) discussed the effect of climate policy uncertainty on the forecasting ability of renewable energy index fluctuation from energy stability and sustainable development. Based on the forecasting framework, Habiba et al. (2022) evaluated the interaction and impact of finance, green technology innovation, and renewable energy development on the world's major carbon emitters. Khan et al. (2023) pre-judged the operation degree of renewable energy power generation systems in urban energy systems from the generated power forecasting perspective. These foresight findings provide important decision-making references on energy management for society, government, and enterprises (Wang et al., 2022; Mayer & Yang, 2023).

Renewable energy generation forecasting forms consist of physical and data-driven models (Jonas et al., 2019). By contrast, the physical model focuses more on causal relationships and equation simulations in renewable energy systems, while data-driven models focus more on information mining of system output power data. Therefore, data-driven models reduce complex experiment processes than physical models. Many scholars select data-driven models for renewable energy forecasting work. Popular applied data-driven models mainly include statistical, artificial intelligence, and grey models (Lu, 2019; Zheng et al., 2023).

2.1. Statistical forecasting model

Statistical models include time series and regression forecasting models, which provide reliable forecast estimates for the uncertainties and complex problems associated with renewable energy (Wei et al., 2021; Costa et al., 2021). Applying more extended time series data, statistical models can accurately forecast renewable energy sources when the data samples are sufficient. Cribari-Neto et al. (2023) forecasted the stored hydroelectric energy proportion in South Brazil with beta autoregressive moving average models based on the assumed values. Kahvecioglu et al. (2022) applied weather predictors to optimize the autoregressive moving average model for conditional direct irradiance forecasting for solar energy. However, statistical models usually require assumptions about the distribution and relationships of historical data and depend more on the priori results (Cakir, 2023). These classical models cannot conduct the nonlinear and non-normal data samples well. When faced with insufficient data samples, individual observations interfere with the model's stability. The parameter estimates and significance tests are unreliable. When the data sample is too large, the computational efficiency of the statistical models is low, and the generalization ability decreases significantly.

2.2. Artificial intelligence forecasting model

Artificial intelligence models are at the forefront of predictive modeling with the continuous growth of data scale and structural complexity (Manuel & Maldonad, 2020; Sharda et al.,2021). These big data forecasting models are represented by Artificial Neural Networks (ANN), Machine Learning (ML), Deep Learning (DL), and Support Vector Machine (SVM). They are breaking through the upper limit of data volume and structure of traditional statistical forecasting models and further realizing the novel intersection between the application of data science and artificial intelligence in the forecasting field (Herrera et al., 2022; Hu & Man, 2023). Artificial intelligence models are usually directly applied or combined with statistical models for energy forecasting. Al-Alimi et al. (2023) designed a novel time series model combining Long Short-Term Memory (LSTM) and ANN to predict energy supply and demand effectively. Li and Song (2023) selected the statistical model for the linear trend component and the ML method for the non-linear component forecasting. They established a novel multi-scale model to predict the futures prices of oil and gas, and the model's accuracy improved by 6.11 % and 2.05 %, respectively. Somu et al. (2021) proposed a DL framework that combines the K-means, Convolutional Neural Networks, and LSTM for building energy forecasting. Hou et al. (2021) proposed an optimized ANN combined with the pathfinder algorithm to forecast the hydropower generation demand. They further explored the relationship between weather change and power supply. By contrast, artificial intelligence models can better capture the complex non-linear relationships between data sets and perform feature learning based on extensive data amount.

Although the forecasting effects of artificial intelligence models are better than those of statistical and grey forecasting models in processing large amounts and complex dimension data sets, they also have limitations. These models are more dependent on data volume requirements than statistical models. High-precision models require massive data as modeling support and more significant investment in computing resources and training time. The massive data often leads to overfitting, and the generalization ability weakens when new data is processed. Black-box modeling makes the internal operating mechanism and calculation process of artificial intelligence models hard to explain.

2.3. Grey forecasting model

However, energy data with years as the time dimension cannot form a large sample set. Statistical models and artificial intelligence models have poor applicability. When forecasting with small sample sets, the grey models usually show the advantages of more flexibility, fair complexity, ideal forecasting effect, and high practicality (Xie, 2022). Therefore, the grey models are widely applied in energy and environment development planning and solve the prediction problems due to the small samples (Duan & Wang, 2023; Xie et al., 2023). The grey models mainly focus on the establishment and optimization of univariate grey models and multivariable grey models.

For the univariate grey model research, Xia et al. (2023) proposed a fractional univariate grey model with double error correction to forecast China's installed renewable energy capacity. Zhang et al. (2022) applied the Caputo fractional derivative to improve the fractional accumulation mechanism. They combined it with the Grey Wolf Optimizer to design a novel renewable energy forecasting model. Ding et al. (2022) conducted the seasonal fluctuations with the data-restacking technique. They established the dynamic structure for grey modeling to forecast Americans' monthly renewable energy consumption. Wang et al. (2022) pointed out a fractional time-delayed grey Bernoulli model for renewable energy forecasting with nonlinear characteristics. Qian and Sui (2021) designed a novel discrete grey model combined with the nonlinear and periodic terms for adaptive structure.

For the multivariable grey model research, Ding et al. (2023) introduced the time lag coefficient based on the convolution analytical solution, proposed a multivariable time-delayed grey model, and conducted a step-by-step prediction study on China's carbon emissions. Ren et al. (2023) proposed the SOGM(1,N) based on the cyclic modification of multiple dummy variables for China's seasonal hydropower generation forecasting. Zhang et al. (2022) integrated trends and constant terms and considered the interaction terms to propose the trend interaction, multivariable grey model. The parameter improvement of the multivariable grey model is complicated. In addition to the initial and background values, optimization involves time-delayed, nonlinear optimization with power index, interaction, and dummy variables to improve prediction performance (Du et al., 2023).

Research on grey model optimization focuses on optimizing the modeling parameters and extending the model forms. Generally, for model parameters optimization, scholars modify the initial and background values of the traditional grey model to minimize errors. They optimize the initial conditions of the initial value by combining the priority and adaptability of modeling information to the system sequence (Zhou et al., 2022; Heidari & Zeng, 2023). Some scholars focus on weakening the interference of extreme values in the accumulation process to improve the grey models' performance. They construct a new background value sequence by adjusting the weights of adjacent elements. The improved background values are usually set as a value in the interval of 0 and 1 instead of 0.5 to achieve smooth processing of data mutation and further improve the accuracy of the grey model (Huang et al., 2021; Wang & Zhang, 2022).

Regarding grey model form optimization, existing studies mainly focus on establishing the fractional order grey model and grey Bernoulli model by constructing fractional order accumulation and power parameters. They solve the forecasting data with nonlinear characteristics by changing the models' time-variable and cumulative structures (Zhang et al., 2023). Yan et al. (2023) applied fractional order cumulations to the time-delay driving of the multivariate grey models to alleviate the uncertainty of online public opinion data. Wang and Si (2024) introduced different power parameters to simulate the nonlinear characteristics of interaction between different related factors and forecast the future carbon emission intensity of China. In addition, some studies combine univariate grey models as trend terms with dynamic nonlinear factors to construct nonlinear seasonal grey models (Wang et al., 2018). Du et al. (2021) proposed the expression of FGM(1,1) replacement trend fluctuation to construct a seasonal fractional grey model to forecast the evolution trend of $PM_{2.5}$ under air pollution. Zhu et al. (2024) optimized the seasonal grey model's seasonal factors using adaptive adjustment to weaken the differences in seasonal information and improve air quality prediction accuracy in China's provinces.

However, the existing research still has some limitations. From the perspective of energy forecasting research, based on hour, day, and month time units, the scale of available data samples is enormous. Artificial intelligence and statistical models based on intelligent algorithm optimization are more suitable than other methods. However, the renewable energy industry is emerging, and the national development plan mainly uses years as the time unit for research. The annual data samples are few and cannot meet these models' data sample size requirements. By contrast, the grey models are more suitable for the renewable energy forecasting scenario.

From the perspective of grey models' optimization, the univariate grey model's structural singleness, parameter optimization, and nonlinear limitations are not solved from the modeling process. The performance is poor when fitting the samples with significant nonlinearity. The multivariable grey models have broader optimization space due to the multivariate model structures. They improve the models' flexibility in response to nonlinear changes by introducing multiple relevant factor variables. They can interchangeably integrate information on various development factors and have the applicability of multidimensional forecasting. However, the traditional multivariable grey model has poor universality, and its preliminary prediction ability for sequences is often far from ideal. The accumulation mechanism of the relevant factors is unreasonable, and the processing of the model parameters is more complicated than that of the univariate grey models.

Therefore, this paper proposes the following innovations to solve the literature review's limitations gradually. The following sections propose and apply the comprehensively improved novel multivariable grey model for forecasting China's renewable energy. The proposed model introduces dual adaptive parameters to flexibly improve the information data accumulation mechanism of the traditional multivariable grey model. Under this novel mechanism, new data information can adjust adaptively according to the system sequence, and historically accumulated related factor data can also accumulate and adaptively optimize according to the system sequence. It innovatively optimizes the traditional modeling methods and forms a novel grey-driver item structure from the related factor sequences. The model structure includes initial, background, and power parameter optimization. The proposed model reduces the parameter selection complexity by combining the whale optimization algorithm (WOA) (Mirjalili & Lewis, 2016). It can transform into various improved derivative models with flexible and stable applicability according to different optimization parameter conditions.

3. Methodology

3.1. Preliminaries

Definition 1. (Zeng et al., 2019) The traditional multivariate grey model GM(1,N) contains system and related factor sequences. The system sequence represents the prediction target data, and factors related to the prediction target constitute the related factor sequence.

Suppose the system sequence is $a^{(0)}(1), a^{(0)}(2), \dots, a^{(0)}(n)$*, expressed as* $A_1^{(0)}$*, and the related factor sequences* $A_j^{(0)}$ *are:*

$$
\begin{gathered}
(a_2^{(0)}(1), a_2^{(0)}(2), a_2^{(0)}(3), \dots, a_2^{(0)}(n)) \\
(a_3^{(0)}(1), a_3^{(0)}(2), a_3^{(0)}(3), \dots, a_3^{(0)}(n)) \\
\dots \\
(a_j^{(0)}(1), a_j^{(0)}(2), a_j^{(0)}(3), \dots, a_j^{(0)}(n))
\end{gathered}
$$

According to the first-order accumulated generating operation (1-AGO) and traditional background value calculation, this paper generates the background value sequence $S_1 = (s_1(2), s_1(3), \dots, s_1(n))$ and the accumulating sequence of related factors $A_j^{(1)} = (a_j^{(1)}(2), a_j^{(1)}(3), \cdots, a_j^{(1)}(n))$, as shown in Eq. (1).

$$
\begin{cases}
s_1(k) = (a_1^{(1)}(k) + a_1^{(1)}(k-1))/2 \\
a_j^{(1)}(k) = \sum_{i=1}^{k} a_j^{(0)}(i), k = 1, 2, \dots, n
\end{cases}
\tag{1}
$$

Definition 2. (Ding et al., 2017) Construct the matrix M and matrix N from S_1 and $A_j^{(1)}$.

$$
M = \begin{bmatrix} -s_1(2) & a_2^{(1)}(2) & \cdots & a_j^{(1)}(2) \\ -s_1(3) & a_2^{(1)}(3) & \vdots & a_j^{(1)}(3) \\ \vdots & \vdots & \ddots & \vdots \\ -s_1(n) & a_2^{(1)}(n) & \cdots & a_j^{(1)}(n) \end{bmatrix} N = \begin{bmatrix} a_1^{(0)}(2) \\ a_1^{(0)}(3) \\ \dots \\ a_1^{(0)}(n) \end{bmatrix}
$$

