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# Models for forecasting growth trends in renewable energy

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A B S T R A C T

The advantages of renewable energy are that it is low in pollution and sustainable. Energy shortages do not apply to renewable energy. In this study, we primarily forecast growth trends in renewable energy consumption in China. Renewable energy is an emerging technology, and thus this study comprises only 22 pieces of sample data. Because the historical data comprised a small sample and did not fit a normal distribution, big data analysis was not an appropriate prediction method. Therefore, we used three grey prediction models, the GM(1,1) model, the NGBM(1,1) model, and the grey Verhulst model, for theoretical derivation and scientific verification. The accuracy and fitness of the prediction models were compared using regression analysis. Regarding the three indicators of mean absolute error, mean squared error, mean absolute percentage error, this study's comparison of the forecast accuracy of the three grey prediction models and regression analysis indicated that NGMB(1,1) had the highest forecast accuracy, followed by the grey Verhulst model and the GM(1,1) model. Regression analysis exhibited the lowest results. In addition, this study confirmed that, for predictions that use small data samples, the modified grey NGBM(1,1) model and the grey Verhulst model had higher forecast accuracy than the original GM (1,1) model did. The models used in this study for forecasting renewable energy can be applied to predicting energy consumption in other countries, which affords insight into the global trend of energy development.



## 1. Introduction

Renewable energy refers to the use of natural environmental cycles to generate an infinite supply of energy that is nonpolluting [1,2]. Renewable energy includes solar energy, hydropower, wind energy, marine energy, geothermal energy, hydrogen power, and biomass energy. A number of people also call these "green energies" [3,4].

Renewable energy is sustainable and low in pollution and energy consumption. In addition, it is unaffected by energy shortages [4–6]. However, they are influenced by natural conditions—for example, hydraulic, wind, and solar power generation are all necessarily dependent on resource availability [7–9]. In addition, investment and maintenance costs are high, and efficiency is low. Therefore, the costs of power generation are high [10,11]. A number of scientists are seeking new technologies and methods for improving renewable energy. Renewable energy is certain to play an increasingly critical role as Earth's resources are depleted [11–13].

Renewable energy offers renewability and cleanliness as two advantages over conventional energy [14,15].

China surpassed the United States as the number one consumer of primary energy in 2010 and retained this position in both 2011 and 2012, truly becoming a major energy consumer. In 2012, annual growth in Chinese petroleum consumption was 5.3%, which was once again the highest increase in petroleum consumption globally. Chinese coal consumption also constituted 50.2% of global coal consumption in 2012; this marked the first time that China exceeded 50% of global coal consumption. China's primary energy consumption structure remains focused on coal. In 2012, coal was

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67.8% of China's primary energy consumption, followed by petroleum at 18.2% and natural gas at 4.8%. Renewable energy constituted 9.2% of Chinese energy consumption [16].

China is currently the world's second-largest economy, the top energy consumer, and the top emitter of greenhouse gases; however, its energy efficiency remains low. Because of increased global warming, the deterioration of the ecological environment, and shortages in conventional energy, the importance of developing renewable energy has achieved an international consensus. In response to environmental demands and the exhaustion of oil supplies, the development of renewable energy has become the core focus of China's energy policy [17].

On January 1, 2006, China passed the Renewable Energy Law. The purpose of this law is to promote the development and use of renewable energy, to increase the energy supply, to improve the energy structure, to ensure energy security, to protect the environment, and to realize sustainable economic and social development. Renewable energy refers to wind energy, solar energy, hydropower, biomass energy, geothermal energy, ocean energy, and other nonfossil energy sources [17,18].

In addition, China presented the Outline of the Twelfth Five-Year Plan for the National Economic and Social Development of the People's Republic of China. This plan proposed specific indicators for renewable energy: "We hope for renewable energy consumption to reach approximately 10% of total energy consumption by 2015 and 15% of total energy consumption by 2020." Therefore, forecasting the development trends in China's consumption of renewable energy has become a critical task. If the development trends in China's consumption of renewable energy could be predicted accurately, the development direction of renewable energy in China and even worldwide could be determined [17–20].

This study forecasted growth trends in the consumption of renewable energy in China. Because the historical data on renewable energy comprise a limited sample size and do not conform to a normal distribution, forecasting methods used in analyzing large data amounts (e.g., conventional regression analysis, neural networks, and genetic algorithms) are unsuitable.

Deng [21] proposed grey system theory, which is directed primarily at the uncertainties and incomplete information of system models. System relational analysis and model construction are performed. Prediction and decision-making methods are used to investigate and understand the condition of a system. Originally, grey system theory was primarily applied to the control field. It has since been developed for application in other fields including management decisions, socioeconomic research, and weather and water resource forecasting. It is a prediction model that uses quantitative analysis.

Grey system theory is applied primarily in system models with incomplete information, uncertain behavior patterns, and unclear operating mechanisms. It can be used for performing comprehensive analysis, observing system developments, and making long-term predictions. Its most useful feature is that a model can be established using only four pieces of data. In addition, the population distributions of the samples do not require numerous rigorous assumptions to be made. Numerous studies have shown that the GM(1,1) model has extremely high forecast accuracy with small data samples [22–25].

However, multiple studies have also indicated that, although the GM(1,1) model has high accuracy when the experimental sample data exhibits steady growth trends, if the sample data contain substantial fluctuations, the GM(1,1) model must be modified to improve its forecast accuracy. Examples of revised models include the modified nonlinear Bernoulli model and the modified Markov model [26–30].

