Assessment and prediction of environmental sustainability: Novel grey models based comparative analysis of China vs. USA

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Abstract

Emission forecasting is vital for policy-making and emission reduction goals. This research aimed to perform an accurate model for forecasting and assessing CO_2 emissions and the production of renewable electricity for the top two countries contributing to these emissions, the USA and China. In this study, we employe three novel advanced mathematical grey models: Optimized Discrete Grey Model (ODGM), Nonhomogeneous Discrete Grey Model (NDGM), and Variable Speed and Adaptive Structure Grey Model (VSSGM) to estimate the future trends of CO_2 emissions and renewable electricity production . These breakthrough models added value in this field of research by reducing uncertainty surrounding ambiguity and numerical ranges, and improving accuracy in assessments by using small samples and imperfect information. The findings show that by 2026, China's electricity production by renewable sources will be higher than that of the USA. We find CO_2 emissions in a downward trend with more significant reductions in the USA than in China by the year 2026. The contributions of this study are the application of novel VSSGM and the use of synthetic relative growth rate modeling for predicting the overall growth of CO_2 emissions and the production of renewable electricity in analyzed countries. The originality of this study lies in proposing a novel synthetic doubling time model to compute how long it will take, for China and the USA, to reduce their CO_2 emissions and doubling their increase in renewable electricity production.

Keywords: Environmental sustainability; prediction; Carbon Emissions; Renewable Energy; Emission Forecasting; Grey Models

Highlights

- The modeling in this study improves our ability to predict energy and emissions between the two largest countries contributing to GHG emissions.
- Synthetic relative growth rate modeling predicts the overall growth of CO_2 emissions and the production of renewable electricity.
- Use of a novel synthetic doubling time model to compute how long it will take for China and the USA to reduce CO_2 emissions.
- By 2026, China's electricity production by renewable sources will be higher than that of the USA.

1. INTRODUCTION

A global increase in the rate of carbon dioxide (CO_2) emissions caused by increased industrialization and heightened generation of electricity through non-renewable energy sources, is in turn, accelerating global warming (Ko et al. 2017). It appears that high CO_2 emitting countries may only be concerned with expanding their economies while, at the same time, experiencing growth in population, and this comes at the expense of environmental

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sustainability. Actions need to be taken, especially by high CO_2 emitting countries, in order to reduce waste in the form of CO_2 emissions, and the subsequent effects of global warming (Paramati et al., 2017a; Shahbaz et al., 2016). A major cause of CO_2 emissions is the expansion of the agriculture sector as it meets the needs of an increasing population, increasing greenhouses (GHGs). These GHGs are notorious in producing detrimental impacts on the environment, and whose major component is CO_2 in sum with other gases normalized to a CO_2 equivalent (Rouholamini et al., 2019; Yildiz and Karan, 2020). As proposed by the Kyoto Protocol framework, annual reductions of these greenhouse gases annually are necessary to try and head off a 2^0C increase in global temperature to meet the required goals to help stop climate changes (Özdingiş, Bayrakçı and Koçar, 2018; Chen and Nie, 2020; Shahbaz et al., 2019). Another primary source of CO_2 is deforestation and the overconsumption of fossil fuels from increased industrialization. Over the last two decades, global warming and the increased threat of climate change have reached alarming levels worldwide (Sato, 2016; Shahbaz et al., 2019a). The International Energy Outlook Report estimates a growth rate of approximately 7.6% of CO_2 to hit 43.2B metric tons by the year 2040, up from 35.6B metric tons in the year 2020 (Zhang et al., 2015; Dogan et al., 2020).

A critical need for more research and modeling of emissions and energy production is noticed, to enable decision making for practitioners and new research opportunities. Scholars have approached their research using qualitative and quantitative methodologies for predicting emissions and renewable energy production. In this study, an empirical investigation is conducted aiming to test models and future impacts. This modeling approach was choose in part to verify if it could be confirmed or disputed prior arguments while using advanced Optimized Discrete Grey Model - ODGM, Nonhomogeneous Discrete Grey Model - NDGM, and Variable Speed and Adaptive Structure Grey Model – VSSGM, to forecast renewable electricity production and CO_2 emissions (Xie et al., 2015). All three models provide an opportunity to increase forecasting accuracy over prior modeling not able to accurately describe results given the features of a small sample size data and proposed estimation methods, which require detailed information of various socioeconomic scenarios (Knüppel, 2014; Mazzeu et al., 2018). Therefore, new contributions from this study include the ability to handle this complexity as the production activities and the standards of living at the country level were integrated in this modeling (Weron 2014).

Due to rapid acceleration of economic development, energy consumption is growing, specially in fast growing countries such as China, resulted in higher rates of CO_2 and GHGs emissions. In this scenario, various framwework and approaches have been used to predict CO_2 emissions with excellent outcomes. These frameworks and approaches considered the use of Artificial Intelligence, spatial econometrics, series analysis, to name a few (García-Martos et al., 2013; Chen and Yang, 2015; Sun et al., 2017). Large samples are used in such methods and, to reduce the uncertainty, data needs to be in accordance with statistical assumptions (Feng et al. 2014). The GM (1,1) and GM (1,N) models were commonly used to estimate the CO_2 emissions, since both models are characterized as 'grey models'. In the research of Li et al. (2020) it is found the application of nonlinear grey model named 'Bernoulli NGBM (1,1), and was applied for forecasting CO_2 emissions by China. Then, these authors proposed a more accurate iterative numerical method in order to optimize used parameters. On the other hand, in the research of Wu et al. (2015), CO_2 emissions were forecasted in the context of BRICS countries by the application of a multivariable grey model that considered the growth of Gross Domestic Product (GDP) in such countries, in adition to energy consumption.

Another intent to forecast CO_2 emissions in China is seen in Ding et al. (2017). The authors used another grey model that was integrated with an optimization algorithm and considering data from fuel combustion, GDP, the urban population, and energy consumption. In the same thematic of CO_2 emissions forecasting, Wang and Li. (2019) tested a nonlinear grey model based on multivariables based on fossil fuel-based energy consumption and GDP.

The China's National Bureau Statistics (NBS) stated that, in 2017, from the total energy consumption increased 2.9% if compared with 2016. It represents an incease of 4.36 gigatons (Yang & Shi 2017). China's is aiming to reduce the energy-intensive consumption (which is measured as energy consumption per unit of GDP) is 3.4%, with a reduction of 3.7% in 2017, and the share of coal in total energy consumption declined by 1.7 % (Enerdata 2017). While the gas, hydropower, nuclear and wind energy increased by 1.5% in 2017 and the electricity consumption increased by 6.6%, as announced by the Chinese National Energy Administration (NEA) in 2017, there was a 5.5% growth in industrial power consumption. The installed power generation capacity of the country grew by 137 GW to above 1,800 GW; during the year, nearly 13 GW of hydropower capacity and nearly 46 GW of thermal capacity were installed (Agency 2017). In the USA, from all types of energy, about 82% came from fossil fuels sources (Meschi & Norheim-Hansen 2020). Moreover, the largest USA's sources of energy in 2014 came from petroleum (35%) and by natural gas (28%), followed by coal (18%), nuclear power (8%). Renewable sources contributed to only 10% of these energy sources (Rahman et al., 2017; Shahbaz et al., 2019c).

Considering the aforementioned context, this research aims to develop an accurate model for CO_2 emissions and use of renewable electricity forecasting. The model was tested using data from top two CO_2 emitters, the USA and China, through the application of the ODGM, NDGM and VSSGM grey modeling. These models are useful for this study as it helps to minimize uncertainty, ambiguity, and data bias. The application of this model eliminates uncertainty and bias by offering more in-depth analyses of renewable energies and emissions. Outcomes of this study provide prospective trends in the amount of electricity generation and CO_2 in order to help policymakers in decisions making regarding the future expected outcomes. The methodology is empirical and relying on available data. The reliability of the outcomes of this study are supported by the application of information from relevant authorities, namely weather and climate scientists, governments, and researchers in this field.

Additional insights and contributions came from the Relative Growth Rate (RGR) application, by doubling time (D_t) modeling and performance criteria methods to estimate future generation of renewable electricity and CO_2 emission proposed by Javed and Liu (2018) and successfully utilized by Ikram et al. (2019). The methodology suggested for this study is a breakthrough in forecasting the generation of renewable electricity energy and emissions. This validated method is applicable due to the significant value it can add to renewable sources and CO_2 emissions forecasting studies.

Beyond this introduction, this paper study is structured as follows. The second section discusses the development steps of ODGM, NDGM, and VSSGM models. Section 3 represents the results with discussion and contributions to the field, and finally, conclusions are presented in the last section.

2. Research framework and Method

The electricity and CO_2 emission data are retrieved from the official website of International Energy Statistics (EIA). China and USA were considered, in the period of 2000 up to 2016, as highest countries in CO_2 emission and consuming electricity from renewable energy sources. A mathematical modeling using a Grey forecasting model is proposed as it is an effective advanced modeling for forecasting and its accurancy is assessed by the use of public available data (Zhao, Wang, Zhao, & Su, 2012; Ikram et al., 2019). The ODGM, NDGM, and VSSGM are proven approaches for application to small data sets and are, therefore, useful tools for using in the context of this study (Ma & Liu 2017). The research framewok and approach structure on China and USA renewable electricity production and CO_2 emission prediction is presented in Figure 1

Insert Figure 1 about here

2.1 Optimized Discrete Grey Model (ODGM)

Five steps operationalize the ODGM forecasting model and are now discussed in sufficient detail to help other researchers replicate this approach.

Step 1: The model testing starts with description of the optimized discrete grey model, based on mathematical modeling adopted to optimize the discrete grey model. This optimization comprised of objective functions. The advantage of grey forecasting models to show high accuracy for uncertain data system and incomplete information, and design of the variables in the forecast (Ma & Liu 2016). Then, CO_2 emission and renewable electricity production data was used from 2000-2016 total amount emission as original sequence during development of ODGM model (see equation 1).

$$Z^{(0)} = \{z^{(0)}(1), z^{(0)}(2), \ldots, z^{(0)}(m)\} \tag{1}$$

Step 2: The minimum orthogonal array level is developed in second step of ODGM model construction, while taking into account to consider the inner array variables. Further, a repitative trail approach is needed for outer arrey of variables to make a refine assense performance of function through fluctuations of the function. A acquired sequence of operations can be drawn see the equation 5.

$$Z^{(1)} = \{z^{(1)}(1), z^{(2)}(2), \ldots\ldots z^{(1)}(n)\} \tag{2}$$

Taking this part a step futher, which involves the transformation of carbon emission and renewable electricity production sequences presented by $Z^{(1)}$, can be written as follows

$$z^{(1)}(l) = \sum_{i=1}^{l} z^{(0)}(i), \quad l = 1,2,\ldots,\mathrm{m} \tag{3}$$

Step 3: With the help of equation 3, the coefficient of relation is calculated to develop ODGM which based on accumulated weights of relation coefficient and vlue of prediction sequence. The prior studies confirm the construction of prediction model the coefficient weight is derived from principal component analysis of variable function. If Carbon emission and electricity generation by renewable sources is a parameter series $\hat{\beta} = (\beta_1, \beta_2)^T$. Then the following equation can be written.

$$B = \begin{bmatrix} z^{(1)}(1) & 1 \\ z^{(1)}(2) & 1 \\ \vdots & \vdots \\ z^{(1)}(m-1) & 1 \end{bmatrix}$$

$$z^{(1)}(l+1)=\beta_1 z^{(1)}(l)+\beta_2, \quad l=1,2,\ldots,\mathrm{m}-1 \tag{4}$$