Suppose the driving coefficient matrix is $\widehat{\alpha} = [\alpha_1, \alpha_2, \dots, \alpha_N]^T$*, and* $\widehat{\alpha} = (M^T M)^{-1} M^T N$ *then the traditional GM(1,N) can be expressed as:*

$$
a_1^{(0)}(k) + \alpha_1 s_1(k) = \sum_{j=2}^{N} \alpha_j a_j^{(1)}(k) \tag{2}
$$

α_1 is the model development coefficient, $\sum_{j=2}^{N} \alpha_j a_j^{(1)}(k)$ is the grey driving term, and $\alpha_j (j \geqslant 2)$ is the driving coefficient. The first-order inverse accumulated generating operation (IAGO) calculates the fitted and forecasting values, as shown in Eq. (3). The whitening differential equation of the GM(1,N) is as follows.

$$
\widehat{a}^{(0)}(k) = \widehat{a}_1^{(1)}(k+1) - \widehat{a}_1^{(1)}(k),\ k = 1, 2, \cdots, n \tag{3}
$$

Definition 3. (Wang, 2017) Suppose the grey driving term's amplitude of variation changes less, $\sum_{j=2}^{N} \alpha_j a_j^{(1)}(k)$ can be set as the grey constant. The whitening differential equation of the GM(1,N) is as Eq. (4).

$$
\begin{cases}
da_1^{(1)}(t)/dt + \alpha_1 a_1^{(1)}(t) = \sum_{j=2}^{N} \alpha_j a_j^{(1)}(k) \\
a_1^{(1)}(k) = e^{-\alpha_1 (k-1)} \left[a_1^{(0)}(1) - \frac{\sum_{j=2}^{N} \alpha_j a_j^{(1)}(k)}{\alpha_1} \right] + \frac{\sum_{j=2}^{N} \alpha_j a_j^{(1)}(k)}{\alpha_1}
\end{cases}
\tag{4}
$$

3.2. The proposed flexible data information accumulation mechanism

The traditional GM(1,N) applies 1-AGO to accumulate data information on related factors directly. This method simplifies the modeling process but cannot reflect the difference between new and old information. It ignores the information fitness between the relevant factor sequences and the system sequence. Therefore, this section proposes a novel data information accumulation (IA) mechanism. Under this mechanism, the entire forecasting system model flexibly combines new data and old data information accumulation through two different adaptive factors considering the information characteristics of the system sequence.

When the related factor sequences accumulate, the IA mechanism defines the adjacent data as new and old information based on historical time. It adds two adaptive factors, β_1 and β_2, to adjust the data information value for participating in the novel accumulating process. In combining old and new information, the IA mechanism determines the adaptive factors according to the system sequence's target of minimum errors. Unlike the adaptive factor for new information, the factor for old information further describes the cumulative impact of historical information on the future development of the system sequence through cyclic accumulation. The old information adaptive factor β_2 continuously updates until the latest information participates in the last accumulation. On the contrary, the new information adaptive factor β_1 does not include the cumulative effect of time and directly acts on the accumulation process, reflecting the timeliness of new information. The specific expression is as shown in Theorem 1.

Theorem 1. Suppose N kinds of related factors form the related factor sequences of $N \times n$. When there are adaptive factors β_1 and β_2 to adjust the accumulated value of the old data information with new information of the related factor sequences, the grey driving term transforms from $\sum_{j=2}^{N} \alpha_j a_j^{(1)}(k)$ to $\sum_{j=2}^{N} \alpha_j \sum_{i=1}^{n} \beta_1 \beta_2^{n+1-k} a_j^{(0)}(k)$.

Proof. *Based on the GM(1,N) modeling setting, assign the adaptive factor* β_1 *to the new data information and adaptive factor* β_2 *to the old data information accumulation.*

When $k = 1$*, the initial information accumulation is updated to* $\beta_1 \beta_2 a_j^{(0)}(1)$.

When $k = 2$, the new data information updates to $\beta_1 a_j^{(0)}(2)$, the grey information accumulation of related factors updates to:

$$
\beta_2(\beta_1 \beta_2 a_j^{(0)}(1) + \beta_1 a_j^{(0)}(2)) = \beta_1 \beta_2^2 a_j^{(0)}(1) + \beta_1 \beta_{j2}^{(0)} a \tag{2}
$$

When $k = 3$, the new data information updates to $\beta_1 a_j^{(0)}(3)$, then the grey information accumulation updates to:

$$
\begin{aligned}
&\beta_2(\beta_1 \beta_2^2 a_j^{(0)}(1) + \beta_1 \beta_2 a_j^{(0)}(2) + \beta_1 a_j^{(0)}(3) \\
&= \beta_1 \beta_2^3 a_j^{(0)}(1) + \beta_1 \beta_2^2 a_j^{(0)}(2) + \beta_1 \beta_2 a_j^{(0)}
\end{aligned}
\tag{4}
$$

Therefore, when $k = n$, the grey information accumulation can update to

$$
\begin{aligned}
&\beta_2(\beta_1 \beta_2^{n-1} a_j^{(0)}(1) + \beta_1 \beta_2^{n-2} a_j^{(0)}(2) + \dots + \beta_1 a_j^{(0)}(k) = \beta_1 \beta_2^n a_j^{(0)}(1) \\
&+ \beta_1 \beta_2^{n-1} a_j^{(0)}(2) + \dots + \beta_1 \beta_2 a_j^{(0)}(k) \\
&= \sum_{i=1}^{n} \beta_1 \beta_2^{n+1-k} a_j^{(0)}(k)
\end{aligned}
\tag{5}
$$

The grey driving term coefficient is known to be $\alpha_j (j \geqslant 2)$, so when the grey driving term constructed by the traditional model is $\sum_{j=2}^{N} \alpha_j a_j^{(1)}(k)$, under the proposed accumulation mechanism the new grey driving term will be updated as follows.

$$\alpha_2\sum_{i=1}^{n}\beta_1\beta_2^{n+1-k}a_2^{(0)}(k)+\alpha_3\sum_{i=1}^{n}\beta_1\beta_2^{n+1-k}a_3^{(0)}(k)+\dots+\alpha_N\sum_{i=1}^{n}\beta_1\beta_2^{n+1-k}a_N^{(0)}(k)=\sum_{j=2}^{N}\alpha_j\sum_{i=1}^{n}\beta_1\beta_2^{n+1-k}a_j^{(0)}(k) \tag{6}$$

This paper entitles the multivariable grey model as the IAGM(1,N). The model expression is:

$$a_1^{(0)}(k)+\alpha_1 s_1(k)=\sum_{j=2}^{N}\alpha_j\sum_{i=1}^{n}\beta_1\beta_2^{n+1-k}a_j^{(0)}(k) \tag{7}$$

Theorem 2. When the initial and background values of the IAGM(1,N) are $a_1^{(0)}(1)$ and $s_1(n)$, respectively, the M and N matrices are:

$$M=\begin{bmatrix}-s_1(2) & \beta_1\beta_2^2a_2^{(0)}(1)+\beta_1\beta_2a_2^{(0)}(2) & \dots & \beta_1\beta_2^2a_j^{(0)}(1)+\beta_1\beta_2a_j^{(0)}(2)\\ -s_1(3) & \beta_1\beta_2^3a_2^{(0)}(1)+\beta_1\beta_2^2a_2^{(0)}(2)+\beta_1\beta_2a_2^{(0)}(3) & \dots & \beta_1\beta_2^3a_j^{(0)}(1)+\beta_1\beta_j^2a_2^{(0)}(2)+\beta_1\beta_2a_j^{(0)}(3)\\ \dots & \dots & \dots & \dots\\ -s_1(k) & \sum_{i=1}^{n}\beta_1\beta_2^{n+1-k}a_2^{(0)}(k) & \dots & \sum_{i=1}^{n}\beta_1\beta_2^{n+1-k}a_j^{(0)}(k)\end{bmatrix} N=\begin{bmatrix}a_1^{(0)}(2)\\ a_1^{(0)}(3)\\ \dots\\ a_1^{(0)}(n)\end{bmatrix}$$

The grey driving term coefficient matrix $\widehat{\alpha}=[\alpha_1,\alpha_2,...,\alpha_N]^T$ *should satisfy:*

When $n=N+1$, $\widehat{\alpha}=M^{-1}N, |M\neq 0|N.$

When $n>N+1$, $\widehat{\alpha}=(M^TN)^{-1}M^TN, |M^TM\neq 0|.$

When $n<N+1$, $\widehat{\alpha}=M^T(M^TM)^{-1}N, |M^TM\neq 0|.$

In the accumulation process, whether β_1 and β_2 have a weakening effect between zero and one or a strengthening effect greater than one is determined flexibly according to the system sequence characteristics.

Theorem 3. When ***Theorem 1*** and ***Theorem 2*** hold, the approximate time response function of the IAGM(1,N) is:

$$a_1^{(1)}(k)=e^{-\alpha_1(k-1)}\left[a_1^{(1)}(1)-\frac{\sum_{j=2}^{N}\alpha_j\sum_{i=1}^{n}\beta_1\beta_2^{n+1-k}a_j^{(0)}(k)}{\alpha_1}\right]+\frac{\sum_{j=2}^{N}\alpha_j\sum_{i=1}^{n}\beta_1\beta_2^{n+1-k}a_j^{(0)}(k)}{\alpha_1} \tag{8}$$

Through the IAGO, the forecasting results are:

$$\begin{cases}a_1^{(0)}(k)=a_1^{(1)}(k)-a_1^{(1)}(k-1),(k\geqslant 2)\\ a_1^{(0)}(1)=a_1^{(1)}(1),(k=1)\end{cases}$$

According to the above Theorem 1 to Theorem 3 derivation process, the IA proposed mechanism is considered more from the flexibility perspective. It sets the adjusted factors β_1 and β_2 that adapt more to the system sequence development and eliminates complex evaluating the strength of old and new information. The selected optimization algorithm determines the value of the adaptive factors according to the development trend of the system sequence updates. The optimal solution's constraint condition is the system sequence's minimum fitting and forecasting errors during the factors determined. Under the whole IA mechanism, this paper highlights the flexible feature in the action processes of β_1 and β_2. In information accumulation, the enhancement and weakening of the action of new and old information are determined more around the system sequence updating rather than artificial settings.

3.3. The proposed model and its relations with existing methods

Based on the proposed IAGM(1,N), this paper constructs a comprehensive and optimized multivariate grey model (IACOGM(1,N)). The optimized parameters contain the initial and background values and nonlinear optimization. The grey model usually sets the initial value as a and the background value as 0.5. However, Xie et al. (2009) proved that a correction factor can optimize the initial value. Wang et al. (2010) proposed the idea of calculating background values based on solving undetermined parameters with weights. Wang (2017) extended the combination of power parameters and grey models to describe the nonlinear feature optimization. Therefore, considering these optimized aspects, this paper proposes the final IACOGM(1,N).

$$\begin{cases}a_1^{(1)}(k)=e^{-\alpha_1(k-1)}\left[a_1^{(0)}(1)+\xi-\frac{\sum_{j=2}^{N}\alpha_j\sum_{i=1}^{n}\beta_1\beta_2^{n+1-k}(a_j(k))^{r_j-1}}{\alpha_1}\right]+\frac{\sum_{j=2}^{N}\alpha_j\sum_{i=1}^{n}\beta_1\beta_2^{n+1-k}(a_j(k))^{r_j-1}}{\alpha_1}\\ s_1(k)=(1-\lambda)\times a_1^{(1)}(k-1)+\lambda\times a_1^{(1)}(k)\\ a_1^{(0)}(k)=a_1^{(1)}(k)-a_1^{(1)}(k-1)\\ \widehat{\alpha}=(\alpha_1,\alpha_2,\alpha_3,...,\alpha_N)\end{cases} \tag{9}$$

Considering that the hyperparameter solution of IACOGM(1,N) is complex and WOA has excellent stability and convergence, this paper selects MAPE as the constraint target, and WOA solves the parameters optimization. The solving constraints are as Eq.(10).

$$F(r_j,\beta_1,\beta_2,\lambda,\zeta) = \text{argmin}\left(\frac{1}{n}\sum_{i=1}^{n}\left|\frac{a_1^{(0)}(i) - \widehat{a}_1^{(0)}(i)}{a_1^{(0)}(i)}\right|\right) \quad (10)$$

Based on the specific values of the undetermined parameters, the proposed IACOGM(1,N) can transform to other improved IAGM(1,N) derived models flexibly or degenerate to the traditional GM(1,N).