In this study, we used the GM(1,1) model and two revised models, the nonlinear grey Bernoulli model and the grey Verhulst model, to improve the inadequate diversity of prior forecasting methods while simultaneously increasing forecast accuracy. Theoretical derivation and verification were performed using these three grey prediction models. The forecast accuracy of these models was also compared using regression analysis. Finally, we determined an optimal prediction method from the four prediction models.

## 2. Literature review

### 2.1. Development trends in global renewable energy

Along with the trend of environmental sustainability induced by the green revolution of the twenty-first century, the connection between environmental protection and industrial development has changed from contradictory to complementary. The renewable energy industry has become the economic mainstream in the twenty-first century regarding high oil prices and limited resources [14].

Even countries such as United Arab Emirates (UAE) and Russia, which have the most oil reserves worldwide, must use renewable energy. For instance, UAE generated more than 50% of its electricity from oil in 2011. In 2012, its solar power capacity was near zero. The King Abdullah City for Atomic and Renewable Energy project expects to reduce the 50% crude oil and natural gas that is currently used for its electricity supply by developing climate- and environment-friendly solar energy. According to governmental plans, more than 10% of its electric consumption or 5 GW of electricity by 2020 will be generated by solar energy. In 2014, the Minister of Petroleum and Mineral Resources reported in Paris that the goal of UAE was to become a global leader of solar power and wind power, expecting one day to export clean green energy instead of oil [14,15].

Clean Edge published the annual *Clean Energy Trends* report in March 2011, reporting developmental trends in global green energy. Growing 35.2% compared with 2009, the total global output value of major renewable energies such as biofuels, wind power, and solar energy reached $188.1 billion (30 times higher than in 2000) and is expected to reach $349.2 billion by 2020. In 2010, the global production of biofuels, wind power, and solar energy reached $ 56.4 billion, $60.5 billion, and $71.2 billion, respectively; by 2020, it is expected to reach $112.8 billion, $122.9 billion, and $113.6 billion (growth rates of 116%, 103%, and 60%), respectively. It is forecasted that the global renewable energy industry will prosper over the next twenty years [19,20].

### 2.2. Grey system theory

Jasemi and Kimiagari [31] stated that forecasting is estimating events or situations that an organization is unable to control in the future and providing managers with a foundation for planning. Therefore, forecasting is critical to the decision-making process [32–35].

The "grey" in grey theory is a combination of black and white, where black represents a complete lack of information and white represents complete information. Grey refers to incomplete information; in other words, information that is partially clear and partially unclear. In this study, the characteristics and structure of the system itself were explored. Information is supplied at appropriate times to allow the system to shift from grey to white. This prompted the development of grey theory. The real world contains numerous systems, which may contain multiple subsystems while simultaneously being enclosed by multiple subsystems. Because systems comprise complex and multileveled

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**Table 1**
Differences between grey theory, probability, and fuzzy theory.
Source: Deng [23].

| Item | Grey theory | Probability theory | Fuzzy theory |
|---|---|---|---|
| Content | Small-sample uncertainty | Large-sample uncertainty | Cognitive uncertainty |
| Foundation | Grey hazy sets | Cantor sets | Fuzzy sets |
| Basis | Information coverage | Probability distribution | Membership function |
| Method | Generation | Statistics | Boundary values |
| Feature | Few data | Plentiful data | Boundary values |
| Requirement | Arbitrary distributions allowed | Typical distribution required | Functions |
| Goal | Laws of reality | Historical statistical laws | Cognitive expression |
| Mode of thinking | Multiple perspectives | Reproducibility | Extended quantization |
| Information criterion | Minimal information | Unlimited information | Experience information |

subsystems, attaining a comprehensive understanding of a system is typically prevented by incomplete or uncertain information. A system that cannot be described in detailed is referred to as a “grey system” [36–42].

Grey theory can effectively process uncertainty, multiple inputs, discrete data, and incomplete data. Grey theory is used primarily to investigate small-sample uncertainty. It differs from probability statistics, which is used to investigate large-sample uncertainty, and fuzzy theory, which is applied to cognitive uncertainty [43–46].

Deng [23,47,48] organized the characteristics and applicability of grey theory, probability, and fuzzy theory (Table 1). Grey theory views all random variables as quantities of grey that change within a certain range and as grey processes related to time. The processing of the quantity of grey does not involve methods for determining statistical laws. Rather, disorganized raw data is processed before the inherent regularity of the data is determined. The processed sequence is converted into a differential equation to establish the grey model. This model is subsequently used for forecasting. This is referred to as “grey prediction” [49–51].

Deng [23] compiled grey prediction and multiple common conventional forecasting methods and compared the data, data patterns, data intervals, preparation times, and mathematical requirements (Table 2).

Studies on grey system theory can be divided into the following classes: (1) grey generating techniques, (2) grey relational analysis, (3) grey model construction, (4) grey prediction, (5) grey decision making, and (6) grey control [52–55].

(1) Grey generating

Grey generating is the collation of supplementary information. It is an approach for finding rules within numbers. Using grey generating can reveal the concealed laws and characteristics of disorganized data. In other words, grey generating can be used to reduce the randomness of data and to increase their regularity. The following are common generation methods:

(a) Accumulated Generation Operation (AGO): This method accumulates data within a series to obtain a new series and data. The series is called the original series before accumulation and the generated series after accumulation.
(b) Inverse Accumulated Generation Operation (IAGO): This refers to the difference between the first and last datum in a sequence. It is an inverse operation with accumulated generating.