A least square method is applied to copute the ODGM series parameters which can be seen in equation 5 and further the formula of $\hat{\beta}$ is presented in Equation 6:

$$z^{(1)}(l+1)=\beta_1 z^{(1)}(l)+\beta_2, \quad l=1,2,\ldots,\mathrm{m}-1 \tag{5}$$

$$\hat{\beta}=(\beta_1,\beta_2)^T=(B^T B)^{-1}B^T Z \tag{6}$$

By taking the transpose of matrix B indicate by B^T in equation 6 the value of datum iteration is not consider equal to value of $z^{(1)}(1)$ so far. To differaniate between both iteration sequences $\hat{z}^{(1)}(1)$ and $z^{(1)}(1)$, a modification is required in β_3 and can be written as $\hat{z}^{(1)}(1)=z^{(1)}(1)+\beta_3$. By aking least square method taking into consideration , which assist to solve the complexity of β_3 by using unconstrained optimized method is as follows:

$$\min_{\beta_3}\sum_{m}^{l=1}[\hat{z}^{(1)}(l)-z^{(1)}(l)]^2 \tag{7}$$

Step 4: Simulated/forecasting values $z^{(1)}(L+1)$ and $z^{(0)}(L+1)$ represents the vlaue of prediction/ simulation function and can be written can as follows:

$$\hat{z}^{(1)}(l+1)=\beta_1^l(\hat{z}^{(1)}(1)+\beta_3)+\frac{1-\beta_1^l}{1-\beta_1}\cdot\beta_2, \quad l=1,2,\ldots,\mathrm{m}-1 \tag{8}$$

$$\hat{z}^{(0)}(l+1)=\hat{z}^{(1)}(l+1)-\hat{y}^{(1)}(l)=\left(\beta_1^l-\beta_1^{l-1}\right)\left(\hat{y}^{(1)}(1)+\beta_3-\frac{\beta_2}{1-\beta_1}\right), \quad l=1,2,\ldots,\mathrm{m}-1 \tag{9}$$

In addition

$\left\{\hat{z}^{(0)}(1),\hat{z}^{(0)}(2),\ldots,\hat{z}^{(0)}(m)\right\}$ presented the simulation values, whereas

$\left\{\hat{z}^{(0)}(m+1),\hat{z}^{(0)}(m+2),\ldots,\hat{z}^{(0)}(m+n)\right\}$, indicated the values of prediction operating sequence.

Step 5: The final step involves the validation and performance accuracy of ODGM model by using the most adaptable approach namely Mean Absolute Percentage Error (MAPE %) have been widely used in previous studies (Ikram et al. 2020) .

2.2 Nonhomogeneous Discrete Gey Model (NDGM)

The NDGM system is based on non-homogenous exponential growth approximation law in order to comply with the assumptions of an actual data sequence.

Wu et al. (2014) recommended that the real data sequence competes with a homogeneous pattern, such as GM (1, 1). The accuracy of the NDGM model is significantly improved over the other grey models as far as the mean sequence value, and the value of the intervals are concerned. NDGM model has been used in various disciplines, such as predicting Turkey's electricity consumption and analyzing the NDGM is best fit and predicting more accurately than other grey predicting models. Moreover, Duan et al. (2018) predicted the consumption of crude oil in China and analyzed that the NDGM showed superior performance.

In the model of NDGM, $z^{(0)}$ denotes the original data sequence and $z^{(1)}$ represents the accumulated sequence of data. So, it is written as follows:

$$\hat{z}^{(1)}(l+1)=\beta_1\hat{z}^{(1)}(l)+\beta_2 . l+\beta_3 \tag{10}$$

$$\hat{z}^{(1)}(1)=z^{(1)}(1)+\beta_4 \tag{11}$$

$\hat{z}^{(1)}(l)$, represents the predicted value of $z^{(1)}$ along with their parameters β_1,β_2,β_3 and β_4. So, the above equation is presented in the matrix form as below, where L=1, 2, and 3….m-1:

$$\begin{bmatrix} z^{(1)}(2) \\ z^{(1)}(3) \\ \vdots \\ z^{(1)}(m) \end{bmatrix} = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \end{bmatrix} \begin{bmatrix} z^{(1)}(1) & 1 & 1 \\ z^{(1)}(2) & 2 & 1 \\ \vdots & \vdots & \vdots \\ z^{(1)}(m-1) & m-1 & 1 \end{bmatrix}$$

The input data in a single case indicates a constant sequence for the NDGM parameters β1, β2, β3, and β4. So, by applying this relation in equation (3), we get it as:

$$\hat{\beta} = (B^{\mathrm{T}}B)^{-1}B^{\mathrm{T}}Z = [\beta_1, \beta_2, \beta_3]^{\mathrm{T}} \tag{12}$$

Whereas,

$$B = \begin{bmatrix} z^{(1)}(1) & 1 & 1 \\ z^{(1)}(2) & 2 & 1 \\ \vdots & \vdots & \vdots \\ z^{(1)}(m-1) & m-1 & 1 \end{bmatrix} Y = \begin{bmatrix} z^{(1)}(2) \\ z^{(1)}(3) \\ \vdots \\ z^{(1)}(m) \end{bmatrix},$$

Further, in order to calculate β4, the following formula is being used where we minimize the sum of square error as:

$$\beta_4 = \frac{\sum_{l=1}^{m-1}\left[z^{(1)}(l+1)-\beta_1^l z^{(1)}(1)-\beta_2\sum_{j=1}^{l} j\beta_1^{l-j}-\frac{1-\beta_1^l}{1-\beta_1}.\beta_3\right].\beta_1^l}{1-\sum_{l=1}^{m-1}\left(\beta_1^l\right)^2} \quad (13)$$

$$\hat{z}^{(1)}(L+1)=\beta_1^l\,\hat{z}^{(1)}(1)+\beta_2\sum_{j=1}^{l} j\beta_1^{l-j}+\frac{1-\beta_1^l}{1-\beta_1}\cdot\beta_3;\quad l=1,2,\ldots,m-1 \quad (14)$$

For the additional knowledge of the NDGM model, its parameter and properties are suggested (Liu & Yang 2017).

2.3 Variable Speed and Adaptive Structure Grey Model (VSSGM)

The VSSGM model was proposed by Li et al., (2020a). This is first application of VSSGM model employed to forecast the future trends of CO2 emissions and renewanable electricy production of two high emetting countries China and the USA. We have compare VSSGM model with other two novel forecasting models namely ODGM and NDGM. This section explains how the VSSGM model is developed and how it gives better accuracy over other forecasting models. The construction of VSSGM model is comprises on four steps.

Step I: Let suppose $Z^{(0)}$ is a non-negative sequence of raw data, can be written as $Z^{(0)} = z^{(0)}(1), z^{(0)}(2),\ldots, z^{(0)}(m))$, with

α called the sequential operator in which the opearion function is satisfying and can be presented as $Z^{(1)} = z^{(1)}(1), z^{(1)}(2),\ldots, z^{(1)}(m))$, whereas, $z^{(1)}(l)=\sum_{j=1}^{l} z^{(0)}(j), l=1,2,\ldots,m.$ According to definition of sequential operator α is known as first-order accumulating generation operator and presented by (1-AGO). If AGO accumulating α is

applied n times on raw data sequence which is $Z^{(0)}$, then we can write the equation like $Z^{(0)}\alpha^n = Z^{(n)} = (z^{(n)}(1), z^{(n)}(2),\ldots z^{(n)}(m))$, where $z^{(l)}=\sum_{j=1}^{l} z^{(n-1)}(j), l=1,2,\ldots,m.$ Further, the AGO is used inversely which is called inverse AGO, can be be presented as $\beta^{(n)}z^{(0)}(l)=\alpha^{(n-1)}z^{(0)}(l)-\alpha^{(n-1)}z^{(0)}(l-1).$ Moreover, the β is also

known as AGO in above equation. To make the grey model more effective the randomness of accumulating generation operation of raw sequence data can be attenuated. Conversely, inverse AGO is mirror of the inverse process of the accumulating generation operation, and which has important sifnificance role in regression of AGO (Li et al. 2020c).

Step II: Let suppose $Z^{(1)}$ is a non-negative eequence of raw data same as mentioned in step I. Afterw, $Z^{(0)}$ newly generated raw data sequence is determined, can be written as $Z^{(1)} = z^{(1)}(1), z^{(1)}(2),\ldots, z^{(1)}(m))$, in which $z^{(1)}(i)=0.5*[z^{(1)}(i)+z^{(1)}(l-1)], l=2,3,\ldots m,$ Whereas, consecutive adjacent elements generated a new data sequence called even generation sequence represented by $Z^{(1)}$ in the (1-AGO) data sequence indicated by $Y^{(1)}$.

Step 3: If $Z^{(0)}, Z^{(1)}$ and $Y^{(1)}$ are derieved from steps I and II. Then, the equation can be written as follows:

$$z^{(0)}(k) + az^{(1)}(k) = b_1 k^3 + b_2 k^2 + b_3 k + b_4, k \in \mathrm{Z}, k \geq 2 \tag{15}$$

$z^{(0)}(k) = a_0 p^k \rightarrow$ without perturbation

$z^{(0)}(k) = a_0 p^k + a_1 \rightarrow$ with constant perturbation term

$z^{(0)}(k) = a_0 p^k + a_2 k + a_1 \rightarrow$ with perturbations of constant and velocity

$z^{(0)}(k) = a_0 p^k + a_3 k^2 + a_2 k + a_1 \rightarrow$ with disruption of constant, velocity and acceleration

The above equations are based on grey based system theory and this can be called a grey forecasting model with variable speed and structureMoreover, the development index is presented by -a. Whereas, $b_i (l = 1, 2, 3, 4)$ is known as grey actuating quantit $a_{0,} a_{1,} a_{2,} a_3$ and p has the constants value, which can be expresses $a_0 \neq 0, p > 0.$ We can say this is improved and extended form of basic grey forecasting model of GM (1,1) model having the additional accuracy features $b_1 k^3, b_2 k^2$ and $b_3 k$ to the actual constant term presented by b_4. Further, by applying the alterable structuring process in order to obtained a different combimation of altering sequences and which is characterized as follows $b_1 k^3, b_2 k^2, b_3 k$ and b_4. There is a significant feature of VSSGM model, in which homogeneous exponential sequence and approximate nonhomogeneous exponential sequence with velocity acceleration and constact term can be simulated simentaneouly. Moreover, there is an other superior advantage of VSSGM it can change the forecasting structuring accorinf to data nature if $b_1 = 0$, VSSGM can be simulated and downgrade itself as a grey model with velocity and constant tem only, which makes the VSSGM model more superior over other forecasting models.

Step IV: If $Z^{(0)}, Z^{(1)}$ and $X^{(1)}$ are exterted and treated as same like in step 3 then $\hat{a} = (a, b_1, b_2, b_3, b_4)$ is called the estimated parameter vector is presented as follows:

$$Y = \begin{bmatrix} z^{(0)}(2) \\ z^{(0)}(3) \\ \ldots\ldots \\ z^{(0)}(m) \end{bmatrix}, B = \begin{bmatrix} -z^{(1)}(2) & 2^3 & 2^2 & 2 & 1 \\ -z^{(1)}(3) & 3^3 & 3^2 & 3 & 1 \\ & & & & \\ -z^{(1)}(m) & m^3 & m^2 & m & 1 \end{bmatrix}$$

Which implies, the least square estimation of the VSSGM model is satisfies and can be written as follows:

$$\hat{a} = (a, b_1, b_2, b_3, b_4)^T = (B^T B)^{-1} B^T Y. \tag{16}$$

Step V. In the final step of VSSGM construction, $\hat{z}^{(1)}(t)$ dessribes the time response sequence and $\hat{z}^{(0)}(t)$ express the regressive reduction sequence which obtained from the Eq.(7) and cannot be utlized for forecasting operation directly.