Property 1. The IACOGM(1,N) can transform to the IAGM(1,N) with initial value optimization (IAGM(1,N,ξ)).

Proof. *Let $\lambda = 0.5$, $r = 1$, the Eq.(9) can transform to the IAGM(1,N,ξ) as follows.*

$$\begin{cases} a_1^{(1)}(k) = e^{-\alpha_1(k-1)}\left[a_1^{(0)}(1) + \xi - \frac{\sum_{j=2}^{N}\alpha_j\sum_{i=1}^{n}\beta_1\beta_2^{n+1-k}(a_j^{(0)}(k))}{\alpha_1}\right] + \frac{\sum_{j=2}^{N}\alpha_j\sum_{i=1}^{n}\beta_1\beta_2^{n+1-k}(a_j^{(0)}(k))}{\alpha_1} \\ s_1(k) = [a_1^{(1)}(k-1) + a_1^{(1)}(k)]/2 \end{cases} \quad (11)$$

Property 2. The IACOGM(1,N) can transform to the IAGM(1,N) with background value optimization (IAGM(1,N,λ)).

Proof. *Let $\xi = 0$, $r = 1$, the Eq.(9) can transform to the IAGM(1,N, λ) as follows.*

$$\begin{cases} a_1^{(1)}(k) = e^{-\alpha_1(k-1)}\left[a_1^{(0)}(1) - \frac{\sum_{j=2}^{N}\alpha_j\sum_{i=1}^{n}\beta_1\beta_2^{n+1-k}(a_j^{(0)}(k))}{\alpha_1}\right] + \frac{\sum_{j=2}^{N}\alpha_j\sum_{i=1}^{n}\beta_1\beta_2^{n+1-k}(a_j^{(0)}(k))}{\alpha_1} \\ s_1(k) = (1-\lambda)\times a_1^{(1)}(k-1) + \lambda\times a_1^{(1)}(k) \end{cases} \quad (12)$$

Property 3. The IACOGM(1,N) can transform to the IAGM(1,N) with power exponential structure optimization (IAGM(1,N,r)).

Proof. *Let $\xi = 0$, $\lambda = 0.5$, the Eq.(9) can transform to the IAGM(1,N,r) as follows.*

$$\begin{cases} a_1^{(1)}(k) = e^{-\alpha_1(k-1)}\left[a_1^{(0)}(1) - \frac{\sum_{j=2}^{N}\alpha_j\sum_{i=1}^{n}\beta_1\beta_2^{n+1-k}(a_j^{(0)}(k))^{r_j}}{\alpha_1}\right] + \frac{\sum_{j=2}^{N}\alpha_j\sum_{i=1}^{n}\beta_1\beta_2^{n+1-k}(a_j^{(0)}(k))^{r_j}}{\alpha_1} \\ s_1(k) = [a_1^{(1)}(k-1) + a_1^{(1)}(k)]/2 \end{cases} \quad (13)$$

Property 4. The IACOGM(1,N) can degenerate to the tradional GM(1, N)

Proof. *Let $\xi = 0$, $\lambda = 0.5$, $r = 1$, $\beta_1 = \beta_2 = 1$, the Eq.(9) can degenerate to the GM(1,N).*

$$\begin{cases} a_1^{(1)}(k) = e^{-\alpha_1(k-1)}\left[a_1^{(0)}(1) - \frac{\sum_{j=2}^{N}\alpha_j a_j^{(1)}(k)}{\alpha_1}\right] + \frac{\sum_{j=2}^{N}\alpha_j a_j^{(1)}(k)}{\alpha_1} \\ s_1(k) = [a_1^{(1)}(k-1) + a_1^{(1)}(k)]/2 \end{cases}$$

Fig. 1 shows the flexible variations between these models.

Therefore, the proposed multivariable grey model based on the IA mechanism may flexibly realize the transformation of different forms and change into the traditional GM(1,N). In the realistic study, the IACOGM(1,N) may also flexibly adjust the initial values, background values, and nonlinear parameters according to the system data information characteristics. It may transform into an adaptive model structure with the ideal fitting and forecasting accuracy for further forecasting research.

3.4. The modeling procedure and accuracy evaluation

According to the IA optimization mechanism and transformation mode in sections 3.2 and 3.3, Fig. 2 is the modeling process of the IACOGM(1,N).

Step 1. Collect data and group into the system sequence and related factor sequences.

Step 2. Introduce the adaptive factors β_1 and β_2. Set the related factor sequences' initial, background, and power parameters. Generate new grey driver terms based on the proposed IA mechanism.

Step 3. Set MAPE as the constraint target. Establish the optimized control functions for initial, background, and power parameters (ξ, λ, r).

Step 4. Apply the WOA to calculate and obtain the optimal parameter solutions through the MAPE test. If the MAPE is $<$ 5 %, the procedure passes. The procedure continues the test loop if the MAPE is $>$ 5 %.

Step 5. Reconstruct the traditional GM(1,N) based on the optimal parameter solutions to form the proposed IACOGM (1,N). Calculate the forecasting results by IAGO.

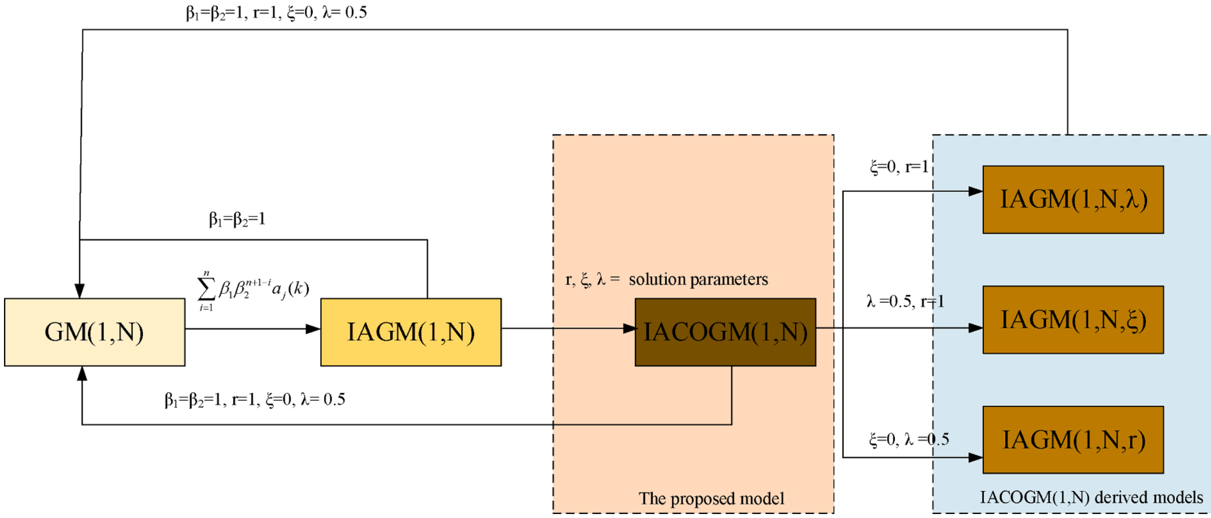


Fig. 1. The variations between these multivariate grey models.

This paper selects four calculating methods to evaluate the validity and stability of the grey models' fitting and forecasting test results: Mean Square Error (MSE), MAE, Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Comprehensive MAPE.

$$ComprehensiveMAPE = \frac{(FittingMAPE + TestMAPE)}{2}$$

4. Empirical analysis and results

4.1. Data description and model establishment

In Table 1, this paper applies China's renewable energy generation from 2011 to 2022 as the system sequence and the annual output value of China's primary, secondary, and tertiary industries as the related factors sequences.

The development stages of China's 12th Five-Year Plan and 13th Five-Year Plan are 2011 to 2020. This paper selects the renewable energy generation of these two development stages as the fitting values and the data in 2021 and 2022 as the test values. Finally, this paper forecasts China's renewable energy generation until 2030 based on the 12th Five-Year Plan and 13th Five-Year Plan data.

The system sequence is:

$$A_1^{(0)} = (104.30, 136.80, 183.80, 229.50, 279.10, 369.50, 502.00, 636.40, 742.00, 863.20)$$

The related factors sequences are:

$$A_2^{(0)} = (44781.5, 49084.6, 53028.1, 55626.3, 57774.6, 60139.2, 62099.5, 64745.2, 70473.6, 78030.9)$$

$$A_3^{(0)} = (227035.1, 244639.1, 261951.6, 277282.8, 281338.9, 295427.8, 331580.5, 364835.2, 380670.6, 383562.4)$$

$$A_4^{(0)} = (216123.6, 244856.2, 277983.5, 310654, 349744.7, 390828.1, 438355.9, 489700.8, 535371, 551973.7)$$

The traditional GM(1,N) is:

$$104.3 + 0.0048 s_1^{(1)}(k) = -0.0057 a_2^{(1)}(k) + 0.0013 a_3^{(1)}(k) + 9.3152 a_4^{(1)}(k)$$

The expression is:

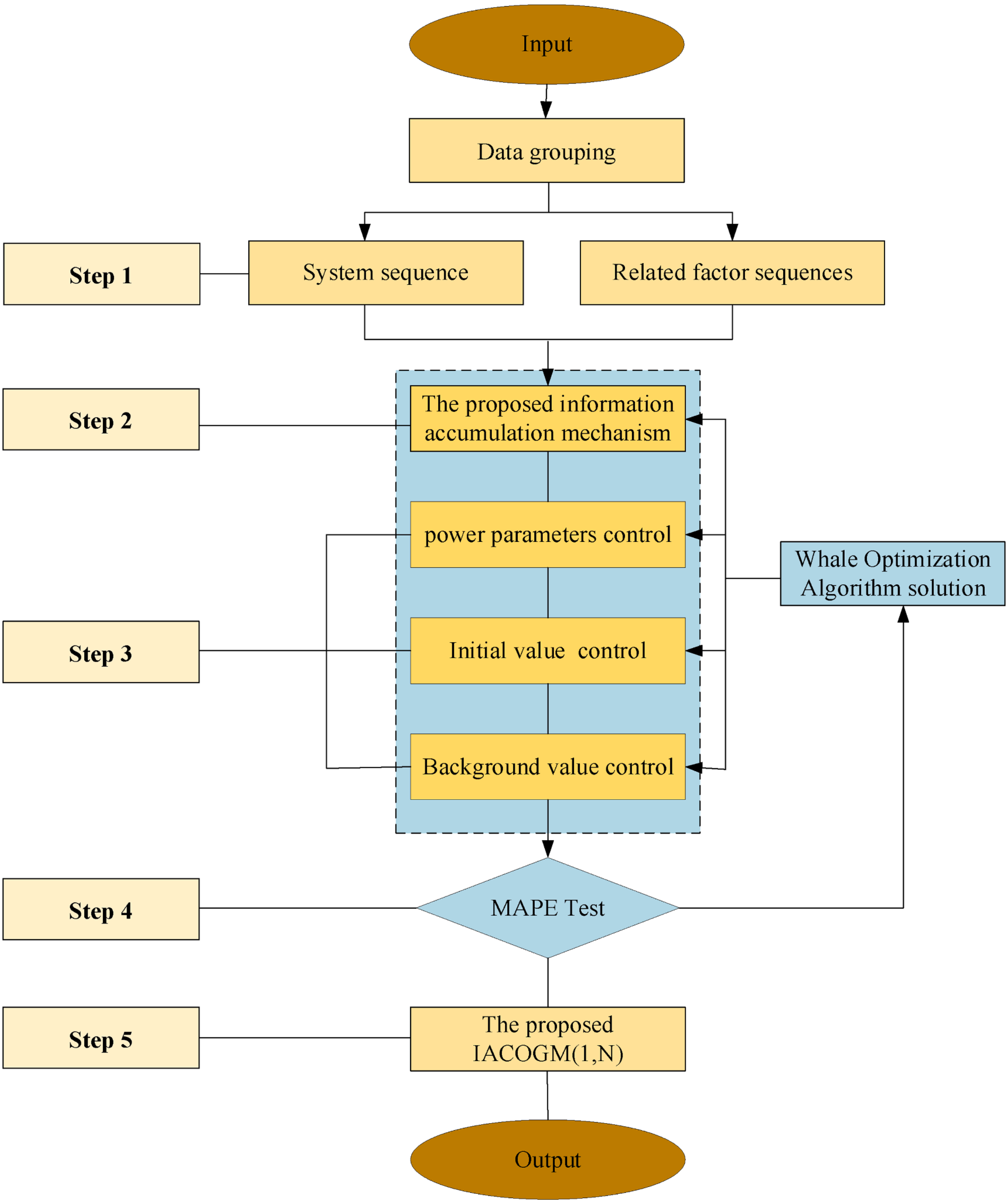


Fig. 2. The modeling procedure.