(2) Grey relational analysis
This is a measurement method in grey system theory for analyzing the degree of correlation between discrete series.
(3) Grey model construction

In general, grey model construction can be divided into the following types:

(a) GM(1,1): This expresses a first-order differential with one input variable. It is generally used for prediction.
(b) GM(1,N): This expresses a first-order differential with N input variables. It is generally used for multivariate correlation analysis.
(c) GM(0,N): This is a special case of GM(1,N) that expresses a zero-order differential with N input variables. It is generally used for multivariate correlation analysis.

(4) Grey prediction
Grey prediction uses GM(1,1) as a foundation for predicting existing data. In reality, this model seeks the future dynamic conditions of elements within a series. The primary advantage of grey prediction is that it does not require substantial amounts of data and has a simple mathematical foundation.
(5) Grey decision making
Because different countermeasures for an event may produce different results, the decisions made by combining countermeasures and models are called grey decision making.
(6) Grey control
Implementing decisions is called “control.” Conventional control provides control after an event. In other words, the dynamic relationship between input and output data in a system with known behavioral characteristics is sought. These methods are unable to provide instant remedies and control. Grey control uses the data of a system's behavioral

**Table 2**
Comparison of grey prediction and conventional forecasting methods.
Source: Deng [23].

| Prediction model | Amount of data required | Data pattern | Data interval | Preparation time | Mathematical requirements |
|---|---|---|---|---|---|
| Grey prediction | 4 pieces | Equally spaced | Short, medium, or long interval | Short | Basic operations |
| Simple exponential | 5–10 pieces | Equally spaced | Short interval | Short | Basic operations |
| Holt's exponential | 10–15 pieces | Same trend | Short or medium interval | Short | Higher requirements |
| Winters' exponential | At least 5 pieces | Same trend with regularity | Short or medium interval | Short | Moderate |
| Regression analysis | At least 10–20 pieces | Same trend with regularity | Short or medium interval | Short | Moderate |
| Causal regression | At least 10 pieces | Same pattern with mutual complementation | Short, medium, or long interval | Long | Higher operations |
| Time series compression | At least 2 pieces | Same trend with regularity | Short or medium interval | Short | Basic operations |
| Box–Jenkins method | At least 50 pieces | Equally spaced | Short, medium, or long interval | Long | Higher operations |

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characteristics to determine the development laws of the system's behavior. Future behavior is then predicted. After obtaining predicted values, these values are fed back into the system for system control.

### 2.3. Grey prediction

Traditional probability and statistical methods use probability statistics to determine regularity. These methods are more capable of revealing the statistical properties of larger data amounts that satisfy certain distributions. By contrast, grey system theory assumes that the variables in any stochastic process are quantities of grey that change within a certain range and time. Therefore, stochastic processes are referred to as grey processes in grey systems. The simulation of grey processes involves using original series to produce clear exponential laws through AGOs. These laws are then used as the basis for establishing grey differential equations to fit new data. Therefore, the amount of data required is relatively small. Typically, a minimum of only four pieces of data is required. In addition, establishing the grey model does not require numerous strict assumptions to be made regarding the population distribution of the sample. Moreover, grey prediction models, such as GM(1,1) and GM(1,N), are continuous-time differential equations. Therefore, their use does not lead to the problems encountered when using intermittent equations [56–59].

Grey prediction can be applied to the following types of forecasting:

(3) Series forecasting
This is the most basic type of grey prediction. Based on a given series, the GM(1,1) model is established directly for forecasting. When a prediction model that was established using all the data in a given series is used for forecasting, this is referred to as full-series forecasting. Grey predictions generate numerical models through AGOs to predict the size of the next or next several values. This is a prediction of the developments in the eigenvalues of system behavior and is referred to as forecasting the changes in a system behavior data series or, more simply, series forecasting. It can be used for unemployment rate forecasting, economic growth forecasting, stock fluctuations, and forecasting economic indicators. It is the most commonly used prediction model.

(4) Disaster forecasting:
Predicting whether a disaster will occur within a certain period or when certain outliers will reappear is referred to as disaster forecasting. It predicts when system behavior eigenvalues will exceed a certain threshold and is used to forecast when outliers will reappear. For example, factory volume over a certain threshold is noise and substances over a certain threshold in the environment are pollution.

(5) Seasonal disaster forecasting:
This refers to forecasting the time distributions of disasters that occur at specific times each year by predicting seasonal changes. For example, frost appears in the winter and floods occur during the summer. Alternatively, the time distribution of the month in which cotton pests appear is predicted.

(6) Topology forecasting:
A known series is connected to form a graph. Intersecting data are sought from certain values on the curve. GM(1,1) is then used to predict the time they will appear in the future. The values that will occur in the future are then connected to form a curve to determine the future developments of the data curve. This is referred to as topology forecasting.

(7) System prediction:
The GM(1,1) and GM(1,N) models are combined to predict all the variables within a system, to find their dynamic relationships, and to create a dynamic chart of a system.

(8) GM(1,N) multiple factor analysis:
The grey prediction that uses GM(1,N) multiple factor analysis differs from system prediction in that it has only one behavior and multiple influencing factors, none of which may be diluted. In general, GM(1,N) is used only for system analysis and not for forecasting.