First there is need to deduct the the time response sequence written as $\hat{Z}^{(1)}=\{\hat{z}^{(1)}(k),k\in \bullet\ ,k\geq 1\}$ and regressive reduction corresponding sequence $\hat{Z}^{(0)}=\{\hat{z}^{(0)}(k),k\in \bullet\ ,k\geq 1\}$. According to estimation parameters $\hat{a}=(a,b_1,b_2,b_3,b_4)^T$, sequence of time response $\hat{z}^{(1)}(k)$ and the reductive regressive sequence which is $\hat{z}^{(0)}(k)$ can be written as follows:

$$\begin{cases}\hat{z}^{(1)}(k)=m^{k-1}\hat{z}^{(1)}(1)+n\sum_{j=1}^{4}b_j\sum_{l=2}^{k}m^{k-l}i^{4-j},k\in \bullet\ ,k\geq 2,\\ \hat{z}^{(1)}(1)=z^{(1)}(1);\end{cases} \tag{17}$$

and

$$\begin{cases}\hat{z}^{(0)}(k)=\hat{z}^{(1)}(k)-\hat{z}^{(1)}(k-1),k\in \bullet\ ,k\geq 2,\\ \hat{z}^{(0)}(1)=z^{(0)}(1).\end{cases} \tag{18}$$

Where $m=\dfrac{1-0.5a}{1+0.5a},n=\dfrac{1}{1+0.5a}$ and $\hat{a}=(a,b_1,b_2,b_3,b_4)^T$ is estimated.

When k = 1, the conclusion can be drawn. If k = 2, it can be written as

$$\hat{z}^{(1)}(2)=m\hat{z}^{(1)}(1)+n(b_1 2^3+b_2 2^2+b_3 2+b_4) \tag{19}$$

$$=m^{2-1}\hat{z}^{(1)}(1)+n\sum_{j=1}^{4}b_j\sum_{i=2}^{2}m^{2-i}i^{4-j} \tag{20}$$

(2) when if the the conclusion is correct in any contionsand when $k=p\in \bullet$ and p>2, then the following sequence of equation can be drawn:

$$\hat{z}^{(1)}(p)=m^{p-1}\hat{z}^{(1)}(1)+n\sum_{j=1}^{4}b_j\sum_{l=2}^{p}m^{p-l}l^{4-j} \tag{21}$$

When if k = p + 1, can be presented as follows:

$$\hat{z}^{(1)}(p+1)=m\hat{z}^{(1)}(p)+n(b_1(p+1)^3+b_2(p+1)^2+b_3(p+1)+b_4) \tag{22}$$

$$=m\left(m^{p-1}\hat{z}^{(1)}(1)+n\sum_{j=1}^{4}b_j\sum_{l=2}^{p}m^{p-l}l^{4-j}b_j\right)+n(b_1(p+1)^3+b_2(p+1)^2+b_3(p+1)+b_4) \tag{23}$$

$$= m^{p}\hat{z}^{(1)}(1) + n\left(b_{1}\sum_{l=2}^{p} m^{p+1-l} l^{3} + b_{2}\sum_{i=2}^{p} m^{p+1-l} l^{2} + b_{3}\sum_{l=2}^{p} m^{p+1-l} l \;\; + b_{4}\sum_{l=2}^{p} m^{p+1-l} \right)$$
$$+ n(b_{1}(p+1)^{3} + b_{2}(p+1)^{2} + b_{3}(p+1) + b_{4}) \quad (24)$$

$$= m^{p}\hat{z}^{(1)}(1) + n\left(b_{1}\sum_{l=2}^{p+1} m^{p+1-l} l^{3} + b_{2}\sum_{l=2}^{p+1} m^{p+1-l} l^{2} + b_{3}\sum_{l=2}^{p+1} m^{p+1-l} l \;\; + b_{4}\sum_{l=2}^{p+1} m^{p+1-l} \right) \quad (25)$$

$$= m^{p}\hat{z}^{(1)}(1) + n\sum_{j=1}^{4} b_{j}\sum_{l=2}^{p+1} m^{p+1-l} l^{4-j} \quad (26)$$

Therefore, $\hat{Z}(1)$ is the time response sequence. Whereas, $\hat{Z}(0)$ is the regressive reduction sequence and established automatically because it is deduced by $\hat{X}(1)$, as shown in Figure 2.

Insert Figure 2 about here

After successful step-by-step development of all the three grey prediction models based on their properties and structure, it is noticed that the VSSGM model showed to be more then a prediction model. VSSGM model allows the unification of traditional grey prediction model with the homogeneous/non-homogenous exponential model and single variable linear autoregressive model. We employed three novel grey models to predict the renewable electricity production and CO_2 emission for China and the USA. MAPE % method is used to check the performance accuracy, of all the three predicting model, which has widely used in several studies (Ikram et al., 2020; Javed and Liu, 2018), by measuring ODGM, NDGM and VSSGM criteria between CO_2 and production of renewable electricity and can be written as follows:

$$MAPE(\%) = \frac{1}{m}\sum_{m}^{k=1}\left| \frac{z^{(0)}(k) - \hat{z}^{(0)}(k)}{z^{(0)}(k)} \right| \quad (27)$$

Here $z^{(0)}(k)$ and $\hat{z}^{(0)}(k)$ in equation (27) are expressing a model based on the original sequence and forecasted sequence data values. MAPE represents the performance criteria for comparative analysis between three grey models (Kim & Kim 2016). This study adopted the three novel grey forecasting models to estimate estimating the CO_2 emissions and production of electricity production in 2026, is considered for the USA and China. Moreover, comparison criteria of MAPE % accuracy level is presented in table 1.

Table 1: Accuracy level of MAP %

MAPE %	Forecasting accuracy
Higherr than 50 %	Poor prediction accuracy
20–50 %	Moderate
10–20 %	Good
Lower than 10%	Highly accuracy level

Source: (Lewis 1982).

2.4 The growth of electricity production, CO_2 emissions and doubling time analysis

There is no model that considers both CO_2 emissions and renewable electricity generation for monitoring growth rate. For example, the RGR model was applied to analyze the USA and China CO_2 emissions and electricity production relative growth. Then, the literature underlined the need for considering relative growth rate and doubling time models, applied in ISO 14001 certification and research output growth over time (Ikram et al., 2019; Javed and Liu, 2018).

Using the NDGM method, two parameters (D_t and RGR) were used to forecast GHGs emissions in five major sectors of Pakistan. The RGR formula is given by:

$$\mathrm{RGR} = (\ln N_2 - \ln N_1)/(t_2 - t_1) \tag{28}$$

Where N_2 depicts cumulative electricity production and CO_2 emissions in the year t_2 & t_1 signifies CO_2 emissions in the year t_1. In the analysis, as $t_2 - t_1$ is one year, equation (7) can be interpreted as equation (8).

$$\mathrm{RGR} = \ln(N_2/N_1) \tag{29}$$

Although doubling time (D_t) depicts the time required to reduce CO_2 emissions double in numbers concerning specified RGR. So, the (D_t) is presented as:

$$D_{\mathrm{t}} = (t_2 - t_1)\ln[2/(\ln N_2 - \ln N_1)] \tag{30}$$

We can also rewrite this equation as follows:

$$D_{\mathrm{t}} = \ln[2/(\ln N_2 - \ln N_1)] \tag{31}$$

If the RGR and Doubling Time (Dt) gives a different pattern for actual and simulated data, in any case, the synthetic RGR ($\mathrm{RGR_{syn}}$) and Synthetic Doubling Time ($\mathrm{D_{syn}}$) models have been introduced to jump into the conclusion for further accuracy. The synthetic Relative Growth Rate ($\mathrm{RGR_{syn}}$) model is characterized in the following equation as:

$$\mathrm{D_{syn}} = \theta(\mathrm{D_a}) + (1-\theta)(D_{\mathrm{f}}) \tag{32}$$

Whereas, $\mathrm{RGR_a}$ is a Relative Growth Rate of actual values of data. While $\mathrm{RGR_f}$ depicts forecasted values of the Relative Growth Rate. However, θ represents the relative weights coefficient, and is considered to be 0.5.

The Synthetic Doubling Time ($\mathrm{D_{syn}}$) model is shown below in equation (12)

$$D_{syn} = \theta(D_a) + (1-\theta)(D_f) \tag{33}$$

Where, D_a signifies the Doubling Time acquired from actual values, whereas RGR_f represents the Relative Growth Rate of forecasted values.

3. Results and Discussion

This research tested three novel grey models (ODGM, NDGM, and VSSGM) for forecasting the electricity generated by renewable sources and CO_2 emissions by comparing USA and China data out to 2026. These tests used an available dataset comprising the period of 2002-2016. Simulations used the mathematical grey forecasting models for assessing values presented in Tables 7, 8, 9 and 10. According to the ODGM model, China's electricity production by renewable sources has increased from 3.056 to 534.5311 (Billion Kwh) for the period 2000 to 2016. Meanwhile, in the case of China, NDGM calculated that electricity production by renewable sources has also shown an increasing trend from 3.056 to 509.07727 (Billion Kwh) in the same period. Whereas, the VSSGM simulation model values showed interesting results (Table 7) and represents the results for China's electricity production for the period of 2000 to 2016.

The result revealed that China's electricity production by renewable sources has increased from 3.056 to 391.5979 (Billion Kwh) for the period 2000 to 2016. It has observed in our analysis, VSSGM contains the smaller simulative errors than other models, as shown in Table 7. By comparison, it is found that the VSSGM has the best prediction performance over ODGM and NDGM models. Further, China's electricity forecasting values obtained from 2017 to 2026 by the three prediction models are presented in Table 7. Less gap was observed between forecasting values of ODGM (5751.89433; Billion Kwh) and NDGM (5477.9946; Billion Kwh) on 2026 can be seen in Figure 3. Whereas, the VSSGM forecasting value recorded for China's electricity production by renewable sources in 2026 is 4213.842; Billion Kwh). As shown in Table 7, VSSGM has a smaller predictive error value in %, which is (7.42 %) followed by NDGM (9.75%) and ODGM (12.67%), respectively.

Insert Figure 3 about here

Moreover, CO_2 emission showed an increasing trend at the same time present in Figure 4. In China's CO_2 emission values calculated by ODGM, NDM, and VSSGM is presented in Table 9. According to the ODGM model, China's CO_2 has increased from 3523.15 to 14056.49 (mm tons) for the period 2000 to 2016. Meanwhile, in NDGM simulation, CO_2 emission value for China also showed an increasing trend from 3523.15 to 13387.13571 (mm tons) at the same period of time. Whereas, the VSSGM model calculated the simulation values for China's CO_2 emission from 3523.15 to 11066.34 for the period of 2000 to 2016. For any given random sequence X5, VSSGM has (2.54%) simulative errors than ODGM (2.83%) NDGM (3.97%), as shown in Table 9. By comparison, it is found that VSSGM and ODGM have the best prediction performance.

Insert Figure 4 about here

Further, China's CO_2 emission forecasting values obtained from 2017 to 2026 by three prediction models are presented in Table 9. All the three prediction models showed the inclined forecasting trends of China's CO_2 emission. There is a slightly less difference observed between forecasting values of China CO_2 emission obtained by ODGM (17551.99 mm tons) and NDGM (16716.18 mm tons) on 2026. Whereas, the VSSGM forecasting value recorded for China's electricity production by renewable sources in 2026 is (12858.6 mm tons). As shown in Figure 4, VSSGM has shown better prediction performance than NDGM and ODGM.

Firstly, ODGM, NDGM and VSSGM models are used by taking first seventeen original data sequences into consideration for prediction results (k = 1; 2; : : : ; 17). Taking this to astep further, ODGM, NDGM and VSSGM, the were utilized to commpute the 10 years prediction result such as (k = 18; 12; 13; 14; 15: : :26). All the three models simulattion and forecasting performances were assesed and comparatively analyzed. The modeling procedure is given, followed by the analysis and prediction among these models.

The first 17 numbers of $Z(1)$ based on the 1-AGO $Z^{(1)}(1)$ are analyzed, whereas the mean sequence $Z^{(1)}(1)$ for different models, estimating parameters are shown in Table 2.