$$\begin{cases} a_1^{(1)}(k) = [104.3 - (-0.0057a_2^{(1)}(k) + 0.0013a_3^{(1)}(k) + 9.3152a_4^{(1)}(k))/0.0048]e^{[-0.0048(k-1)]} \\ \qquad +(-0.0057a_2^{(1)}(k) + 0.0013a_3^{(1)}(k) + 9.3152a_4^{(1)}(k))/0.0048 \\ \qquad a_1^{(0)}(k) = a_1^{(1)}(k) - a_1^{(1)}(k-1) \end{cases}$$

Table 1
The renewable energy generation and output value of three major industries in China.

Year/Data	Renewable energy generation	Primary industry	Secondary industry	Tertiary Industry
Unit	TWh	100 million yuan	100 million yuan	100 million yuan
2011	104.30	44781.50	227035.10	216123.60
2012	136.80	49084.60	244639.10	244856.20
2013	183.80	53028.10	261951.60	277983.50
2014	229.50	55626.30	277282.80	310654.00
2015	279.10	57774.60	281338.90	349744.70
2016	369.50	60139.20	295427.80	390828.10
2017	502.00	62099.50	331580.50	438355.90
2018	636.40	64745.20	364835.20	489700.80
2019	742.00	70473.60	380670.60	535371.00
2020	863.20	78030.90	383562.40	551973.70
2021	1152.50	83216.50	451544.10	614476.40
2022	1367.00	88207.00	473789.90	642727.10

The output values of three major industries are all from the National Bureau of Statistics of China.
The renewable energy generation is from the BP Statistical Review of World Energy 2022 and Statistical review of world energy 2023.

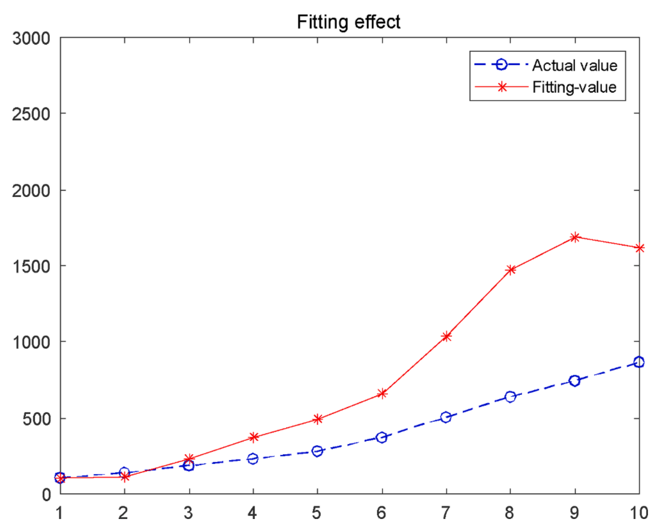


Fig. 3. The fitting effect of the GM(1,N).

Fig. 3 shows the fitting effect of the traditional GM(1,N).

This paper improves the GM(1,N) based on the IA mechanism and optimization of modeling parameters. Fig. 4 simulates the continuous optimization process.

It is clearly shown in Fig. 3 and Fig. 4 that the IA echanism significantly improves the fitting accuracy of GM(1,N) and solves the traditional GM(1,N) general application defect.

According to the proposed IACOGM(1,N) in section 3, the power parameters r_j are added to the relevant factors for the data nonlinear adaption when accumulating the data information. Meanwhile, the initial and accumulative adaptive factors β_1 and β_2 are introduced to optimize the accumulation process of the GM(1,N).

The preliminary form of the IACOGM(1,N) is:

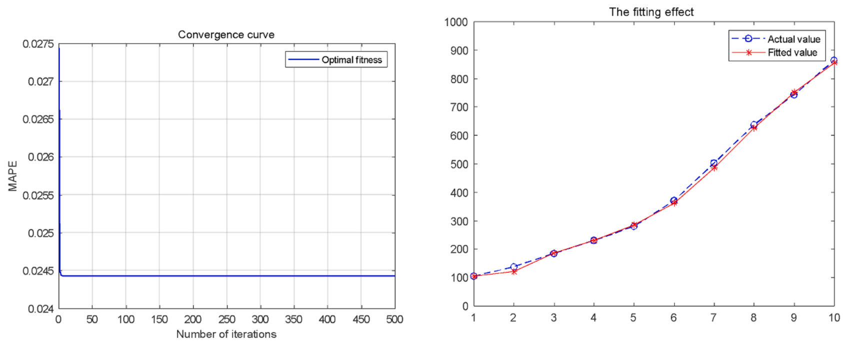
$$104.3+\xi+\alpha_1 s_1^{(1)}(k)=\alpha_2\sum_{i=1}^{10}\beta_1\beta_2^{(11-k)}\left(a_2^{(0)}(k)\right)^{r_2}+\alpha_3\sum_{i=1}^{10}\beta_1\beta_2^{(11-k)}\left(a_3^{(0)}(k)\right)^{r_3}+\alpha_4\sum_{i=1}^{10}\beta_1\beta_2^{(11-k)}\left(a_4^{(0)}(k)\right)^{r_4}$$

The $s_1^{(1)}(k)$ updates to $s_1^{(1)}(k)=(1-\lambda)a_1^{(0)}(k-1)+\lambda a_1^{(0)}(k)$, the IACOGM(1,N) expression is:

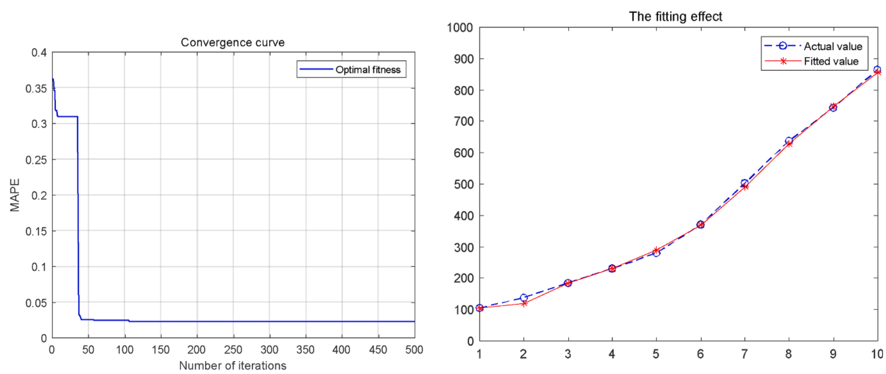
$$\begin{cases} a_1^{(1)}(k)=\left(104.3+\xi-\sum_{j=2}^{4}\alpha_j\sum_{i=1}^{10}\beta_1\beta_2^{(11-k)}\left(a_j^{(0)}(k)\right)^{r_j}/\alpha_1\right)e^{-\alpha_1(k-1)}+\sum_{j=2}^{4}\alpha_j\sum_{i=1}^{10}\beta_1\beta_2^{(11-k)}\left(a_j^{(0)}(k)\right)^{r_j}/\alpha_1 \\ a_1^{(0)}(k)=a_1^{(1)}(k)-a_1^{(1)}(k-1) \end{cases}$$

As shown in Fig. 5, based on Eq.(9), this section adopts the WOA to solve and obtain the optimized parameters of the IACOGM(1,N).

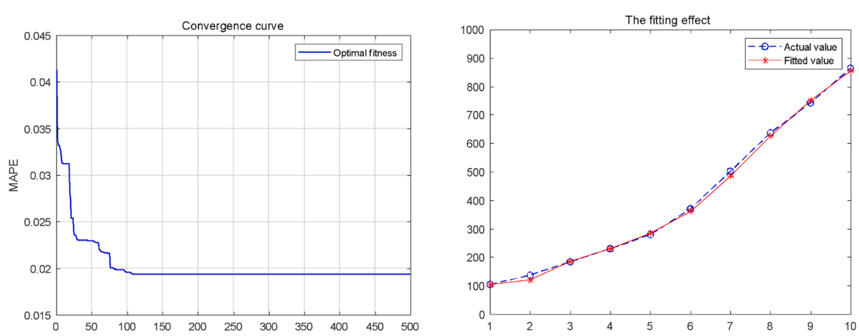
The modeling parameters and optimized parameters are as follows.



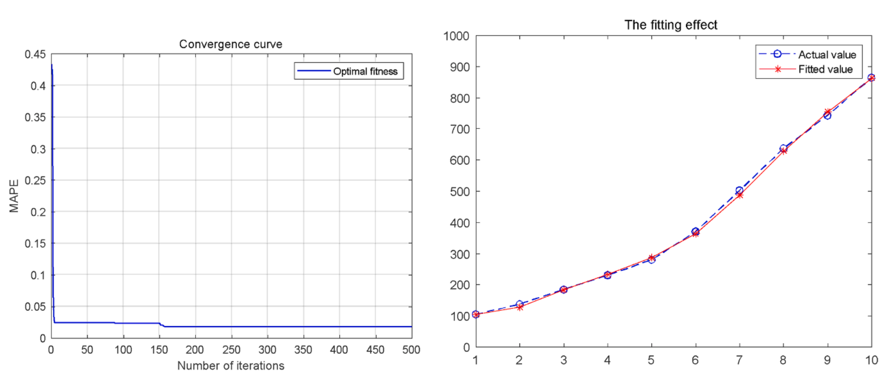
(a) The fitting effect of the IAGM(1,N)



(b) The fitting effect of the IAGM(1,N,r)

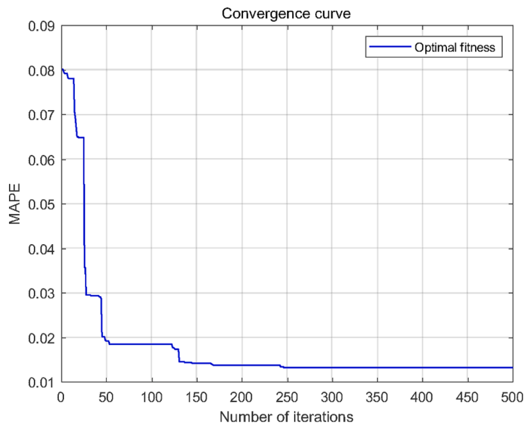


(c) The fitting effect of the IAGM(1,N,λ)

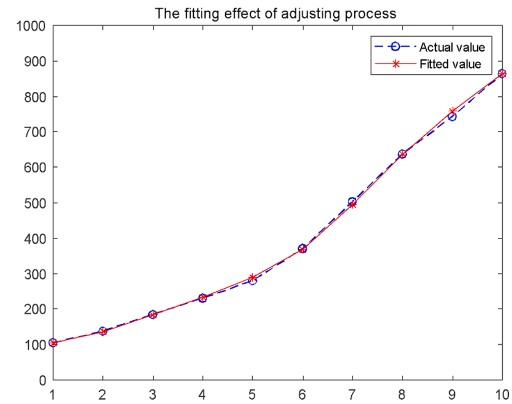


(d) The fitting effect of the IAGM(1,N,ξ)

Fig. 4. The fitting effect based on the IA accumulation mechanism.