(9) Envelope prediction:
This is prediction of the upper (upper envelope) and lower (lower envelope) bounds of a data series. A portion of the data is derived from the boundary points of the original series. Other points are obtained through observation based on envelope rules.

(10) Grey relational prediction by analogy:
The index sequence of the research subjects is used as the reference series. After the subjects are categorized by analogy, several comparison series are made. Grey relational analysis is used to clarify which subject of the analogy has the greatest correlation with the investigated subject. The subject of analogy with the greatest correlation and the investigated subject are used to develop a variation model. The variations that occur in this model are used to predict developments in the investigated subject.

To solve a considerable number of practical problems in production, life, and scientific research, the range of applications of grey system theory has been expanded to numerous fields including industry, agriculture, economics, energy, transportation, oil, geology, water conservancy, meteorology, ecology, the environment, medicine, education, physical education, the military, law, and finance. Hu [44] used GM(1,1) to establish a prediction model to assist consumers who wish to purchase new cars in making optimal selections. Consumers need input only brand, price, safety, functionality, and fuel consumption to find the optimal choice. Wang [29] used an improved GM (1,1) model to forecast the number of tourists from Hong Kong, the United States, and Germany to travel to Taiwan between 1989 and 2000. The conclusion of the study indicated that the forecast accuracy of the improved GM(1,1) model was extremely high. In addition, because it does not require a large sample, it substantially reduces the cost and time required to collect data. Kayacan, Ulutas and Kaynak [60] used NGBM and the grey Markov model to forecast the USD–EUR exchange rate from 2005 to 2007, indicating that the model had high accuracy when the experimental sample data revealed a stable growth trend. Akay et al. [30] used various models to forecast electricity demand in Turkey and found that grey theory demonstrated optimal predictive capability. Lee, Wu, and Tsai [17] used grey system theory and fuzzy time series to predict trends in electrochromic materials, showing that the modified GM(1,1) model was an optimal prediction model for small samples of data.

The literature review indicates that grey prediction has the following advantages: (1) Grey prediction does not require large amounts of historical data. The size of the data is selected based only on actual circumstances and needs. In general, as long as at least four pieces of data are used, a prediction model can be established and forecasting can be performed. (2) Grey prediction does not require numerous related factors. Data is easy to acquire, substantially reducing the time and cost of collecting data. (3) The accuracy of grey prediction is high.

## 3. Methodology

### 3.1. GM(1,1) model

The amount of data for the GM(1,1) model can be as little as four pieces. Therefore, for any series with at least four pieces of data, rolling checks can be used to test the reliability of the prediction model. In addition, the residuals between the predicted and actual values reflect the reliability of the prediction model. Smaller residuals indicate higher reliability [22–25].

In this study, we addressed series prediction problems. Series prediction involves establishing a grey prediction model directly based on given data. The steps in the construction of the grey prediction model GM(1,1) are as follows:

(a) Define all of the data obtained as the original series:

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

(b) Perform one AGO to add together the established original series and obtain the following generated series:

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

$$x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i),\ k = 1, 2, 3 \ldots n \tag{3}$$

(c) Establish the GM(1,1) differential equation. This is a first-order differential equation with one variable, as follows, where $b$ is a constant term:

$$\frac{dX^{(1)}}{dt} + aX^{(1)} = b \tag{4}$$

The derivative definition reveals the following:

$$\frac{dX^{(1)}(t)}{dt} \cong \frac{X^{(1)}(k+\Delta t) - X^{(1)}}{\Delta t} \tag{5}$$

Take $\Delta t = 1$, leading to

$$\frac{dX^{(1)}(t)}{dt} \cong X^{(1)}(k+1) - X^{(1)}(k) = X^{(0)}(k) \tag{6}$$

Additionally, $X^{(1)} \cong Z^{(1)}$

$$Z^{(1)}(k) \cong \frac{X^{(1)}(k) + X^{1}(k+1)}{2},\ k = 2, 3, 4 \ldots, n \tag{7}$$

Using (Eqs. (4)–7), the following is obtained:

$$X^{(0)}(k) + aZ^{(1)} = b \tag{8}$$

(d) Use the least square method and differential and difference equations to obtain parameters $a$ and $b$, and let

$$\theta = \left[ a\ ,\ b\ \right]^{T} = (B^{T}B\ )^{-1}B^{T}Y\ ,\ Y = B\theta \tag{9}$$

$$Y = \left[ X^{(0)}(2), X^{(0)}(3).. ., X^{(0)}(n) \right]^{T} \tag{10}$$

$$B = \begin{bmatrix} -\frac{1}{2}[(X^{(1)}(1) + X^{(1)}(2)], & 1 \\ -\frac{1}{2}[(X^{(1)}(2) + X^{(1)}(3)], & 1 \\ \vdots & \\ -\frac{1}{2}[(X^{(1)}(n-1) + X^{(1)}(n)], & 1 \end{bmatrix} \tag{11}$$

(e) Use the grey differential equation to obtain the grey AGO equation as follows:

Next, use an inverse AGO (IAGO) for reduction to obtain the following demand model:

$$\hat{X}^{(1)}(k+1) = \left[ X^{(0)}(1) - \frac{b}{a} \right] e^{-ak} + \frac{b}{a},\ k = 1, 2, 3 \ldots, n \tag{12}$$

$$\hat{X}^{(0)}(k) = \left[ X^{(0)}(1) - \frac{b}{a} \right] (1-e^{a}) e^{-a(k-1)},\ k=1, 2, 3 \ldots n \tag{13}$$

GM(1,1) is a model used to make predictions in grey theory. It is expressed as a first differential and has a single input variable. Grey prediction uses the GM(1,1) model as a foundation for forecasting from existing data. It discovers the future dynamic conditions of multiple elements within a series. Its primary advantage is that it does not require a substantial amount of data and that the mathematical foundation is simple.