Table 2: Homogeneous exponential sequence X1 parameters

Model	Exponential Sequence	Parameters	Models structuring
NDGM	homogeneous	$\hat{\beta}_1 = (1.7, 1.63)^T$	$\hat{z}^{(1)}(k+1) = 1.7z^{(1)}(k) + 1.63$
ODGM	homogeneous	$\hat{\beta}_2 = (1.7, 0.0, 1.63, 0.0)^T$	$\hat{z}^{(1)}(k+1) = 1.7z^{(1)}(k) + +0.0k + 1.63, \hat{z}^{(1)}(1) = z^{(1)} + 0.0$
VSSGM	homogeneous	$a_3 = (-0.61143, 0.0, 0.0, 0.0, 1.1542)^T$	$\hat{z}^{(0)}(k) - 0.61143z^{(1)}(k) = 0.0k^{(3)} + 0.0k^{(2)} + 0.0k + 1.1542$

The first 17 numbers of X2 based on the 1-AGO $X^{(1)}(2)$ is analyzed. Table 3 presented the whereas the mean sequence $Z^{(1)}(2)$ for ODGM, NDGM and VSSGM, and estimating parameter can be seen in Table 3. Whereas all the three models simulative values, forecasting values and the relative corresponding error values are presented in Table 8.

Table 3: Nonhomogeneous exponential sequence X2 with constant term parameters

Model	Exponential Sequence	Parameters	Models structuring
NDGM	non-homogeneous	$\hat{\beta}_1=(1.7779,1-0.72994)^T$	$\hat{z}^{(1)}(k+1)=1.7779z^{(1)}(k)-0.72994$
ODGM	non-homogeneous	$\hat{\beta}_2=(1.8,-1.40,4.10,0.0)^T$	$\hat{z}^{(1)}(k+1)=1.8z^{(1)}(k)-1.40k+4.10, \hat{z}^{(1)}(1)=z^{(1)}$
VSSGM	non-homogeneous	$a_3=(-0.72997,0.0,0.0,-0.89810,4.0511)^T$	$\hat{z}^{(0)}(k)-0.72997z^{(1)}(k)=0.0k^{(3)}+0.0k^{(2)}-0.89810k+4.0511$

The first 17 numbers of X3 based on the 1-AGO $X^{(1)}(3)$ are analyzed, whereas the mean sequence $Z^{(1)}(3)$ for ODGM, NDGM, and VSSGM models, and estimating parameters are presented in Table 4. Whereas all the three models simulative values, forecasting values and the relative corresponding error values can been seen in Figure 10.

Table: 4 Nonhomogeneous exponential sequence X3 parametrs with velocity and constant terms

Model	Exponential Sequence	Parameters	Models structuring
NDGM	non-homogeneous	$\hat{\beta}_1=(1.9745,-2.9854)^T$	$\hat{z}^{(1)}(k+1)=1.9745z^{(1)}(k)-2.9854$
ODGM	non-homogeneous	$\hat{\beta}_2=(2.5584,-2.995,8.0121,-0.4152)^T$	$\hat{z}^{(1)}(k+1)=2.5584z^{(1)}(k)-2.9950k+8.0121, \hat{z}^{(1)}(1)=z^{(1)}-0.4152$
VSSGM	non-homogeneous	$a_3=(-0.71254,0.0,-0.16247,-0.39152,4.2395)^T$	$\hat{z}^{(0)}(k)-0.71254z^{(1)}(k)=0.0k^{(3)}-0.16247k^{(2)}-0.39152k+4.2395$

Insert Figure 10 about here

Similarly, like result presente 4 the first 17 numbers of X4 based on the 1-AGO $X^{(1)}(4)$ is analyzed, whereas the mean sequence $Z^{(1)}(4)$ for ODGM, NDGM, and VSSGM models, and estimating parameters are presented in Table 5. Meanwhile, the simulatation and forecasting trends are presented in Figure 7.

Table 5: Nonhomogeneous exponential sequence X4 parameters with acceleration, velocity, and constant terms

Model	Exponential Sequence	Parameters	Models structuring

NDGM	non-homogeneous	$\hat{\beta}_1 = (1.425, -9.8542)^T$	$\hat{z}^{(1)}(k+1) = 1.425z^{(1)}(k) - 9.8542$
ODGM	non-homogeneous	$\hat{\beta}_2 = (1.1235, 2.6145, 6.0152, -0.02541)^T$	$\hat{z}^{(1)}(k+1) = 1.12235z^{(1)}(k) + 2.6145k + 6.0152, \hat{z}^{(1)}(1) = z^{(1)} - 0.02541$
VSSGM	non-homogeneous	$a_3 = (-0.3, -0.07, 0.0, 2.01, 3.12)^T$	$\hat{z}^{(0)}(k) - 0.3z^{(1)}(k) = -0.07k^{(3)} + 0.0k^{(2)} + 2.01k + 3.12$

Insert Figure 7 about here

Finally, the first 17 numbers of X5 based on the 1-AGO $X^{(1)}(5)$ are analyzed, whereas the mean sequence $Z^{(1)}(5)$ for ODGM, NDGM, and VSSGM models, and estimating parameters are presented in Table 6. Meanwhile, all the three models simulation and forecasting values and the relative corresponding error values are presented in tables 7 to 10.

Insert Figure 8 about here

Table 6: Random number sequence X5 parameters

Model	Exponential Sequence	Parameters	Models structuring
NDGM	non-homogeneous	$\hat{\beta}_1 = (1.077538, -41.96)^T$	$\hat{z}^{(1)}(k+1) = 1.077538z^{(1)}(k) - 41.96$
ODGM	non-homogeneous	$\hat{\beta}_2 = (1.00165, 19.5416, 26.2541, 0.16904)^T$	$\hat{z}^{(1)}(k+1) = 1.00165z^{(1)}(k) + 19.5416k + 26.2541, \hat{z}^{(1)}(1) = z^{(1)} + 0.16904$
VSSGM	non-homogeneous	$a_3 = (0.21254, -0.087164, 1.5977, 8.4239, 22.854)^T$	$\hat{z}^{(0)}(k) + 0.21254z^{(1)}(k) = -0.087164k^{(3)} + 1.5977k^{(2)} + 8.4239k + 22.854$

According to VSSGM simulation model values, exciting results can be found in Table 8 and represent the results for USA electricity production for the period of 2000 to 2016 on the basis of the original data. Results revealed that USA electricity production by renewable sources has increased from 81.012 to 379.2908 (Billion Kwh) for the period 2000 to 2016. NDGM calculated that electricity production by renewable sources has also shown the increasing trend from 81.012 to 493.07804 (Billion Kwh) in the same period. Whereas, ODGM model values showed that USA electricity production by renewable sources has increased from 81.012 to 517.731942 (Billion Kwh) for the period 2000 to 2016.

Meanwhile, in the case of the USA, NDGM and ODGM have more significant simulation error than VSSGM model as shown in Figure 5. Moreover, it is found that the VSSGM is better predictor if compared with ODGM and

NDGM. Further, USA electricity forecasting values obtained from 2017 to 2026 by three prediction models are presented in Table 8. The less gap was observed between forecasting values of ODGM (1950.74197 Billion Kwh) and NDGM (1857.8495 Billion Kwh) in 2026. Whereas, the VSSGM forecasting value recorded for USA electricity production by renewable sources in 2026 is 1429.115 Billion Kwh). As shown in Table 8, VSSGM has a smaller predictive error value, which is (6.57 %) followed by NDGM (8.54%) and ODGM (11.10%), respectively.

Insert Figure 5 about here

Moreover, USA CO_2 emission showed a decreasing trend at the same time present in Figure 6. In the USA, CO_2 emission values calculated by ODGM, NDM, and VSSGM is presented in Table 10. VSSGM model simulation values have observed the declining trend for USA CO_2 emission from 8034.64834 to 4944.509 (mm tons) considering 2000 up to 2016. Meanwhile, the ODGM model identified that CO_2 emissions by the USA have decreased from 8034.64834 to 6749.254785 (mm tons) for the same period.

Insert Figure 6 about here

Similarly, NDGM simulation CO_2 emission value for the USA also showed an increasing trend from 8034.64834 to 5832.5483 (mm tons) at the same period. Interestingly in the USA CO_2 simulations case, VSSGM showed better performance with smaller simulation errors (3.67%) followed by NDGM (5.14%) and ODGM (7.20%) as shown in Table 10. Similarly, Figure 6 indicates, in the case of the USA, CO_2 emission decreased to 61% in (mm tons) meanwhile, electricity generation through renewable sources has increased from 81.012591 to 374.199554 in (Billion Kwh), as presented in Table 8.

Further, USA CO_2 emission forecasting values obtained from 2017 to 2026 by three prediction models are presented in Table 10. All the three prediction models showed the declined forecasting trends of USA's CO_2 emission presented in Figure 6. There is a small gap that was observed between forecasting values of USA CO_2 emission obtained by ODGM (596.216656mm tons) and NDGM (627.59648mm tons) in 2026. Whereas, the VSSGM forecasting value recorded for USA electricity production by renewable sources in 2026 is (896.5664 mm tons). As shown in Table 10, VSSGM has shown better prediction performance than NDGM and ODGM.

Table 7: China's electricity production simulation and prediction values & errors of three models based on random sequence number

Year	Original Value of electricity generation (Billion Kwh)	ODGM ($\beta_1 = 1.1111, \beta_{2=} 2.4444$)		NDGM ($\beta_1 = 1.1111, \beta_2 = 1.1\,2.4444, \beta_3 = 1.1111, \beta_4 = 1.1111$)		VSSGM ($a = 1211, \beta_1 = 1.1111, \beta_2 = 1.1\,2.4444, \beta_3 = 1.1111, \beta_4 = 1.1111$	
		simulative value $\hat{z}^{(0)}(k)$	simulative error $\Delta_k(\%)$	simulative value $\hat{z}^{(0)}(k)$	simulative error $\Delta_k(\%)$	simulative value $\hat{z}^{(0)}(k)$	simulative error $\Delta_k(\%)$
2000	3.056	3.056	0	3.056	0	3.056	0
2001	3.211	4.08526655	1.097831	4.843111	1.0455	3.72547	1.0151
2002	3.343	7.345358475	2.293862	6.9955795	2.1846	5.381215	2.1210
2003	3.524	5.68291542	1.429094	5.4123004	1.3611	4.163308	1.3214
2004	3.814	1.578599295	2.87506	1.5034279	2.7382	1.156483	2.6584
2005	4.623	9.37210638	2.867489	8.9258156	2.7309	6.866012	2.6514
2006	6.474	22.28817045	9.966455	21.226829	9.4919	16.32833	9.2154
2007	8.318	36.85684275	2.798273	35.101755	2.6650	27.00135	2.5874
2008	29.811	55.2314217	5.639806	52.601354	5.3712	40.46258	5.2148
2009	48.145	78.406146	4.558955	74.67252	4.3418	57.4404	4.2154
2010	79.354	107.6350412	1.314455	102.509563	1.2518	78.85351	1.2154
2011	111.342	144.499719	5.296106	137.61878	5.0439	105.8606	4.8970
2012	143.436	190.9947585	4.76482	181.89977	3.1093	139.9229	2.145
2013	206.113	274.2062505	5.675496	261.14881	5.40523	200.8837	5.2478
2014	242.799	323.5971375	4.244347	308.18775	4.04223	237.0675	3.9245
2015	294.441	416.8795995	7.92361	397.02819	7.54629	305.4063	7.3265
2016	388.604	534.5311335	2.934326	509.07727	2.79459	391.5979	2.7132
$\overline{\Delta}(Simulation)s$			5.9799		5.6952		5.5294
		Predictive value $\hat{z}^{(0)}(k)$	Predictive error $\Delta_k(\%)$	Predictive value $\hat{z}^{(0)}(k)$	Predictive error $\Delta_k(\%)$	Predictive value $\hat{z}^{(0)}(k)$	Predictive error $\Delta_k(\%)$
2017		682.91769	15.639429	650.3978	12.03033	500.306	9.2541
2018		870.0688815	10.547628	828.63703	8.11356	637.4131	6.2412
2019		1106.111234	12.192505	1053.43927	9.37885	810.3379	7.2145
2020		1403.816505	16.920956	1336.9681	13.01612	1028.437	10.0124
2021		1779.295245	10.176335	1694.5669	7.82795	1303.513	6.0215
2022		2252.862885	10.547628	2145.5837	8.11356	1650.449	6.2412
2023		2850.145935	15.572843	2714.4247	11.97911	2088.019	9.2147
2024		3603.462135	8.814026	3431.8687	6.78002	2639.899	5.2154
2025		4553.575845	12.405445	4336.7389	9.54265	3335.953	7.3405
2026		5751.89433	13.884026	5477.9946	10.68002	4213.842	8.2154