(a) WOA iterative process



(b) Fitting effect

Fig. 5. The WOA iterative process and the fitting effect of the IACOGM(1,N).

Table 2
The optimized effects under the IA accumulation mechanism.

Year/Model	Actual value	IACOGM(1,N)	IAGM(1,N)	IAGM(1,N,r)	IAGM(1,N,λ)	IAGM(1,N,ξ)
Training value						
2011	104.30	104.30	104.30	104.30	104.30	104.30
2012	136.80	136.19	120.87	120.33	129.66	128.64
2013	183.80	184.24	186.33	184.59	189.73	183.80
2014	229.50	233.57	231.03	231.02	235.02	232.92
2015	279.10	289.50	285.61	289.71	289.82	286.67
2016	369.50	368.65	363.41	369.50	368.21	364.01
2017	502.00	494.87	486.36	491.47	493.79	487.81
2018	636.40	636.40	626.88	628.03	636.50	629.45
2019	742.00	758.70	751.69	747.83	760.65	755.46
2020	863.20	863.63	855.93	855.37	861.90	862.69
MAPE		**1.13 %**	2.71 %	2.45 %	2.15 %	1.93 %

$$\left\{\begin{array}{l}\alpha_1 = 2.5044\\ \alpha_2 = -1.8151\\ \alpha_3 = 0.4519\\ \alpha_4 = 0.2534\end{array}\right. \left\{\begin{array}{l} r_1 = 0.5850\\ r_2 = 0.5988\\ r_3 = 0.5959\\ \beta_1 = 1.1936\\ \beta_2 = 1.7594\\ \lambda = 0.6256\\ \xi = 43.5550\end{array}\right.$$

The final expression of the IACOGM(1,N) for China's renewable energy generation forecasting is:

$$\left\{\begin{array}{l} F(k) = \left(147.8550 - \sum_{j=2}^{4}\alpha_j\sum_{i=1}^{10}1.1936\times1.7594^{(11-k)}\times a_j^{(0)}(k)/2.5044\right)\times e^{-2.5044(k-1)} + \\ \qquad \sum_{j=2}^{4}\alpha_j\sum_{i=1}^{10}1.1936\times1.7594^{(11-k)}\times a_j^{(0)}(k)/2.5044 \\ \qquad \alpha_2 = -1.8151, \alpha_3 = 0.4519, \alpha_4 = 0.2534 \end{array}\right.$$

Table 2 shows the optimization results with different modeling parameters.

Fig. 6 shows the distribution characteristics of absolute errors between the improved multivariate grey models for the system sequence data fitting.

Compared with these calculating results, the prediction performance of the multivariate grey models based on the novel IA mechanism is significantly improved. The IA mechanism optimizes the accuracy by less than 5 %. It dramatically improves the applicability of the traditional multivariate grey models to data samples. Meanwhile, under the IA mechanism, the accuracy of the models derived from the initial value, background value, and nonlinearity is 2.45 %, 2.15 %, and 1.93 %, respectively. It reveals that each parameter optimization can improve the performance of fitting and prediction in different degrees. The proposed IACOGM(1,N) performs much better than other single optimization-derived models.

4.2. Comparative effect between different models

In order to further test the model performance and forecasting ability of the IACOGM(1,N), this paper selected the following models for comparative testing. These models are GM(1,1,λ), FGM(1,1), NGBM (1,1), FANGBM(1,1), GM(1,N), NGM(1,N), ARIMA, and SVM. Table 3 illustrates the results, and Fig. 7 shows the different fitting and forecasting effects. Fig. 8 reveals the models' residual variation.

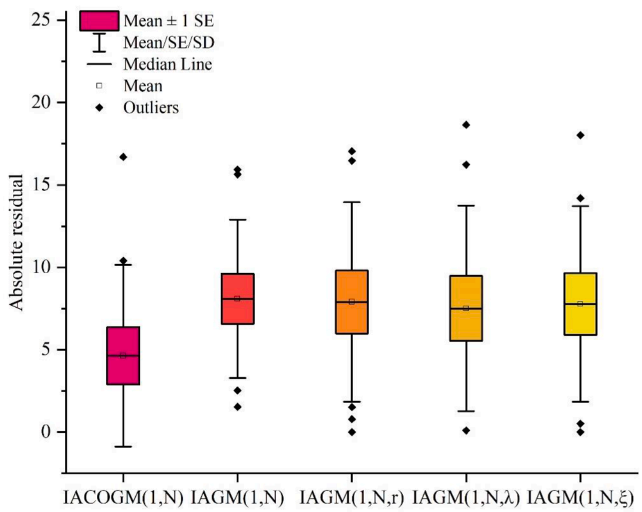


Fig. 6. The absolute residual box type diagram for the models under the IA mechanism.

Considering the results of the fitting values, the traditional GM(1,N) MAPE is the worst among all the models, reaching 79.43 %. Although the fitting accuracy is improved, the MAPE of the fitting result of NGM (1,N) is as high as 30.05 %. It indicates that the traditional multivariate grey models could not directly forecast. Because of the lack of sample size, the fitting and forecasting results of the ARIMA and SVM reflect the limitation, with the MAPE and RMSE at 20.76 %, 63.06, 9.60 %, and 43.79, respectively.

The forecasting results of these univariate grey models are better than the above models. The performance rankings based on the MAPE value are the NGBM(1,1), FGM(1,1), GM(1,1,λ), and FANGBM(1,1). These grey models also have advantages and disadvantages when comparing the MSE and RMSE. Fig. 11 reflects the residual variation. The residuals of these grey models change at certain time points frequently, such that the capability of these models is not stable. However, all comparable indicators of the proposed IACOGM(1,N) are better than these comparison models, and the residual variation fluctuation is much lower than in other models. The absolute fluctuation of the residual shows that the change amplitude of IACOGM(1,N) is better than others.

Moreover, combined with the test values, the comprehensive MAPE of the proposed IACOGM(1,N) is only 2.60 %, which has the best forecasting ability among these models. Combining the development of fitting and test values, as shown in Fig. 7, the fitting and forecasting results of the IACOGM(1,N) maintain a high consistency with the actual values. The data development curve is consistent with the actual trend. The other grey models, SVM and ARIMA, also have better simulations of the development trend than GM(1,N) and NGM(1,N), but there are still apparent errors. The comprehensive MAPE of the univariate grey models and SVM are all higher than 5 %, and the comprehensive MAPE of FANGBM(1,1) is 11.92 %, with a higher error over 10 %. It shows that the forecasting accuracy of these models still needs to be improved. Fig. 8 reflects that the ARIMA and multivariate grey models have a significant fitting error in the early stage. The development trends of GM (1,N) are unreasonable in all the progress, with too many errors. It is necessary to optimize these models' parameters further to improve the forecasting performance.

In summary, IACOGM(1,N) is most adaptable to the research renewable data sources among the five optimization models established based on the IA mechanism. Compared with other forecasting methods selected in this paper, IACOGM(1,N) has the best fitting accuracy and comprehensive accuracy, which is 1.13 % and 2.60 %. Secondly, GM (1,1,λ), FGM(1,1), NGBM(1,1), and FANGBM(1,1), which represent the univariate grey models, have the fitting and comprehensive accuracy basically within the acceptable range. After that, the SVM, whose fitting and comprehensive accuracy are 9.60 % and 11.96 %, is weaker than the above models and needs to be improved. Finally, the fitting errors of the ARIMA and multivariate grey models without the IA mechanism are higher than 20 %, and their forecasting results cannot be referenced directly.

Through these comparisons, this section finds that the proposed IA mechanism could significantly improve GM(1,N) 's adaptability to renewable energy data and effectively realize generation forecasting during the test period. It could solve the problem that GM(1,N) could not directly forecast before. Therefore, applying the proposed IACOGM(1,N) to forecast renewable energy generation in China's plan stages is feasible.

4.3. The forecasting results of the China's renewable energy generation

Based on the IACOGM(1,N) established in Section 4.1, this paper forecasts China's renewable energy generation in the middle and late of

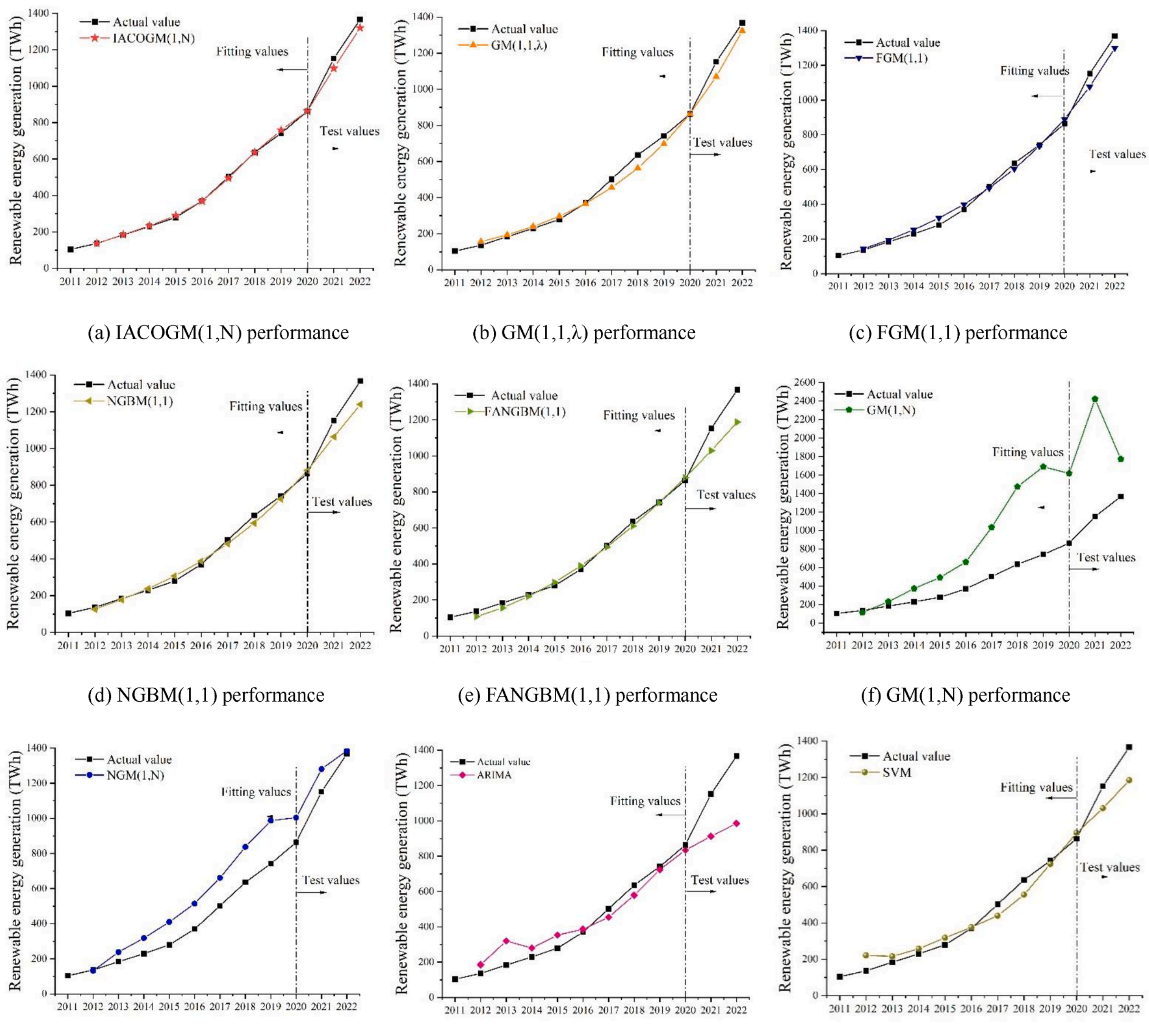
Table 3
The fitting and forecasting results comparisons.