### 3.2. The NGBM(1,1) model

The NGBM model is an original prediction model derived by combining the GM(1,1) model with the basic differential Bernoulli equation [22–26].

GM(1,1) is a specific form of the NGBM prediction model. The NGBM formula is derived as follows:

(a) Define the obtained data as the original series. A new series is obtained after an AGO is used. The first three formulae of the NGBM model are exactly the same as (Eqs. (1)–3) of the GM (1,1) model.

(b) Next, the NGBM formulae begin to differ from those of GM (1,1). Use the Bernoulli equation to establish the NGBM differential equation:

$$\frac{dX^{(1)}}{dt} + aX^{(1)} = b\left[ X^{(1)} \right]^{r} \tag{14}$$

Substitute GM(1,1) (Eqs. (4)–7) into Eq. (18) to obtain the following NGBM difference equation:

$$X^{(0)}(k) + aX^{(1)}(k) = b\left[ Z^{(1)}(k) \right]^{r},\ k=2, 3, 4 \ldots n \tag{15}$$

(c) Use the least squares method with the NGBM differential and difference equations to obtain $a$ and $b$:

$$\text{Let } \theta = \left[ a, b \right]^{T} = (B^{T}B)^{-1}B^{T}Y,\ Y = B\theta \tag{16}$$

$$Y = \left[ X^{(0)}(2), X^{(0)}(3).. ., X^{(0)}(n) \right]^{T} \tag{17}$$

$$B = \begin{bmatrix} -\frac{1}{2}\left[ X^{(1)}(1) + X^{(1)}(2) \right] & \left\{ -\frac{1}{2}\left[ X^{(1)}(1) + X^{(1)}(2) \right] \right\}^{r} \\ -\frac{1}{2}\left[ X^{(1)}(2) + X^{(1)}(3) \right] & \left\{ -\frac{1}{2}\left[ X^{(1)}(1) + X^{(1)}(2) \right] \right\}^{r} \\ \vdots & \vdots \\ -\frac{1}{2}\left[ X^{(1)}(n-1) + X^{(1)}(n) \right] & \left\{ -\frac{1}{2}\left[ X^{(1)}(n-1) + X^{(1)}n \right] \right\}^{r} \end{bmatrix} \tag{18}$$

(d) Use the grey differential equation to obtain the grey accumulation equation:

$$\hat{X}^{(1)}(k+1) = \left[ \left[ X^{(0)}(1)^{(1-r)} - \frac{u}{a} \right]^{e^{-a(1-r)k}} + \frac{b}{a} \right]^{\left(\frac{1}{1-r}\right)},\ k=1, 2, 3 \ldots n \tag{19}$$

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(e) Reduce Eq. (19) by using the IAGO to obtain the demand model:

$$\hat{X}^{(0)}(k) = \hat{X}^{(1)}(k) - \hat{X}^{(1)}(k-1),\ k=1,\ 2,\ 3\ldots,n \tag{20}$$

Not only does the NGBM model retain the simple derivation process of the GM(1,1) and require only four pieces of data for modeling, it simultaneously reduces the prediction errors of the GM(1,1) prediction model and increases its forecast accuracy for nonlinear data types.

### 3.3. Grey Verhulst model

The grey Verhulst model has the same characteristics as the GM (1,1) model. It primarily adds a restriction to the GM(1,1) model [29].

The grey Verhulst model is derived as follows:

(a) First, define the obtained data as the original series. A new series is obtained after an AGO is used. The first three formulae of the grey Verhulst model are exactly the same as (Eqs. (1)–3) of the GM(1,1) model.

(b) Establish the differential and difference models of the grey Verhulst model:

The grey Verhulst differential equation is defined as follows:

$$\frac{dX^{(1)}}{dt} + aX^{(1)} = B\left[X^{(1)}\right]^2 \tag{21}$$

The grey Verhulst difference equation is obtained by substituting GM(1,1) (Eqs. (4)–7) into Eq. (21) to obtain the NGBM differential equation, as follows:

$$X^{(0)}(k) + aX^{(1)}(k) = b\left[Z^{(1)}(k)\right]^2,\ k=2,\ 3,\ 4\ldots n \tag{22}$$

(c) Use the least squares method with the grey Verhulst differential and difference equations to obtain $a$ and $b$:

$$\text{Make } \theta = \left[a\ ,\ b\right]^T = (B^TB)^{-1}B^TY,\ Y = B\theta \tag{23}$$

$$Y = \left[X^{(0)}(2),\ X^{(0)}(3)\ldots,\ X^{(0)}(n)\right]^T \tag{24}$$

$$\begin{bmatrix} -\frac{1}{2}\left[X^{(1)}(1) + X^{(1)}(2)\right] & \left\{-\frac{1}{2}\left[X^{(1)}(1) + X^{(1)}(2)\right]\right\}^2 \\ -\frac{1}{2}\left[X^{(1)}(2) + X^{(1)}(3)\right] & \left\{-\frac{1}{2}\left[X^{(1)}(1) + X^{(1)}(2)\right]\right\}^2 \\ \vdots & \vdots \\ -\frac{1}{2}\left[X^{(1)}(n-1) + Y^{(1)}(n)\right] & \left\{-\frac{1}{2}\left[X^{(1)}(n-1) + X^{(1)}n\right]\right\}^2 \end{bmatrix} \tag{25}$$