$\overline{\Delta}(Forecasting)$	12.6700	9.7462	7.4173

Table 8: USA electricity production simulation and prediction values & errors of three models based on random sequence number

Year	Original Value of electricity generation (Billion Kwh)	ODGM ($\beta_1 = 1.1111, \beta_{2=} 2.4444$) simulative value $\hat{z}^{(0)}(k)$	simulative error $\Delta_k(\%)$	NDGM ($\beta_1 = 1.1111, \beta_2 = 1.1\ 2.4444, \beta_3 = 1.1111, \beta_4 = 1.1111$) simulative value $\hat{z}^{(0)}(k)$	simulative error $\Delta_k(\%)$	VSSGM ($a = 1211, \beta_1 = 1.1111, \beta_2 = 1.1\ 2.4444, \beta_3 = 1.1111, \beta_4 = 1.1111$ simulative value $\hat{z}^{(0)}(k)$	simulative error $\Delta_k(\%)$
2000	81.012591	81.01259	0	81.01259	0	81.01259	0
2001	82.80389	113.601074	2.001552	108.191499	1.42968	83.22423	1.0212
2002	92.7888716	125.0961075	1.945104	119.13915	1.38936	91.6455	0.9924
2003	93.7097026	125.6157767	3.002916	119.634073	2.14494	92.02621	1.5321
2004	97.5207425	133.1007542	1.670704	126.762623	1.19336	97.50971	0.8524
2005	100.482027	146.410992	6.386464	139.43904	4.56176	107.2608	3.2584
2006	109.983481	161.709912	7.575792	154.00944	5.41128	118.4688	3.8652
2007	118.151398	179.2947975	7.881944	170.75695	5.62996	131.3515	4.0214
2008	139.001983	199.5071715	4.549944	190.00683	3.24996	146.1591	2.3214
2009	157.681933	222.739608	5.849228	212.13296	4.17802	163.1792	2.9843
2010	182.357073	249.443376	0.44002	237.56512	0.3143	182.7424	0.2245
2011	211.826314	280.137039	6.517784	266.79718	4.65556	205.2286	3.3254
2012	238.049096	315.416829	5.851384	300.39698	4.17956	231.0746	2.9854
2013	275.227052	355.967976	6.955452	339.01712	4.96818	260.7824	3.5487
2014	303.906652	402.578085	6.942516	383.4077	4.95894	294.9291	3.5421
2015	323.327979	456.1525605	4.98134	434.43101	3.5581	334.1777	2.5415
2016	374.199554	517.731942	8.040116	493.07804	5.74294	379.2908	4.1021
$\overline{\Delta}(Simulation)$			5.03701625		3.59786875		2.5699

		Predictive value $\hat{z}^{(0)}(k)$	Predictive error $\Delta_k(\%)$	Predictive value $\hat{z}^{(0)}(k)$	Predictive error $\Delta_k(\%)$	Predictive value $\hat{z}^{(0)}(k)$	Predictive error $\Delta_k(\%)$
2017		588.512106	5.32145	560.48772	4.52134	431.1444	2.1403
2018		669.8681535	7.198386	637.96967	5.53722	490.7459	4.2594
2019		763.380072	4.296149	727.02864	3.30473	559.2528	2.5421
2020		870.8641305	12.194026	829.39441	9.38002	637.9957	7.2154
2021		994.40796	8.814533	947.0552	6.78041	728.504	5.2157
2022		1136.411231	13.884026	1082.29641	10.68002	832.5357	8.2154

2023		1299.632198	7.124026	1237.74495	5.48002	952.1115	4.2154
2024		1487.24121	10.531235	1416.4202	8.10095	1089.554	6.2315
2025		1702.88118	13.884533	1621.7916	10.68041	1247.532	8.2157
2026		1950.741975	17.297826	1857.8495	13.30602	1429.115	10.2354
$\overline{\Delta}(Forecasting)$			11.0985		8.5373		6.5671

Table 9: China CO_2 emission simulation and prediction values & errors of three models based on random sequence number

Year	Original Value Of CO_2 Emission (mmTons)	ODGM ($\beta_1 = 1.1111, \beta_{2=} 2.4444$) simulative value $\hat{z}^{(0)}(k)$	simulative error $\Delta_k(\%)$	NDGM ($\beta_1 = 1.1111, \beta_2 =$ $1.1\ 2.4444, \beta_3 = 1.1111, \beta_4 =$ 1.1111) simulative value $\hat{z}^{(0)}(k)$	simulative error $\Delta_k(\%)$	VSSGM ($a = 1211, \beta_1 = 1.1111, \beta_2 =$ $1.1\ 2.4444, \beta_3 = 1.1111, \beta_4 = 1.1111$ simulative value $\hat{z}^{(0)}(k)$	simulative error $\Delta_k(\%)$
2000	3523.15227	3523.15227	0	3523.1523	0	3523.152	0
2001	3694.86799	4543.494806	2.001944	3803.328387	1.42996	3701.868	1.0214
2002	3960.51443	5406.102197	3.906672	4048.668759	2.79048	3742.31	1.9932
2003	4625.45309	6313.743468	0.024304	4513.089017	0.01736	4608.054	0.0124
2004	5375.48102	7337.531592	2.37944	5988.125326	1.6996	5401.819	1.2140
2005	6105.59822	8334.14157	1.217944	6937.277686	0.86996	6129.59	0.6214
2006	6739.96121	9200.047052	0.298116	7761.949573	0.21294	6796.854	0.1521
2007	7218.93073	9853.840446	4.340616	8384.609949	3.10044	7408.641	2.2146
2008	7496.67722	10232.96441	9.732772	9045.680386	6.95198	7969.563	4.9657
2009	8188.76519	11177.66448	8.360968	9945.39475	5.97212	8483.85	4.2658
2010	8779.18976	11983.59402	4.608744	11412.94669	3.29196	8955.378	2.3514
2011	9832.27819	13421.05973	13.038704	12781.96165	9.31336	9387.704	6.6524
2012	10362.2039	14144.40832	10.43994	13470.86507	7.4571	9625.201	5.3265
2013	10801.7734	14744.42069	10.348408	14042.30542	7.39172	10147.51	5.2798
2014	10744.2471	14665.89729	4.250652	13967.52123	3.03618	10480.72	2.1687
2015	10603.674	14474.01501	5.634804	13784.7762	4.02486	10786.23	2.8749
2016	10297.7967	14056.4925	8.360968	13387.13571	5.97212	11066.34	4.2658
$\overline{\Delta}(Simulation)$			2.8363		3.9708		2.5362
		Predictive value $\hat{z}^{(0)}(k)$	**Predictive error** $\Delta_k(\%)$	**Predictive value** $\hat{z}^{(0)}(k)$	**Predictive error** $\Delta_k(\%)$	**Predictive value** $\hat{z}^{(0)}(k)$	**Predictive error** $\Delta_k(\%)$
2017		15456.1	7.750678	14720.1	5.96206	11323.15	4.5862
2018		15777.52	8.166249	15026.21	6.28173	11558.62	4.8321
2019		16072.21	9.574526	15306.86	7.36502	11774.51	5.6654

2020		16342.39	8.99756	15564.19	6.9212	11972.45	5.3240
2021		16590.11	7.157826	15800.11	5.50602	12153.93	4.2354
2022		16817.25	6.757465	16016.43	5.19805	12320.33	3.9985
2023		17025.49	8.993166	16214.76	6.91782	12472.89	5.3214
2024		17216.43	8.999926	16396.6	6.92302	12612.77	5.3254
2025		17391.48	8.438508	16563.31	6.49116	12741.01	4.9932
2026		17551.99	9.224189	16716.18	7.09553	12858.6	5.4581
$\overline{\Delta}(Forecasting)$			8.4060		6.4662		4.9740

Table 10: USA CO_2 emission simulation and prediction values & errors of three models based on random sequence number

Year	Original Value of CO_2 emission (mmTons)	ODGM ($\beta_1 = 1.1111, \beta_{2=} 2.4444$) simulative value $\hat{z}^{(0)}(k)$	simulative error $\Delta_k(\%)$	NDGM ($\beta_1 = 1.1111, \beta_2 = 1.1\,2.4444, \beta_3 = 1.1111, \beta_4 = 1.1111$) simulative value $\hat{z}^{(0)}(k)$	simulative error $\Delta_k(\%)$	VSSGM ($a = 1211, \beta_1 = 1.1111, \beta_2 = 1.1\,2.4444, \beta_3 = 1.1111, \beta_4 = 1.1111$ simulative value $\hat{z}^{(0)}(k)$	simulative error $\Delta_k(\%)$
2000	8034.64834	8034.648	0	8034.648	0	8034.648	0
2001	7857.59618	9270.66354	2.2197	8225.7748	1.5855	7890.596	1.1325
2002	7904.99004	11399.00171	8.300796	9656.1921	5.92914	8350.917	4.2351
2003	7994.55215	9703.09954	6.302184	8764.8567	4.50156	8280.659	3.2154
2004	8139.82403	9690.52799	4.557	8657.6457	3.255	8198.189	2.3250
2005	8183.48932	9558.39053	2.598568	8531.8005	1.85612	8101.385	1.3258
2006	8075.5368	9503.28694	2.597784	8538.0828	1.85556	7987.756	1.3254
2007	8201.95287	9121.22324	11.08184	8210.6888	7.9156	7854.376	5.6540
2008	7990.25333	9007.51475	6.400184	8107.1569	4.57156	7697.813	3.2654
2009	7319.03078	9056.66187	7.026404	8068.2494	5.01886	7514.038	3.5849
2010	7579.47733	8962.2068	7.8302	7887.816	5.593	7298.32	3.9950
2011	7479.40495	8816.57242	8.477784	7758.6404	6.05556	7045.108	4.3254
2012	7061.14285	8510.86166	7.026012	7572.2492	5.01858	6747.884	3.5847
2013	5512.01467	8134.633635	12.450116	7018.6987	8.89294	6398.999	6.3521
2014	5555.17602	7775.63201	14.35994	6686.3162	10.2571	5989.474	7.3265
2015	5414.63008	7219.46832	2.420796	6061.3984	1.72914	5508.768	1.2351
2016	5316.90929	6749.254785	11.555572	5832.5483	8.25398	4944.509	5.8957
$\overline{\Delta}(Simulation)$			7.2003		5.1431		3.6736
		Predictive value $\hat{z}^{(0)}(k)$	**Predictive error** $\Delta_k(\%)$	**Predictive value** $\hat{z}^{(0)}(k)$	**Predictive error** $\Delta_k(\%)$	**Predictive value** $\hat{z}^{(0)}(k)$	**Predictive error** $\Delta_k(\%)$