(a)The fitting and test results

Year/Model	Actual value	IACOGM(1,N)	GM(1,1,λ)	FGM(1,1)	NGBM(1,1)	FANGBM(1,1)	GM(1,N)	NGM(1,N)	ARIMA	SVM
Fitting value										
2011	104.30	–	–-	–	–	–	–	–		–
2012	136.80	136.19	156.36	143.94	126.04	107.50	112.90	132.38	185.30	–
2013	183.80	184.24	193.61	194.64	178.10	156.12	231.94	238.27	319.70	216.03
2014	229.50	233.57	239.75	252.80	237.56	219.90	373.70	318.65	280.40	257.54
2015	279.10	289.54	296.87	320.29	306.61	297.59	493.25	409.64	352.90	317.55
2016	369.50	368.65	367.61	399.39	387.44	388.85	660.28	514.54	386.80	375.90
2017	502.00	494.87	455.20	492.70	482.40	493.26	1035.36	661.29	454.70	439.23
2018	636.40	636.40	563.66	603.23	594.16	610.29	1474.66	837.87	579.60	554.65
2019	742.00	758.73	697.97	734.51	725.81	739.18	1689.26	987.06	724.10	723.83
2020	863.20	863.63	864.28	890.73	880.91	879.07	1617.32	1004.02	834.10	895.44
Test value										
2021	1152.50	1098.20	1070.20	1076.86	1063.64	1028.97	2422.90	1280.85	912.70	1030.27
2022	1367.00	1320.18	1323.44	1298.82	1240.13	1187.74	1773.20	1385.63	986.60	1185.02

(b)The comparison results

Effect/Model	IACOGM(1,N)	GM(1,1,λ)	FGM(1,1)	NGBM(1,1)	FANGBM(1,1)	GM(1,N)	NGM(1,N)	ARIMA	SVM
MSE	**45.80**	1147.15	589.133	448.45	383.45	289694.08	21651.20	3976.48	1917.13
RMSE	**6.77**	33.87	24.27	21.18	19.58	538.23	147.14	63.06	43.79
Fitting MAPE	**1.13%**	6.42%	6.15%	4.89%	6.73%	79.43%	30.05%	20.76%	9.60%
Comprehensive MAPE	**2.60%**	5.16%	5.78%	8.50%	11.92%	69.97%	18.15%	24.32%	11.96%



(a) IACOGM(1,N) performance (b) GM(1,1,λ) performance (c) FGM(1,1) performance

(d) NGBM(1,1) performance (e) FANGBM(1,1) performance (f) GM(1,N) performance

(g) NGM(1,N) performance (h) ARIMA performance (i) SVM performance

Fig. 7. The fitting and forecasting effect of the comparison models.

the 14th Five-Year Plan period (2023–2025) and the 15th Five-Year Plan period (2026–2030). This paper calculates the output value of China's three major industries in the same period of the related factor sequences with the improved grey models. The sequences are updated as follows. Table 4 shows the forecasting results from 2023 to 2030.

$$A_2^{(0)} = (91573.15, 97035.53, 102818.30, 108940.74, 115423.18, 122287.14, 129555.33, 137251.81)$$

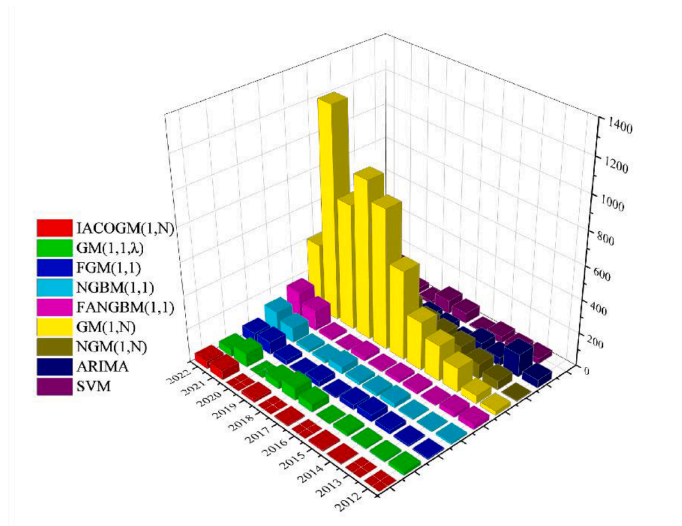
$$A_3^{(0)} = (503491.20, 539193.80, 577398.34, 618282.54, 662036.35, 708862.83, 758979.17, 812617.72)A_4^{(0)}$$
$$= (697556.64, 747514.42, 799801.94, 854591.15, 912055.21, 972370.22, 1035716.69, 1102280.71)$$

Fig. 9 reflects the overall development trend of renewable energy generation from 2011 to 2030.

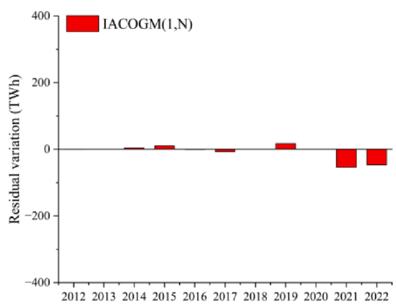
5. Discussion

5.1. The development scale analysis

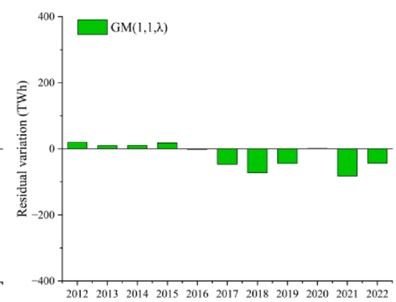
The forecasting results from 2023 to 2025 show that China's renewable energy generation will reach 1602.38TWh, 1934.80 TWh, and 2332.24 TWh. Throughout the 14th Five-Year Plan period, China's renewable energy could grow 19.17 % yearly. According to the 15th Five-Year Plan (2026–2030) results, when China's three major industries maintain the stable development of the current scale and keep the trend growth rate, the renewable energy generation will reach



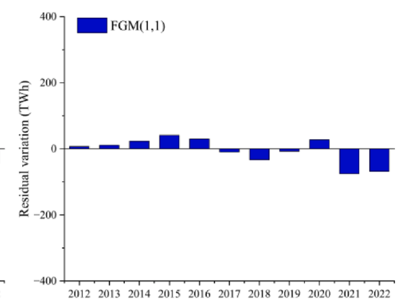
(a) The absolute residual distribution



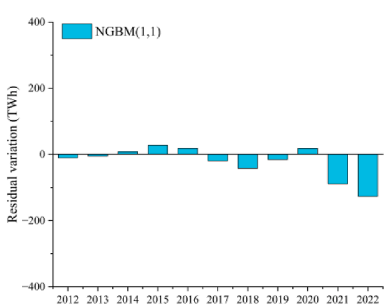
(b) IACOGM(1,N) residuals



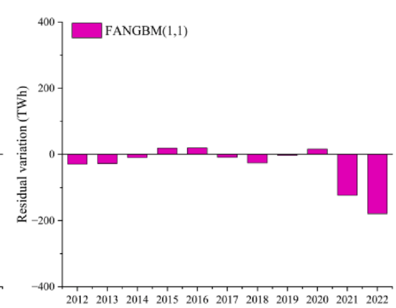
(c) GM(1,1,λ) residuals



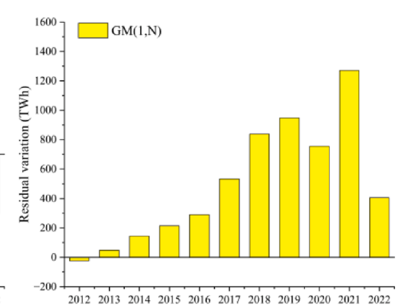
(d) FGM(1,1) residuals



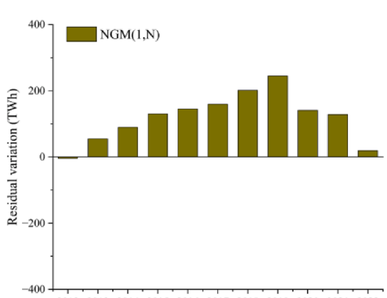
(e) NGBM(1,1) residuals



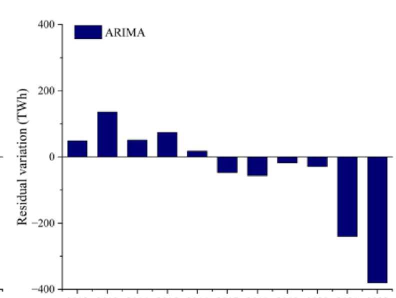
(f) FANGBM(1,1) residuals



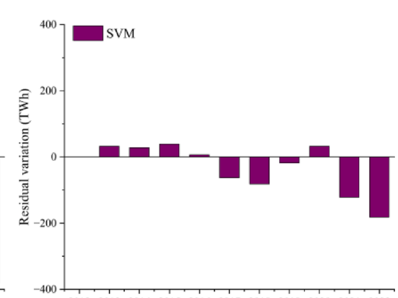
(g) GM(1,N) residuals



(h) NGM(1,N) residuals



(i) ARIMA residuals



(j) SVM residuals

Fig. 8. The residuals of the comparison models.

Table 4
The China's renewable energy generation forecasting results (2023–2030).

Year	2023	2024	2025	2026	2027	2028	2029	2030
Generation (TWh)	1602.38	1934.80	2332.24	2807.35	3375.25	4053.96	4864.98	5834.02

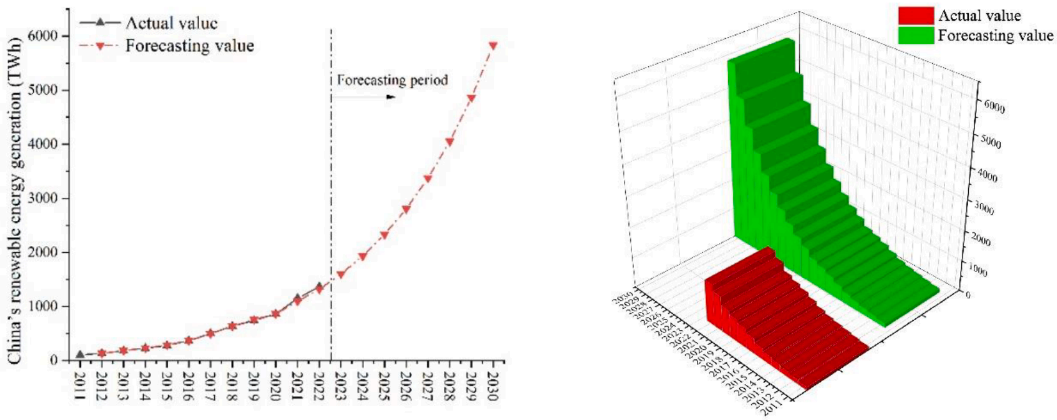


Fig. 9. The development trend of China's renewable energy generation.