(d) Use the grey differential equation to obtain the grey accumulation equation:

$$\hat{X}^{(1)}(k+1) = \left[\left[X^{(0)}(1)^{(-1)} - \frac{b}{a}\right]^{e^{ak}} + \frac{b}{a}\right]^{(-1)},\ k=2,\ 3,\ 4\ldots n \tag{26}$$

(e) Reduce Eq. (26) by using the IAGO to obtain the demand model:

$$\hat{X}^{(0)}(k) = \hat{X}^{(1)}(k) - \hat{X}^{(1)}(k-1),\ k=1,\ 2,\ 3\ldots,n \tag{27}$$

The grey Verhulst model adds one restriction to the GM(1,1) model to reduce forecast error in the prediction model and increase forecast accuracy for nonlinear data types.

### 3.4. Forecast accuracy measurement

The estimated difference between an actual value and the predicted value obtained using a prediction model is considered a prediction error. As a judgment method, determining the prediction error indicates the success of a forecasting model. In this study, we adopted the three most indicative measurement models —mean absolute error (MAE), mean squared error (MSE), and mean absolute percentage error (MAP)—to measure the accuracy of the forecasting models [16,22,61].

The various types of error are defined as follows:

(1) Lower MAE indicates more satisfactory predictive ability.

$$MAE = \frac{\sum |e|}{n} \tag{28}$$

(2) Lower MSE indicates more satisfactory predictive ability.

$$MSE = \frac{\sum e^2}{n-1} \tag{29}$$

(3) Lower MAPE indicates more satisfactory predictive ability.

$$MAPE = \frac{\sum \left|\frac{e}{a}\right|}{n} * 100\%\ a = actual\ value \tag{30}$$

Lower error indicates higher accuracy. According to Lewis [62], MAPE values below 10% indicate predictions with high forecast accuracy (Table 3).

## 4. Results and discussion

### 4.1. Background information

China's energy requirements have increased rapidly in recent years. China now consumes more energy and produces more greenhouse gas emissions than any other country. However, China's energy efficiency remains low. Following trends in environmental regulations and depleting petroleum reserves, the development of renewable energy has become the core focus of Chinese energy policy. In 2006, China implemented the Renewable Energy Law. In 2007, China's National Development and Reform Commission published the Mid- and Long-Term Development Plan for Renewable Energy. In 2012, China presented the Twelfth Five-Year Plan for the National Economic and Social Development of the People's Republic of China. This plan presented specific indicators for renewable energy: “Make full use of economical renewable energy sources with mature technology, such as hydropower, biogas, and solar thermal and geothermal energy. Accelerate the industrial development of wind power, biomass power, and solar power. Gradually increase the ratio of clean and high-quality renewable energy in the energy structure. Strive to increase consumption of renewable energy to approximately 10% of total energy consumption by 2015 and approximately 15% of total energy consumption by 2020.”

After numerous years of development, the proportion of China's primary energy consumption that comprises renewable energy consumption has increased annually. In this study, we collected 22 pieces of data. Renewable energy consumption in China was 4.8% in 1991, 6.1% in 1995, 7.5% in 2001, 6.7% in 2006, 8.6% in 2010, and 9.2% in 2012 (Table 4).

### 4.2. GM(1,1) results

The GM(1,1) model was established using four pieces of data.

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**Table 3**
MAPE forecasting accuracy reference criteria.

| Range of MAPE | Forecasting accuracy |
|---|---|
| ≦10% | High |
| 10–20% | Good |
| 20–50% | Feasible |
| ≥ 50% | Low |

MATLAB was used for calculations related to Eqs. (1)–(13) to obtain predicted values. Out of overall energy consumption, renewable energy consumption was predicted to be 5.3% in 1995, 7.1% in 2001, 7.4% in 2006, 8.4% in 2010, and 9.1% in 2012. Table 5 shows additional details. The predicted values were 9.4% in 2013, 9.6% in 2014, and 10.1% in 2015.

Excel was used for (Eqs. (28)–30) to calculate the forecast accuracy indicators of the GM(1,1) model, yielding a MAE of 0.394%, an MSE of 0.244%, and a MAPE of 5.855%. Table 6 shows additional details.

### 4.3. NGBM(1,1) results

MATLAB was used to apply the NGBM(1,1) model to the calculations. (Eqs. (14)–20) were then used to obtain the predicted values. Out of overall consumption, renewable energy consumption was predicted to be 5.6% in 1995, 7.3% in 2001, 7.4% in 2006, 8.5% in 2010, and 9.1% in 2012. Table 5 shows additional details. The predicted values were 9.5% in 2013, 9.8% in 2014, and 10.3% in 2015.

Excel was then used for (Eqs. (28)–30) to calculate the forecast accuracy indicators of the NGBM(1,1) model, yielding a MAE of 0.333%, an MSE of 0.186%, and a MAPE of 4.893%. Table 6 shows additional details.