2017	2847.646375	8.997898	2997.5225	6.92146	4282.175	5.3242
2018	2330.638135	5.509062	2453.3033	4.23774	3504.719	3.2598
2019	1723.76778	3.923335	1814.4924	3.01795	2592.132	2.3215
2020	1011.41579	9.068033	1064.6482	6.97541	1520.926	5.3657
2021	840.248115	14.077362	884.4717	10.82874	1263.531	8.3298
2022	739.75531	12.379419	778.6898	9.52263	1112.414	7.3251
2023	694.85717	3.744026	731.4286	2.88002	1044.898	2.2154
2024	687.28282	2.241785	723.4556	1.72445	1033.508	1.3265
2025	642.1143575	14.071616	675.90985	10.82432	965.5855	8.3264
2026	596.216656	12.269062	627.59648	9.43774	896.5664	7.2598
$\overline{\Delta}(Forecasting)$		8.6282		6.6371		5.1054

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The ODGM, NDGM, and VSSGM show overall accuracy and effectiveness obtained by Mean Absolute Percentage Error (MAPE) at 91.305%, 93.105%, and 95.435%, respectively, of electricity production and 93.225 %, 94.445% and 95.93% of CO_2 emissions for China and the USA, as presented in Table 11 and Figures 7 to 10. The accuracy of VSSGM is higher than NDGM and ODGM. MAPE % also illustrates that VSSGM is a good fitting model showing an accurate prediction. In Figure 4, the linear trend indicates the amount of CO_2 will increase upward gradually untill 2026 for China is aligned with the works of Xie et al. (2015) and Lakshmi and Visalakshmi (2016) in terms of the measurement procedure. Likewise, in the case of the USA, the growth rate of CO_2 emission gradually decreases untill 2026 in order with an increasing rate of electricity production by renewable resources presented in Figure 6. China has the highest renewable energy consumption with 106.7 million tons of oil equivalent contributing 22% in total world renewable energy consumption; China also has the highest CO_2 emissions, with 466.23 million tons contributing a major portion to total world total CO_2 emissions (US Energy Information Administration 2017).

Insert Figure 9 about here

Table 11: MAPE % by ODGM, NDGM, and VSSGM

	MAPE %					
	Electricity Production			CO_2 Emissions		
	ODGM	NDGM	VSSGM	ODGM	NDGM	VSSGM
China	9.32	7.72	4.57	5.62	5.22	3.75
USA	8.07	6.07	4.56	7.93	5.89	4.39
Average MAPE %	8.695	6.895	4.565	6.775	5.555	4.07
Over all accuracy Level %	91.305	93.105	95.435	93.225	94.445	95.93

The RGR for China in terms of electricity production by renewable resources is 0.677 in Table 4 and comparatively higher than the USA at 0.225 in Table 12, which implies that, until 2026, China will be producing electrivity based on renewable sources even more than the USA. Additionaly, analyses showed that the USA has less relative growth of CO_2 emission 0.161 (Table 15) if compared with China, at 0.264 (Table 13). The VSSGM showed to be effective when dealing with China's data, and the study with these results are comparable to the work of Zhang et al. (2015); Fang et al. (2018) along with Zhang et al. (2012) and McKibbin et al. (2007). The total amount of electricity generation for China is higher at 4213.842 Billion Kwh by the end of 2026, as resented in Figure 3. Data showed that China is the leading country in the world concerning CO_2 emissions, with 12858.597 (mm tons), and the

USA showed lower CO_2 emissions if compared with China, with 896.5663 (mm tons). Then, the USA contributes at 2% of total CO_2 emissions in the world (US Energy Information Administration 2017). The assessment of CO_2 emissions helps us to conclude that there is a mutually agreed-upon consensus that these are critical factors of environmental degradation, global warming, and, climate vulnerability while these uprising levels of environmental deterioration.

Reduction of CO_2 emissions ensure the development of environmental sustainability by decreasing the utilization of nonrenewable sources for electricity production growth, in addition it helps to yeild the total energy consumption. Consequently, the efficient production of electrict by renewable sources such as solar, wind, hydrals could decrease the amount of CO_2 emission upto 75%. Moreover, the inefficient structuring and improper maintenance of national energy consumption is causing the the increase of CO_2 emissions (Şahin, 2019; Chen et al., 2020; Dogan, 2016) . Hence, our analysis uptakes that the China and the USA renewable's electricity generation will increase by 2026 based on ODGM, NDGM and VSSGM prediction results. Coversly, the USA showed a declining trend of CO_2 emission in the future and can be seen in Figure 6.

Table 12: China relative growth rate and doubling time model results of electricity production

Years	Aggrigate values	Relative Growth Rate (RGR)	Mean RGR	Doubling Time (D_t)	Mean D_t
2000	3.056				
2001	6.267	0.718	0.677	1.024	2.813
2002	9.61	0.428		1.543	
2003	13.134	0.312		1.857	
2004	16.948	0.255		2.060	
2005	21.571	0.241		2.115	
2006	28.045	0.262		2.031	
2007	36.363	0.260		2.041	
2008	66.174	0.599		1.206	
2009	114.319	0.547		1.297	
2010	193.673	0.527		1.333	
2011	305.015	0.454		1.482	
2012	152432	6.214		-1.134	
2013	152614.88	0.001		7.419	
2014	152851.95	0.002		7.161	
2015	153157.36	0.002		6.910	
2016	153548.96	0.003		6.663	
2017	500.306		0.399		1.682
2018	1137.7191	0.822		0.890	
2019	1948.0569	0.538		1.313	
2020	2976.4943	0.424		1.551	
2021	4280.0075	0.363		1.706	
2022	5930.457	0.326		1.814	
2023	8018.4763	0.302		1.892	

2024	10658.376	0.285		1.950	
2025	13994.328	0.272		1.994	
2026	18208.17	0.263		2.028	

Table 13: China relative growth rate and doubling time model results of CO_2 emission

Years	Aggrigate values	Relative Growth Rate (RGR)	Mean RGR	Doubling Time (D_t)	Mean D_t
2000	3523.152				
2001	7218.02	0.717225	0.250825	1.025513	2.384292
2002	11178.53	0.437415		1.520021	
2003	15803.99	0.346267		1.753693	
2004	21179.47	0.29277		1.921515	
2005	27285.07	0.253307		2.066299	
2006	34025.03	0.220757		2.203841	
2007	41243.96	0.192408		2.341283	
2008	48740.64	0.167008		2.482858	
2009	56929.4	0.155299		2.555551	
2010	65708.59	0.143418		2.635141	
2011	75540.87	0.139444		2.663238	
2012	152432	0.702045		1.046905	
2013	162579.5	0.064449		3.435035	
2014	173060.2	0.062473		3.466176	
2015	183846.5	0.060461		3.4989	
2016	194912.8	0.058451		3.532708	
2017	11323.15		0.263937		2.207542
2018	22881.77	0.703491		1.044847	
2019	34656.28	0.415138		1.572291	
2020	46628.73	0.296738		1.908053	
2021	58782.67	0.23163		2.155761	
2022	71103	0.190282		2.352393	
2023	83575.89	0.161626		2.51562	
2024	96188.65	0.140556		2.655294	
2025	108929.7	0.124391		2.777473	
2026	121788.3	0.111582		2.886146	

Table 14: USA relative growth rate and doubling time model results of electricity production

Years	Aggrigate values	Relative Growth Rate (RGR)	Mean RGR	Doubling Time (D_t)	Mean D_t
2000	81.01259				
2001	163.8165	0.704142	0.22536	1.043922	2.314844
2002	256.6054	0.448793		1.494342	
2003	350.3151	0.311294		1.860166	
2004	447.8358	0.245594		2.097224	
2005	548.3178	0.202428		2.290516	
2006	658.3013	0.182808		2.392468	
2007	776.4527	0.165073		2.494515	
2008	915.4547	0.164685		2.496867	
2009	1073.137	0.15892		2.5325	
2010	1255.494	0.156943		2.545019	
2011	1467.32	0.155909		2.551632	
2012	1705.369	0.150344		2.587977	
2013	1980.596	0.149616	0.329929	2.592828	1.910243
2014	2284.503	0.142751		2.639804	
2015	2607.831	0.13237		2.715299	

2016	2982.03	0.134086		2.702424	
2017	431.1444				
2018	921.8903	0.759983		0.967606	
2019	1481.143	0.474143		1.439393	
2020	2119.139	0.358196		1.719823	
2021	2847.643	0.295482		1.912295	
2022	3680.178	0.25647		2.053892	
2023	4632.29	0.23009		2.162432	
2024	5721.844	0.21124		2.247909	
2025	6969.376	0.197235		2.316509	
2026	8398.491	0.186526		2.37233	

Table 15: USA relative growth rate and doubling time model results of CO_2 emission

Years	Aggrigate values	Relative Growth Rate (RGR)	Mean RGR	Doubling Time (Dt)	Mean Dt
2000	8034.648				
2001	15892.24	0.682068	0.170841	1.075773	2.79777
2002	23797.23	0.403738		1.600136	
2003	31791.79	0.289639		1.932269	
2004	39931.61	0.22796		2.171731	
2005	48115.1	0.186428		2.372858	
2006	56190.64	0.155154		2.556484	
2007	64392.59	0.136248		2.686423	
2008	72382.84	0.116971		2.838979	
2009	79701.87	0.096324		3.033187	
2010	87281.35	0.090844		3.091762	
2011	94760.76	0.082219		3.191522	
2012	101821.9	0.07187		3.326046	
2013	107333.9	0.052719		3.635918	
2014	112889.1	0.050461		3.679698	
2015	118303.7	0.046849		3.753965	
2016	123620.6	0.043962		3.817572	
2017	4282.175		0.160874		2.890937
2018	7786.895	0.597981		1.207343	
2019	10379.03	0.287345		1.940219	
2020	11899.95	0.136747		2.682767	
2021	13163.48	0.100912		2.986651	
2022	14275.9	0.081126		3.204898	
2023	15320.8	0.070638		3.343328	
2024	16354.31	0.06528		3.422217	
2025	17319.89	0.057364		3.551478	
2026	18216.46	0.05047		3.679527	

When the ODGM model is applied to forecast the total quality of CO_2 and renewable electricity production based on actual and forecast data, different sequences of results are obtained. An important issue will be, in the long term, the emission scenarios between China and the USA. Trying to shed some light on this issue, the grey synthetic index was used through past (actual) and future data (forecasting), $RGR_{synthetic}$ showing relative growth rates, as follows:

$$\mathrm{RGR}_{\mathrm{synthetic}} = \theta(\mathrm{RGR}_{\mathrm{past}}) + (1-\theta)(\mathrm{RGR}_{\mathrm{future}}) \tag{34}$$

Where RGR_{past} present the Relative Growth Rate get from actual data and RGR_{future} indicates the Relative Growth Rate get from future (forecasting) data.

$$D_{synthetic} = \theta\left(D_{past}\right) + (1-\theta)(D_{future}) \tag{35}$$

Where, D_{past} represent the Doubling Time obtained from actual data and RGR_{future} reports the growth rate obtained from simulated/forecasted data. Here, θ states that the coefficient of relative weights and value of θ can be taken as 0.5. If the decision-makers while in decision making process take the relative growth rate of simulated data more influential, then $\theta < 1-\theta$.

Table 16: RGR and Dt result comparison of CO_2 emission and electricity production for USA and China

	Country	RGR (Actual data)	D_t (Actual Data)	RGR (Simulated Data)	D_t (Simulated data)	RGR (Synthetic)	D_t (Synthetic)
Electricity Production	USA	0.225	2.315	0.330	1.910	0.278	2.113
	China	0.677	2.813	0.399	1.682	0.538	2.248
CO_2 Emission	USA	0.171	2.798	0.161	2.891	0.166	2.296
	China	0.250	2.384	0.263	2.208	0.257	2.845

According to the grey synthetic relative growth rate model, China shows a higher quantity of CO_2 emission over the USA, as presented in Table 16. Similarly, the same sequence was obtained for electricity generation through renewable sources by synthetic RGR. Our findings show that, in the long term, the USA could have a competitive edge over China. Moreover, this study proposed the double-time model successfully executed by Paramati et al. (2017b) and Ikram et al. (2019a). In this model, China needs 2.248 number of years to make it renewable electricity double in quantity, as seen in Figure 11(a).