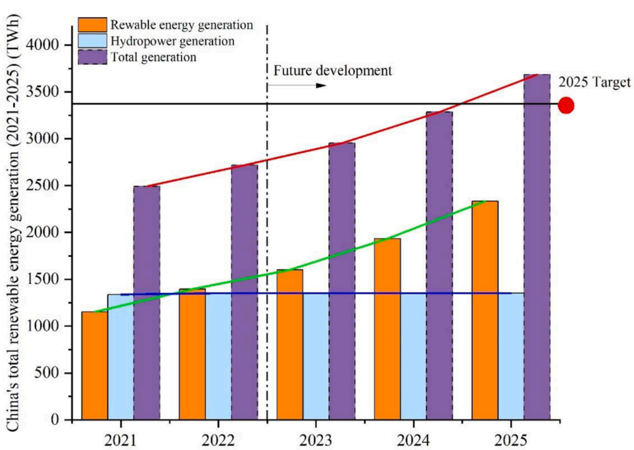


Fig. 10. The total renewable energy generation situation for sustaining the scale of hydropower development.

2807.35 TWh, 3375.25 TWh, 4053.96 TWh, 4864.98 TWh, and 5834.02 TWh with annual growth rate of 20.08 %. Under the development scale of the four five-year plans, China's renewable energy generation may grow from 933.50 TWh and 3113.1 TWh to 8388.93 TWh and 20935.56 TWh. It further reflects the power generation potential of renewable energy in China's energy field and more substantial competitiveness in China's future power market.

As a significant hydropower country, China develops renewable resources and applies its relatively abundant water energy for electricity generation. According to China's 14th Five-Year Renewable Energy Development Plan (NDRC, 2020), the Chinese government has proposed to achieve a total renewable energy generation target of 3300 TWh (including renewable energy and hydropower generation) in 2025. This section discusses the following two types with the hydropower development scales (NBS, 2022) based on the forecasting results in 2024 and 2025 from Table 4. When the Chinese government sustains the current scale of hydropower development, as shown in Fig. 10, China's renewable energy generation will reach 3286.99 TWh and 3684.43 TWh in 2024 and 2025 while maintaining this steady growth.

Fig. 11 shows the situation that the Chinese government continues to promote the development scale of hydropower generation, referring to the forecasting results of this paper and the hydropower forecasting generation in China from 2021 to 2025 (Zeng et al., 2023), the generation in the following 2023 and 2025 will reach 3167.71TWh, 3561.54 TWh, and 4019.98 TWh, respectively. It indicates that in 2024, the Chinese government may approach the planned target of 3300TWh and achieve it before 2025.

Both of these scenarios reflect China's positive momentum in renewable energy generation. Whether it maintains or promotes hydropower development, China can reach its 2025 target ahead of schedule. It also shows the high possibility of realizing or exceeding the 2025 target while maintaining the current development trend of the three industries. The rational development of these renewable energy sources can also relieve the pressure on China's hydroelectric power system.

Based on the conversion index of electricity and coal in China Statistical Yearbook and the Carbon emissions coefficient of coal (Wang & Ye, 2017), Table 5 shows the future carbon emissions reduction from renewable energy generation and hydropower generation in 2023–2030. As shown in Fig. 12, considering the comprehensive environmental protection and dual carbon goals, the Chinese government should flexibly control the hydropower industry and increase renewable energy development to compensate for the differences in carbon reduction between the two scenarios.

Table 5
China's Carbon emission reduction based on clean energy (2023–2030).

Year	2023	2024	2025	2026	2027	2028	2029	2030
Reduction ($MtCO_2$)	142.30	171.83	207.13	250.70	301.41	362.02	434.44	520.97
Scenario 1 ($MtCO_2$)	262.38	291.91	327.21	370.78	421.49	482.1	554.52	641.05
Scenario 2 ($MtCO_2$)	281.31	316.29	357.01	407.02	463.48	530.01	608.52	701.34

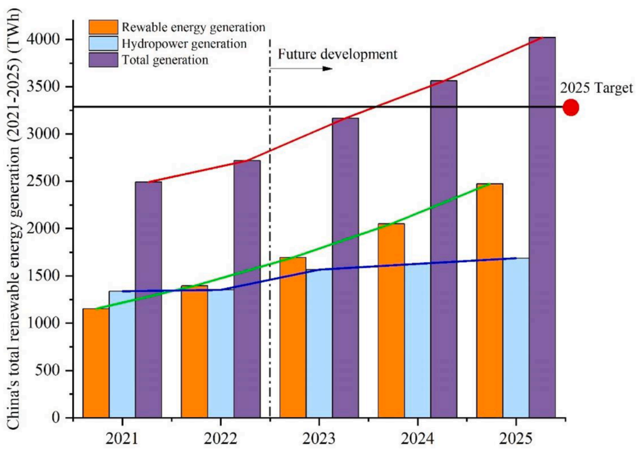


Fig. 11. The total renewable energy generation situation for promoting the scale of hydropower development.

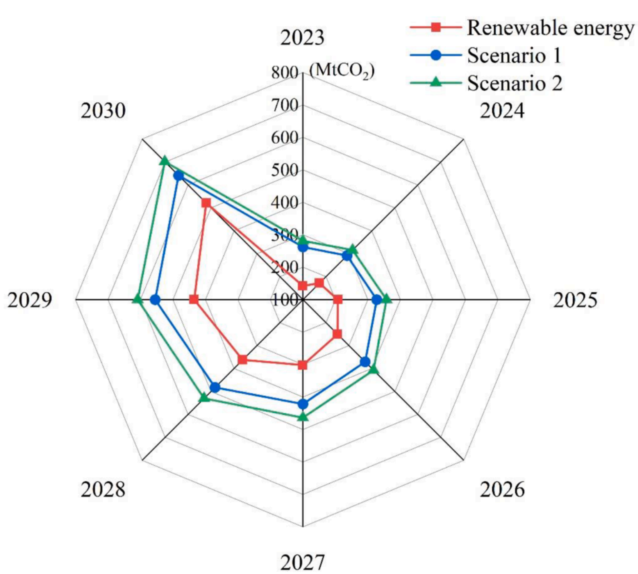


Fig. 12. The carbon emission reduction differences from 2023 to 2030.

5.2. Policy implication

The in-depth development of new renewable energy sources is the novel core driving force leading China towards a clean, green, low-carbon ecological economy. This section makes recommendations based on the forecasting results and discussion analysis.

From the generation forecasting results, China's renewable energy generation will increase from 1602.38 TWh to 2332.24 TWh during the 14th and 15th Five-Year Plan period and to 5834.02 TWh by 2030. It reflects a noticeable annual growth rate from 19.17 % to 20.08 %. Therefore, the Chinese government should strengthen its support for future renewable energy projects to achieve or exceed the forecasted growth of 20.08 %. From the policy perspective, the Chinese government should formulate relevant policies to develop renewable energy. The direct way is to actively provide financial incentives and tax reduction support. From the development perspective, the Chinese government may construct renewable energy infrastructure according to local conditions and establish renewable energy demonstration zones based on China's regional characteristics. It may comprehensively realize regional multi-energy complementarity and nearby balance in China. The regional government may construct demonstration zones for wind, photovoltaic, and geothermal energy in China's Northeast, North, and Northwest areas. Also, it is feasible to actively establish offshore wind power and tidal energy generation platforms along the southeast coast.

Under the scenarios of hydropower scale between promotion and maintenance, the total renewable generation may reach 3684.43TWh and 4019.98TWh in 2025. The forecasting results suggest that a modest short-term slowdown in investment for hydropower may not affect or delay China's 14th Five-Year Plan goal of 3300TWh by 2025. Therefore, during this period, the Chinese government should further increase the development of mainstream renewable energy industries, such as wind power and photovoltaic, based on the current development trend of the three major industries. At the same time, it is also important to explore potential energy innovation technologies such as hydrogen, geothermal, and biomass energy and reduce dependence on hydropower.

However, from the perspective of carbon emission reduction, the carbon emission reduction may reach 701.34MtCO$_2$ and 641.05MtCO$_2$, as forecasted by the above scenarios, by 2030. It shows significant potential in China's renewable energy development to reduce carbon emissions. The forecasting result also suggests that slowing hydropower development may lead to a carbon reduction gap of about 60.29 MtCO$_2$ in 2030, which needs to be compensated. Therefore, China should focus on its hydropower infrastructure's limitations and damage to the local ecology, but this does not mean stopping its development efforts altogether. In the future, the Chinese government should steady the construction of hydropower bases and strengthen the development of hydraulic pumped storage to stabilize the current scale of hydropower generation. Also, the Chinese government should promote the green transformation of major industries such as transportation and construction. The core aim is to achieve carbon reduction support for renewable energy through developing strict environmental standards and promoting low-carbon technologies from social civilization improvement.

6. Conclusion

This paper first creates a novel modeling method for the grey system to optimize the shortcomings of the traditional multivariable grey models in the information accumulation process. Under the designed mechanism, the two adaptive factors can form a flexible accumulation mechanism that adapts to the system sequence characteristics when accumulating the related factor sequences. Combined with the comprehensively optimized modeling parameters, the proposed IAGOGM(1,N) improves the fitting MAPE of the traditional GM(1,N) from 79.43 % to 1.13 %. It also optimizes the comprehensive MAPE from 69.97 % to 2.60 %. The proposed mechanism dramatically improves the practical applicability of GM(1,N) in the complex development system under the multiplicity influence of multivariate factors. The proposed IAGOGM(1,N) has initially formed a forecasting framework to explore the relationship between economic development and renewable energy in China.

The forecasting results by the IACOGM(1,N) from 2023 to 2030 reveal that China's renewable energy will maintain a rapid and stable growth rate. The generation is expected to exceed 20000TWh during the 15th Five-Year Plan period, showing the future colossal potential. The Chinese government should further strengthen the innovation and promotion of renewable and other clean energy to reach the China Carbon Peak in 2030 and construct a solid foundation for China's future green ecological civilization.

CRediT authorship contribution statement

Youyang Ren: Conceptualization, Visualization, Writing – original draft. **Yuhong Wang:** Methodology, Investigation, Writing – review & editing. **Lin Xia:** Data curation, Validation. **Dongdong Wu:** Formal analysis, Resources.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgment

The research reported in this paper was partially supported by the National Natural Science Foundation of China (No. 71871106) and the Fundamental Research Funds for the Central Universities (Nos. JUSRP1809ZD; 2019JDZD06; JUSRP321016). The work was also sponsored by the Major Projects of Educational Science Fund of Jiangsu Province in 13th Five-Year Plan (No. A/2016/01); the Key Project of Philosophy and Social Science Research in Universities of Jiangsu Province (No. 2018SJZDI051); the Major Projects of Philosophy and Social Science Research of Guizhou Province (No. 21GZZB32); Project of Chinese Academic Degrees and Graduate Education (No. 2020ZDB2); Major research project of the 14th Five-Year Plan for Higher Education Scientific Research of Jiangsu Higher Education Association (No. ZDGG02).

References

Al-Alimi, D., AlRassas, A. M., Al-qaness, M. A. A., Cai, Z., Aseeri, A. O., Abd Elaziz, M., & Ewees, A. A. (2023). TLIA: Time-series forecasting model using long short-term memory integrated with artificial neural networks for volatile energy markets. *Applied Energy, 343*, Article 121230.

Aslam, S., Herodotou, H., Mohsin, S. M., Javaid, N., Ashraf, N., & Aslam, S. (2021). A survey on deep learning methods for power load and renewable energy forecasting in smart microgrids. *Renewable & Sustainable Energy Reviews, 144*, Article 110992.

Cakir, S. (2023). Renewable energy generation forecasting in Turkey via intuitionistic fuzzy time series approach. *Renewable Energy, 214*, 194–200.

Costa, M. A., Ruiz-Cardenas, R., Mineti, L. B., & Prates, M. O. (2021). Dynamic time scan forecasting for multi-step wind speed prediction. *Renewable Energy, 177*, 584–595.