### 4.4. Grey Verhulst model results

MATLAB was used to apply the grey Verhulst model to the calculations. (Eqs. (21)–27) were then used to obtain the predicted values. Out of overall energy consumption, renewable energy consumption was predicted to be 5.6% in 1995, 7.4% in 2001, 7.5% in 2006, 8.5% in 2010, and 9.2% in 2012. Table 5 shows additional details. The predicted values were 9.6% in 2013, 9.8% in 2014, and 10.4% in 2015.

Excel was then used for (Eqs. (28)–30) to calculate the forecast accuracy indicators of the grey Verhulst model, yielding a MAE of 0.372%, an MSE of 0.245%, and a MAPE of 5.476%. Table 6 shows additional details.

### 4.5. Regression analysis results

With the data from 1991 to 2012 (Table 4), Minitab was used to establish a regression analysis model and a scatter plot. Table 5 and Fig. 1 show the detailed data. The R2 and Adj R2 of this model were both 1.0. The predicted values were 8.5% in 2013, 8.7% in 2014, and 8.8% in 2015.

The regression equation can be written as follows:

**Table 5**
Predicted values (%) from the four forecasting models.

| Year | Percentage of renewable energy consumption (%) | GM(1,1) predicted values | NGBM(1,1) predicted values | Grey Verhulst predicted values | Regression analysis predicted values |
|---|---|---|---|---|---|
| 1991 | 4.8 | | | | |
| 1992 | 4.9 | | | | |
| 1993 | 5.2 | | | | |
| 1994 | 5.7 | | | | |
| 1995 | 6.1 | 5.3 | 5.6 | 5.6 | 5.7 |
| 1996 | 6.0 | 5.4 | 5.6 | 5.7 | 5.9 |
| 1997 | 6.4 | 5.9 | 6.2 | 6.3 | 6.0 |
| 1998 | 6.5 | 6.2 | 6.5 | 6.6 | 6.2 |
| 1999 | 5.9 | 6.1 | 6.2 | 6.3 | 6.3 |
| 2000 | 6.4 | 6.5 | 6.6 | 6.7 | 6.5 |
| 2001 | 7.5 | 7.1 | 7.3 | 7.4 | 6.6 |
| 2002 | 7.3 | 7.5 | 7.5 | 7.6 | 6.8 |
| 2003 | 7.5 | 7.6 | 7.5 | 7.5 | 6.9 |
| 2004 | 6.7 | 7.6 | 7.6 | 7.8 | 7.1 |
| 2005 | 6.8 | 7.7 | 7.6 | 7.7 | 7.3 |
| 2006 | 6.7 | 7.4 | 7.4 | 7.5 | 7.4 |
| 2007 | 6.8 | 7.3 | 7.2 | 7.3 | 7.6 |
| 2008 | 7.7 | 7.8 | 7.9 | 8.0 | 7.7 |
| 2009 | 7.8 | 8.0 | 8.1 | 8.1 | 7.9 |
| 2010 | 8.6 | 8.4 | 8.5 | 8.5 | 8.0 |
| 2011 | 8.0 | 8.3 | 8.5 | 8.6 | 8.2 |
| 2012 | 9.2 | 9.1 | 9.1 | 9.2 | 8.3 |
| 2013 | | 9.4 | 9.5 | 9.6 | 8.5 |
| 2014 | | 9.6 | 9.8 | 9.8 | 8.7 |
| 2015 | | 10.1 | 10.3 | 10.4 | 8.8 |

**Table 6**
Forecast accuracy indicators for the four forecasting models.

| Forecasting model accuracy indicator | GM(1,1) | NGBM(1,1) | Grey Verhulst | Regression analysis |
|---|---|---|---|---|
| MAE | 0.394 | 0.333 | 0.372 | 0.430 |
| MSE | 0.244 | 0.186 | 0.245 | 0.265 |
| MAPE% | 5.855 | 4.893 | 5.476 | 6.026 |

$$y = 0.1553x - 304.12$$

Excel was then used for (Eqs. (28)–30) to calculate the forecast accuracy indicators of the regression analysis model, yielding a MAE of 0.430%, an MSE of 0.265%, and a MAPE of 6.026%. Table 6 shows additional details.

### 4.6. Discussion

Comparing the three grey prediction models according to the MAE, MSE, and MAPE indicators, NGBM(1,1) had the highest forecast accuracy, followed by the grey Verhulst model and the GM(1,1) model. Of the three revised grey prediction models, we determined that the NGBM(1,1) model and the grey Verhulst model had more accurate predictive capability than the original GM(1,1) model did.

As classified by Lewis [62], MAPE values lower than 10% indicate high forecast accuracy. The NGBM(1,1) model, the grey Verhulst model, and the GM(1,1) model had MAPE values of 4.893%, 5.476%, and 5.855%, respectively. These three grey

**Table 4**
Percentage of renewable energy consumption out of overall energy consumption in China.

| Year | 1991 | 1992 | 1993 | 1994 | 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| % | 4.8 | 4.9 | 5.2 | 5.7 | 6.1 | 6.0 | 6.4 | 6.5 | 5.9 | 6.4 | 7.5 |
| Year | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 |
| % | 7.3 | 7.5 | 6.7 | 6.8 | 6.7 | 6.8 | 7.7 | 7.8 | 8.6 | 8.0 | 9.2 |