Insert Figure 11(a) about here

Meanwhile, the USA required 2.113 number of years to produce electricity double in quantity by a renewable source, as presented in Figure 11(b). Similarly, China required 2.845 number of years to decrease CO_2 emission by two times. The results of this study provide new insights as to emissions and energy production within two of the top countries globally, and evidence in support of scientific consensus that we can do something to fight global warming and climate changes.

Insert Figure 11(b) about here

4. Conclusion remarks

This research aimed to measure an accurate estimation for forecasting CO_2 emissions and renewable electricity production at the year 2026 by considering most poluent countries in the world. Advanced mathematical optimized discrete grey, nonhomogeneous discrete, and variable speed and adaptive structure grey modeling were used. Performance criteria for measuring the accuracy of the model was employed. In the long term, it was predicted that CO_2 emission will decrease dramatically in the USA, while China needs to focus more on its electricity production and renewable energy strategy to reduce CO_2 emission. The proposed methodology is an innovative application in CO_2 emission and renewable energy forecasting while reducing the uncertainty in ambiguity and numerical ranges typically involved in these studies. The results showed that we can successfully utilize ODGM, NDGM, and VSSGM grey models based on existing dataset for forecasting the trends of CO_2 emissions levels. Moreover, the study outcomes confirmed the accuracy of VSSGM model, if compared with two forecastings ODGM and NDGM grey models.

We recommend future studies to continue in this area of study, by comparing China and the USA, as policymakers need to have accurate data for decision analysis. We suggest that researchers continue using VSSGM grey models in the estimation of similar energy and emission forecasting. We can compare these types of forecasts with parametric versus non-parametric comparisons across countries with grey forecasting models. As climate change continues, we need more studies in comparing countries along with the economic development and the prioritization of renewable energy sources globally to enable better decision-making.

Policy-makers must address the Sustainable Development Goals (SDGs) recommended by the United Nations when revising the national policies towards sustainability. As example, the European Union is targeting the Green Deal aiming a balance between growth strategy and resource-efficiency, which emcompasses no net emissions of greenhouse by the year 2050, and decoupling economic growth from natural resources use (European Comission, 2020; European Parliament, 2019). The achievement of such goals also requires the promotion of renewable energies, e.g. renewable electricity production, among European Union Member States. Countries, such as China and the USA, need to consider the formation of Sustainable Energy Action Plans, a set of policies devoted to the increase of energy efficiency use and the consideration of renewable energy sources at local level, as also recommended by European Comission (2020b). Thus, it is recommended to policy-makers the observation of such initiatives in order to implement policies towards sustainability starting by the cities-level (Alhorr, Eliskandarani & Elsarrag, 2014), whose implementation can be fastly implemented and results felt by citizens.

Conflict of Interest: The authors declare that they have no conflict of interest.

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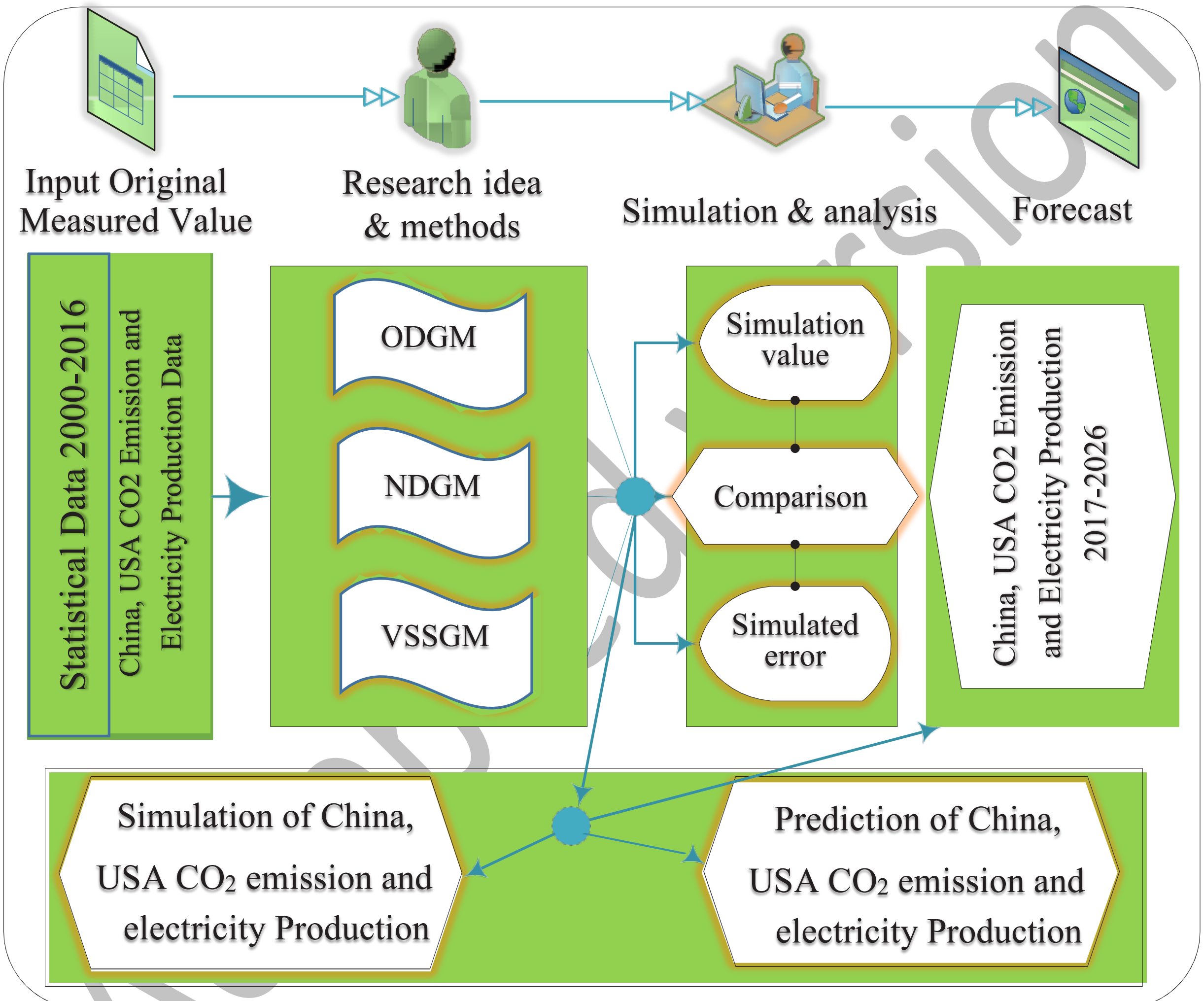


Figure 1: Research framework based on novel grey models

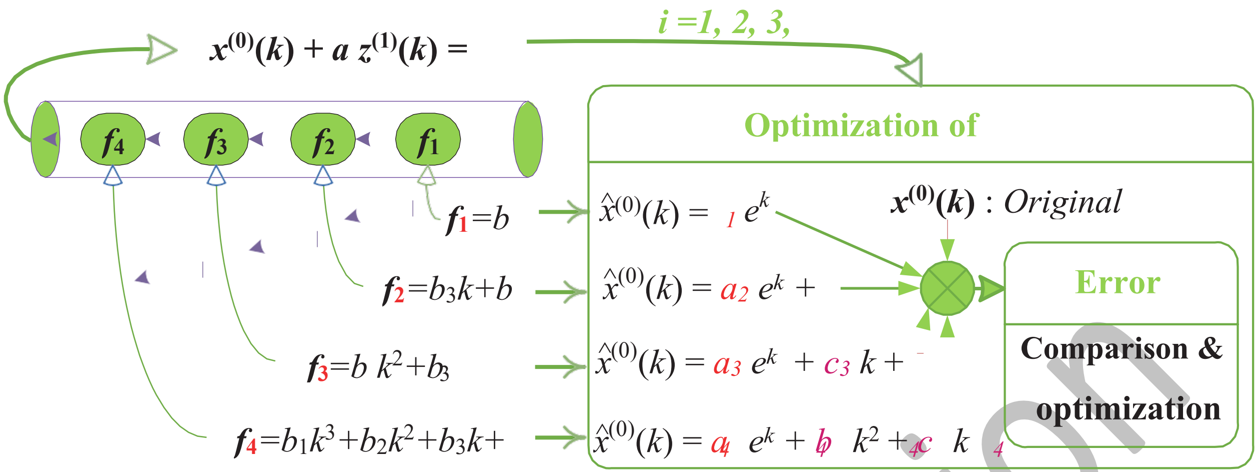


Figure 2: varistructure VSSGM model with optimized characteristics

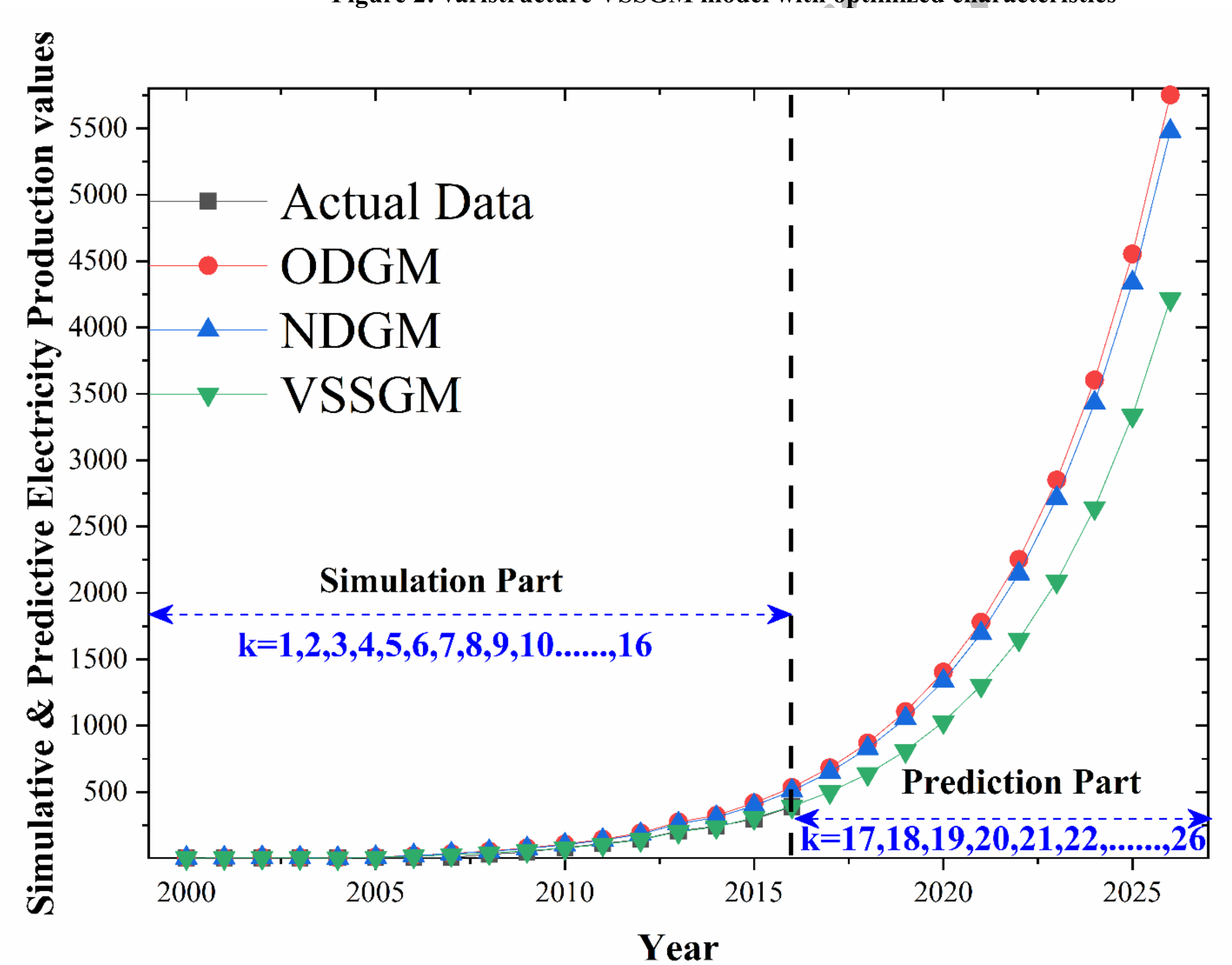


Figure 3: China's Simulation and predictive values of electricity production from 2000-2026