Cribari-Neto, F., Scher, V. T., & Bayer, F. M. (2023). Beta autoregressive moving average model selection with application to modeling and forecasting stored hydroelectric energy. *International Journal of Forecasting, 39*(1), 98–109.

Ding, S., Dang, Y., Li, X., Wang, J., & Zhao, K. (2017). Forecasting Chinese CO2 emissions from fuel combustion using a novel grey multivariable model. *Journal of Cleaner Production, 162*, 1527–1538.

Ding, S., Hu, J., & Lin, Q. (2023). Accurate forecasts and comparative analysis of Chinese CO2 emissions using a superior time-delay grey model. *Energy Ecnomics, 126*, Article 107013.

Ding, S., Tao, Z., Li, R., & Qin, X. (2022). A novel seasonal adaptive grey model with the data-restacking technique for monthly renewable energy consumption forecasting. *Expert Systems with Applications, 208*, Article 118115.

Du, P., Wang, J., Niu, T., & Yang, W. (2021). PM2.5 prediction and related health effects and economic cost assessments in 2020 and 2021: Case studies in Jing-Jin-Ji, China. *Knowledge-Based Systems*, 233, 107487.

Du, X., Wu, D., & Yan, Y. (2023). Prediction of electricity consumption based on GM(1, Nr) model in Jiangsu province. *China. Energy, 262*, Article 125439.

Duan, H., & Wang, G. (2023). Partial differential grey model based on control matrix and its application in short-term traffic flow prediction. *Applied Mathematical Modelling, 116*, 763–785.

Goncalves, C., Bessa, R. J., & Pinson, P. (2021). Privacy-Preserving Distributed Learning for Renewable Energy Forecasting. *IEEE Transactions on Sustainable Energy, 12*(3), 1777–1787.

Habiba, U., Xinbang, C., & Anwar, A. (2022). Do green technology innovations, financial development, and renewable energy use help to curb carbon emissions? *Renewable Energy, 193*, 1082–1093.

Heidari, H., & Zeng, B. (2023). An optimized grey transition Verhulst method. *Engineering Applications of Artificial Intelligence, 120*, Article 105870.

Herrera, G. P., Constantino, M., Su, J. J., & Naranpanawa, A. (2022). Renewable energy stocks forecast using Twitter investor sentiment and deep learning. *Energy Economics, 114*, Article 106285.

Hou, R., Li, S., Wu, M., Ren, G., Gao, W., Khayatnezhad, M., & Gholinia, F. (2021). Assessing of impact climate parameters on the gap between hydropower supply and electricity demand by RCPs scenarios and optimized ANN by the improved Pathfinder (IPF) algorithm. *Energy, 237*, Article 121621.

Hu, Y., & Man, Y. (2023). Energy consumption and carbon emissions forecasting for industrial processes: Status, challenges and perspectives. *Renewable & Sustainable Energy Reviews, 182*, Article 113405.

Huang, H., Tao, Z., Liu, J., Cheng, J., & Chen, H. (2021). Exploiting fractional accumulation and background value optimization in multivariate interval grey prediction model and its application. *Engineering Applications of Artificial Intelligence, 104*, Article 104360.

Jonas, D., Laemmle, M., Theis, D., Schneider, S., & Frey, G. (2019). Performance modeling of PVT collectors: Implementation, validation and parameter identification approach using TRNSYS. *Solar Energy, 193*, 51–64.

Kahvecioglu, G., Morton, D. P., & Wagner, M. J. (2022). Dispatch optimization of a concentrating solar power system under uncertain solar irradiance and energy prices. *Applied Energy, 326*, Article 119978.

Khan, Z. A., Hussain, T., & Baik, S. W. (2023). Dual stream network with attention mechanism for photovoltaic power forecasting. *Applied Energy, 338*, Article 120916.

Li, R., & Song, X. (2023). A multi-scale model with feature recognition for the use of energy futures price forecasting. *Expert Systems with Applications, 211*, Article 118622.

Liang, C., Umar, M., Ma, F., & Huynh, T. L. D. (2022). Climate policy uncertainty and world renewable energy index volatility forecasting. *Technological Forecasting and Social Change, 182*, Article 121810.

Lu, S. (2019). Integrating heuristic time series with modified grey forecasting for renewable energy in Taiwan. *Renewable Energy, 133*, 1436–1444.

Manuel, V. J., & Maldonado, S. (2020). SVR-FFS: A novel forward feature selection approach for high-frequency time series forecasting using support vector regression. *Expert Systems with Applications, 160*, Article 113729.

Mayer, M. J., & Yang, D. (2023). Calibration of deterministic NWP forecasts and its impact on verification. *International Journal of Forecasting, 39*(2), 981–991.

Mirjalili, S., & Lewis, A. (2016). The Whale Optimization Algorithm. *Advances in Engineering Software, 95*, 51–67.

NBS, Total primary energy production 2022 https://data.stats.gov.cn/easyquery.htm?cn=C01&zb=A070B&sj=2022.

NDRC, 2022. The 14th Five-Year Plan (FYP) on Renewable Energy Development (2021–2025). https://www.ndrc.gov.cn/xwdt/tzgg/202206/t20220601_1326720.html.

Qian, W., & Sui, A. (2021). A novel structural adaptive discrete grey prediction model and its application in forecasting renewable energy generation. *Expert Systems with Applications, 186*, Article 115761.

Rasool, S. F., Zaman, S., Jehan, N., Chin, T., Khan, S., & Zaman, Q. U. (2022). Investigating the role of the tech industry, renewable energy, and urbanization in sustainable environment: Policy directions in the context of developing economies. *Technological Forecasting and Social Change, 183*, Article 121935.

Ren, Y., Xia, L., & Wang, Y. (2023). Forecasting China's hydropower generation using a novel seasonal optimized multivariate grey model. *Technological Forecasting and Social Change, 194*, Article 122677.

Sharda, S., Singh, M., & Sharma, K. (2021). RSAM: Robust Self-Attention Based Multi-Horizon Model for Solar Irradiance Forecasting. *IEEE Transactions on Sustainable Energy, 12*(2), 1394–1405.

Somu, N., Raman, G. M. R., & Ramamritham, K. (2021). A deep learning framework for building energy consumption forecast. *Renewable & Sustainable Energy Reviews, 137*, Article 110591.

Wang, H., & Zhang, Z. (2022). Forecasting Chinese provincial carbon emissions using a novel grey prediction model considering spatial correlation. *Expert Systems with Applications, 209*, Article 118261.

Wang, J., Ma, F., Bouri, E., & Zhong, J. (2022). Volatility of clean energy and natural gas, uncertainty indices, and global economic conditions. *Energy Economics, 108*, Article 105904.

Wang, Y., Dang, Y., & Li, Y. (2010). An approach to increase prediction precision of GM (1,1) model based on optimization of the initial condition. *Expert Systems with Applications, 37*(8), 5640–5644.

Wang, Y., He, X., Zhang, L., Ma, X., Wu, W., Nie, R., Chi, P., & Zhang, Y. (2022). A novel fractional time-delayed grey Bernoulli forecasting model and its application for the energy production and consumption prediction. *Engineering Applications of Artificial Intelligence, 110*, Article 104683.

Wang, Y., & Si, Q. (2024). Forecasting Chinese carbon emission intensity based on the interactive effect GM(1, N) power model. *Grey Systems-Theory and Application, 14*(1), 21–48.

Wang, Y., Wang, L., Ye, L., Ma, X., Wu, W., Yang, Z., He, X., Zhang, L., Zhang, Y., Zhou, Y., & Luo, Y. (2022). A novel self-adaptive fractional multivariable grey model and its application in forecasting energy production and conversion of China. *Engineering Applications of Artificial Intelligence, 115*, Article 105319.

Wang, Z. (2017). A weighted non-linear grey Bernoulli model for forecasting non-linear economic time series with small data sets. *Economic Computation and Economic Cybernetics Studies and Research, 51*(1), 169–186.

Wang, Z., Li, Q., & Pei, L. (2018). A seasonal GM(1,1) model for forecasting the electricity consumption of the primary economic sectors. *Energy, 154*, 522–534.

Wang, Z., & Ye, D. (2017). Forecasting Chinese carbon emissions from fossil energy consumption using non-linear grey multivariable models. *Journal of Cleaner Production, 142*, 600–612.

Wei, Y., Wang, Z., Wang, H., & Li, Y. (2021). Compositional data techniques for forecasting dynamic change in China's energy consumption structure by 2020 and 2030. *Journal of Cleaner Production, 284*, Article 124702.

Xia, L., Ren, Y., & Wang, Y. (2023). Forecasting clean energy power generation in China based on a novel fractional discrete grey model with a dynamic time-delay function. *Journal of Cleaner Production, 416*, Article 137830.

Xie, N. (2022). A summary of grey forecasting models. *Grey Systems-Theory and Application, 12*(4), 703–722.

Xie, N., & Liu, S. (2009). Discrete grey forecasting model and its optimization. *Applied Mathematical Modelling, 33*(2), 1173–1186.

Xie, X., Liu, X., & Blanco, C. (2023). Evaluating and forecasting the niche fitness of regional innovation ecosystems: A comparative evaluation of different optimized grey models. *Technological Forecasting and Social Change, 191*, Article 122473.

Xing, L., Udemba, E. N., Tosun, M., Abdallah, I., & Boukhris, I. (2023). Sustainable development policies of renewable energy and technological innovation toward climate and sustainable development goals. *Sustainable Development, 31*(2), 1178–1192.

Xu, X., Niu, D., Xiao, B., Guo, X., Zhang, L., & Wang, K. (2020). Policy analysis for grid parity of wind power generation in China. *Energy Policy, 138*, Article 111225.

Yan, S., Su, Q., Gong, Z., & Zeng, X. (2022). Fractional order time-delay multivariable discrete grey model for short-term online public opinion prediction. *Expert Systems with Applications, 197*, Article 116691.

Yang, H., Jiang, P., Wang, Y., & Li, H. (2022). A fuzzy intelligent forecasting system based on combined fuzzification strategy and improved optimization algorithm for renewable energy power generation. *Applied Energy, 325*, Article 119849.

Zeng, B., Duan, H., & Zhou, Y. (2019). A new multivariable grey prediction model with structure compatibility. *Applied Mathematical Modelling, 75*, 385–397.

Zeng, B., He, C., Mao, C., & Wu, Y. (2023). Forecasting China's hydropower generation capacity using a novel grey combination optimization model. *Energy, 262*, Article 125341.

Zhang, M., Guo, H., Sun, M., Liu, S., & Forrest, J. (2022). A novel flexible grey multivariable model and its application in forecasting energy consumption in China. *Energy, 239*, Article 122441.

Zhang, R., Mao, S., & Kang, Y. (2023). A novel traffic flow prediction model: Variable order fractional grey model based on an improved grey evolution algorithm. *Expert Systems with Applications, 224*, Article 119943.

Zhang, Y., Li, S., Li, J., & Tang, X. (2022). A time power-based grey model with Caputo fractional derivative and its application to the prediction of renewable energy consumption. *Chaos Solitons & Fractals, 164*, Article 112750.

Zheng, J., Du, J., Wang, B., Klemes, J. J., Liao, Q., & Liang, Y. (2023). A hybrid framework for forecasting power generation of multiple renewable energy sources. *Renewable & Sustainable Energy Reviews, 172*, Article 113046.

Zhou, C., Shen, Y., Wu, H., & Wang, J. (2022). Using fractional discrete Verhulst model to forecast Fujian's electricity consumption in China. *Energy, 255*, Article 124484.

Zhu, X., Dang, Y., & Ding, S. (2021). Forecasting air quality in China using novel self-adaptive seasonal grey forecasting models. *Grey Systems-Theory and Application, 11*(4), 596–618.