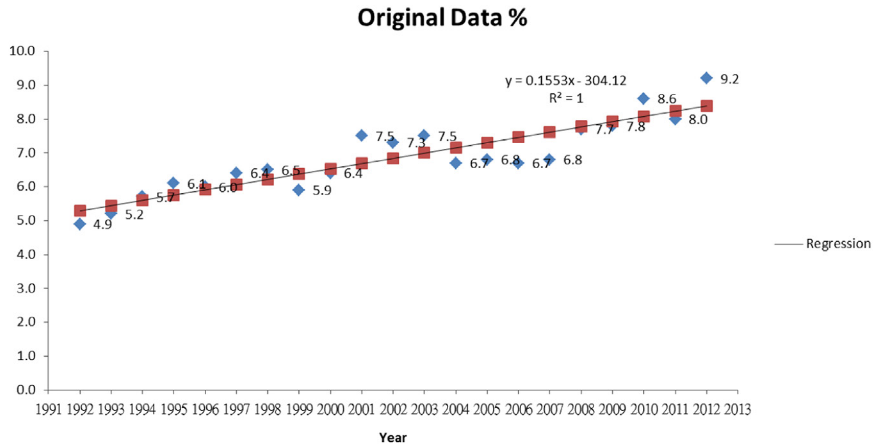


**Fig. 1.** Regression analysis and scatter diagram.

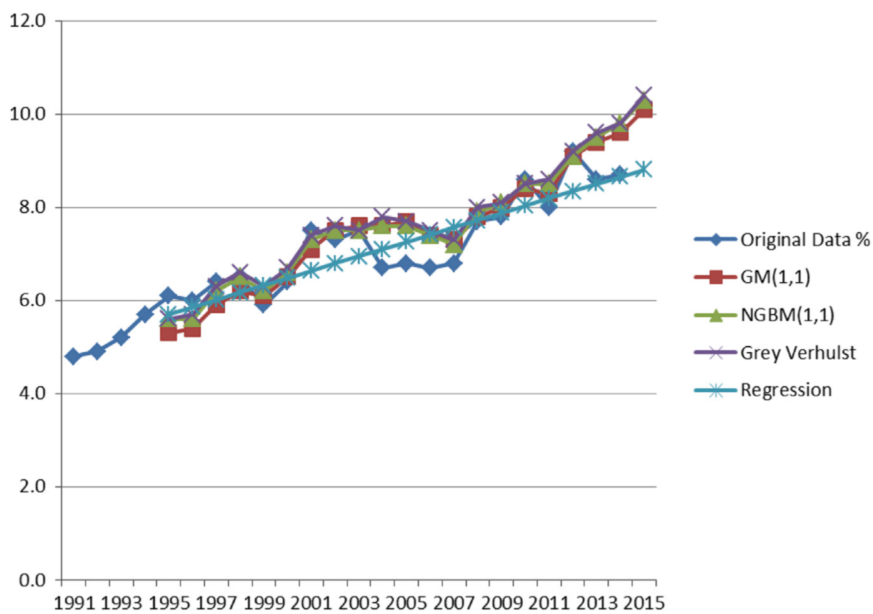


**Fig. 2.** Comparison of the four prediction models.

prediction models all had high forecast accuracy.

We compared the forecast accuracy of the three grey prediction models and regression analysis. Based on MAE, MSE, and MAPE, the three grey prediction models had more accurate predictive capability than did regression analysis or the weighted moving average method.

Fig. 2 shows a comparison of the predicted values of the four models and the original, actual values. The NGBM(1,1) model had the highest forecast accuracy, followed by the grey Verhulst model and the GM(1,1) model. Regression analysis had the lowest results.

## 5. Conclusion

Renewable energy refers to inexhaustible energy produced from the natural environment that does not pollute the environment. In recent years, the energy demand in China has skyrocketed. China has become the top energy consumer and emitter of greenhouse gases worldwide, and its energy efficiency remains low. In response to environmental demands and the exhaustion of oil supplies, developing renewable energy has become the primary focus of China's energy policy.

This study primarily forecasts growth trends in renewable energy consumption in China. Renewable energy is an emerging technology. This study used only 22 pieces of data; because the historical data comprised a small sample and lacked a normal distribution, big data analysis prediction methods were not appropriate. The lack of breadth and diversity of earlier prediction methods was improved. The original GM(1,1) model and two revised models, the nonlinear grey Bernoulli model and the grey Verhulst model, were used for theoretical derivation and confirmation. Finally, the advantages and disadvantages of using these methods with small samples of data were determined by comparing them with regression analysis. Four prediction methods were used for forecasting in this study. The optimal prediction method among the four prediction models was determined.

A comparison of the forecast accuracy of the three grey prediction models and regression analysis according to the MAE, MSE, and MPE indicators showed that the NGBM(1,1) model had the highest forecast accuracy, followed by the grey Verhulst model, the GM(1,1) model, and regression analysis.

This study also confirmed that, when making predictions by using small samples of data, the modified grey NGBM(1,1) model and the grey Verhulst model had higher forecast accuracy than the GM(1,1) model did.

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We forecast that China's renewable energy consumption will be approximately 10.1–10.4% of its overall primary energy consumption by 2015. Growth in renewable energy consumption has already exhibited preliminary results. However, based on this growth rate, reaching the official target of 15% by 2020 will require further effort.

The models used in this study for forecasting renewable energy can be applied to predicting energy consumption in other countries, which affords insight into the global trend of energy development.

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