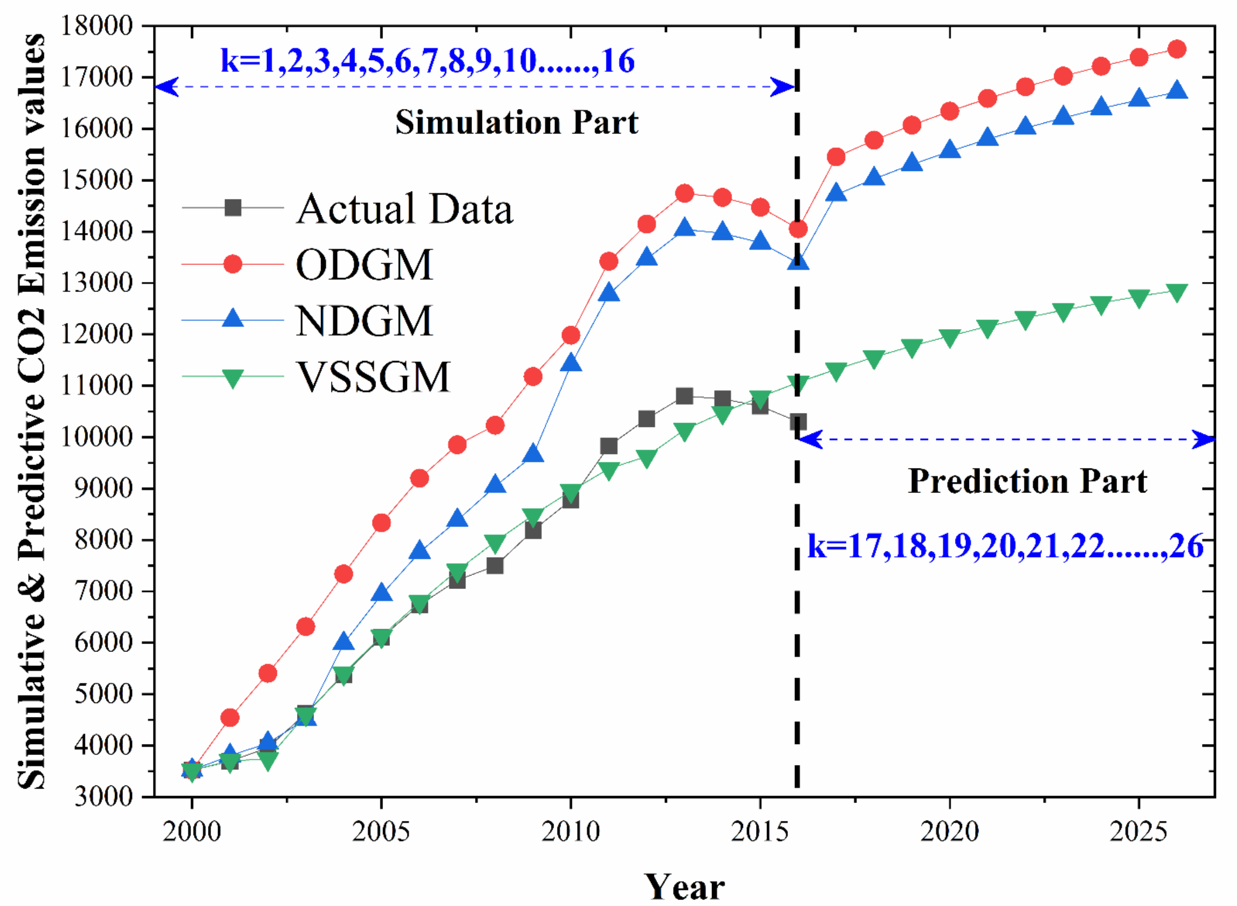


Figure 4: China's Simulation and predictive values of CO2 emissions from 2000-2026

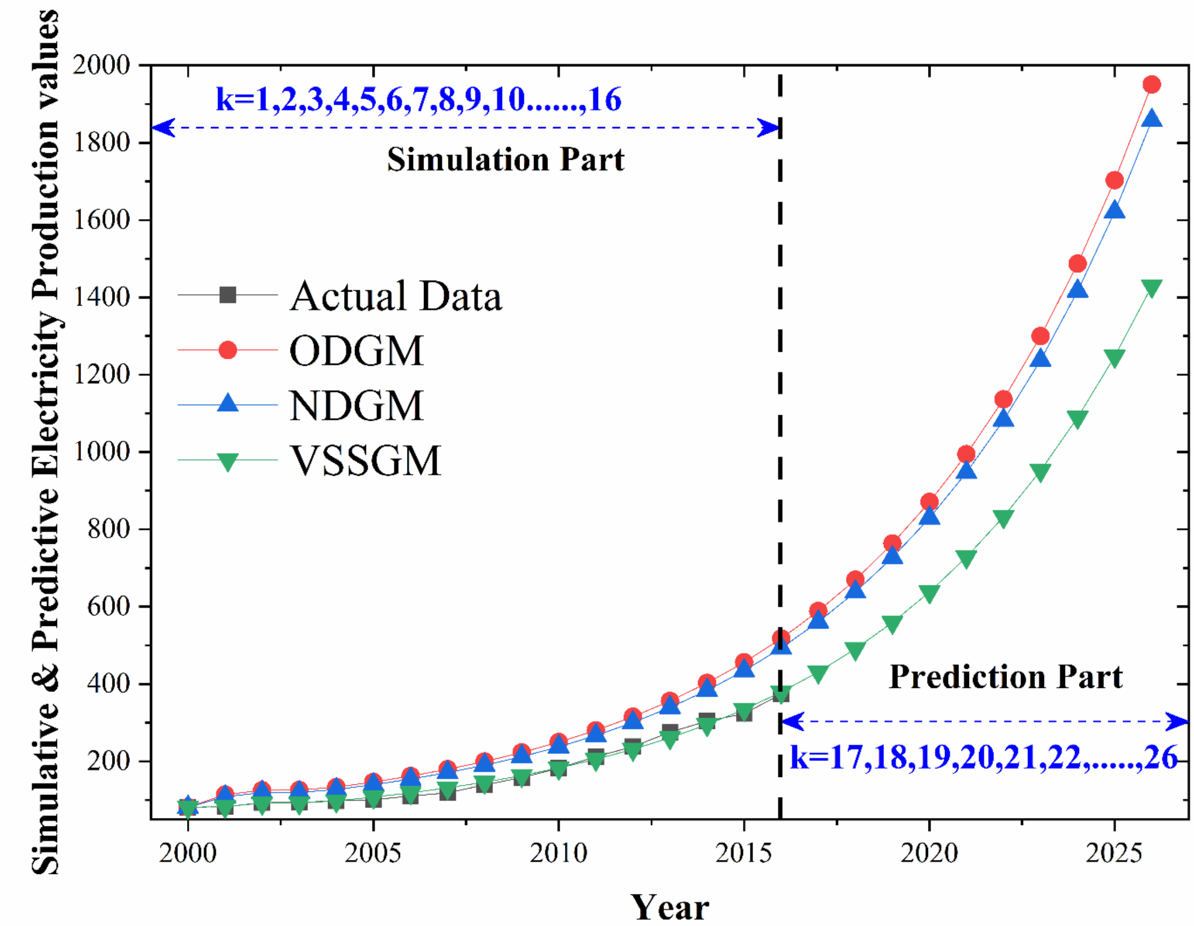


Figure 5: USA Simulation and predictive values of electricity production from 2000-2026

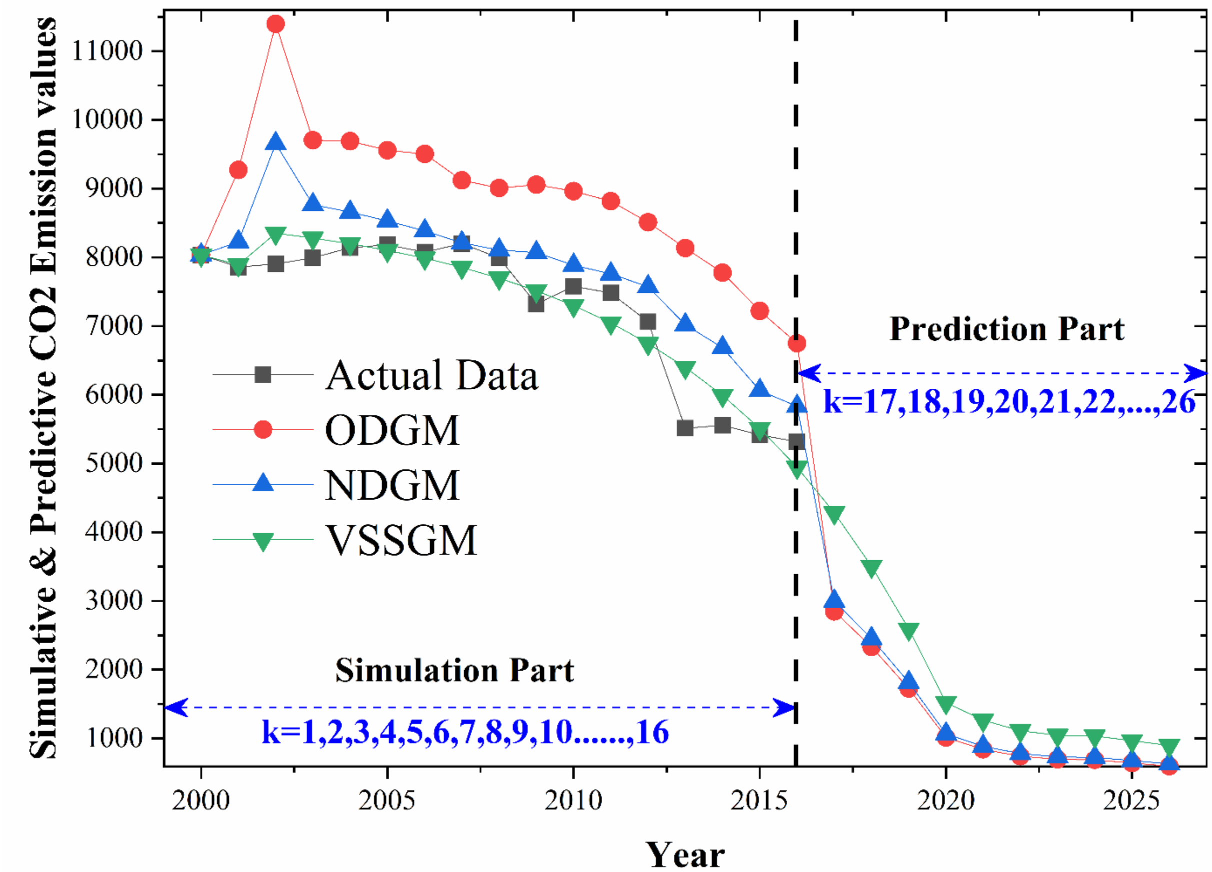
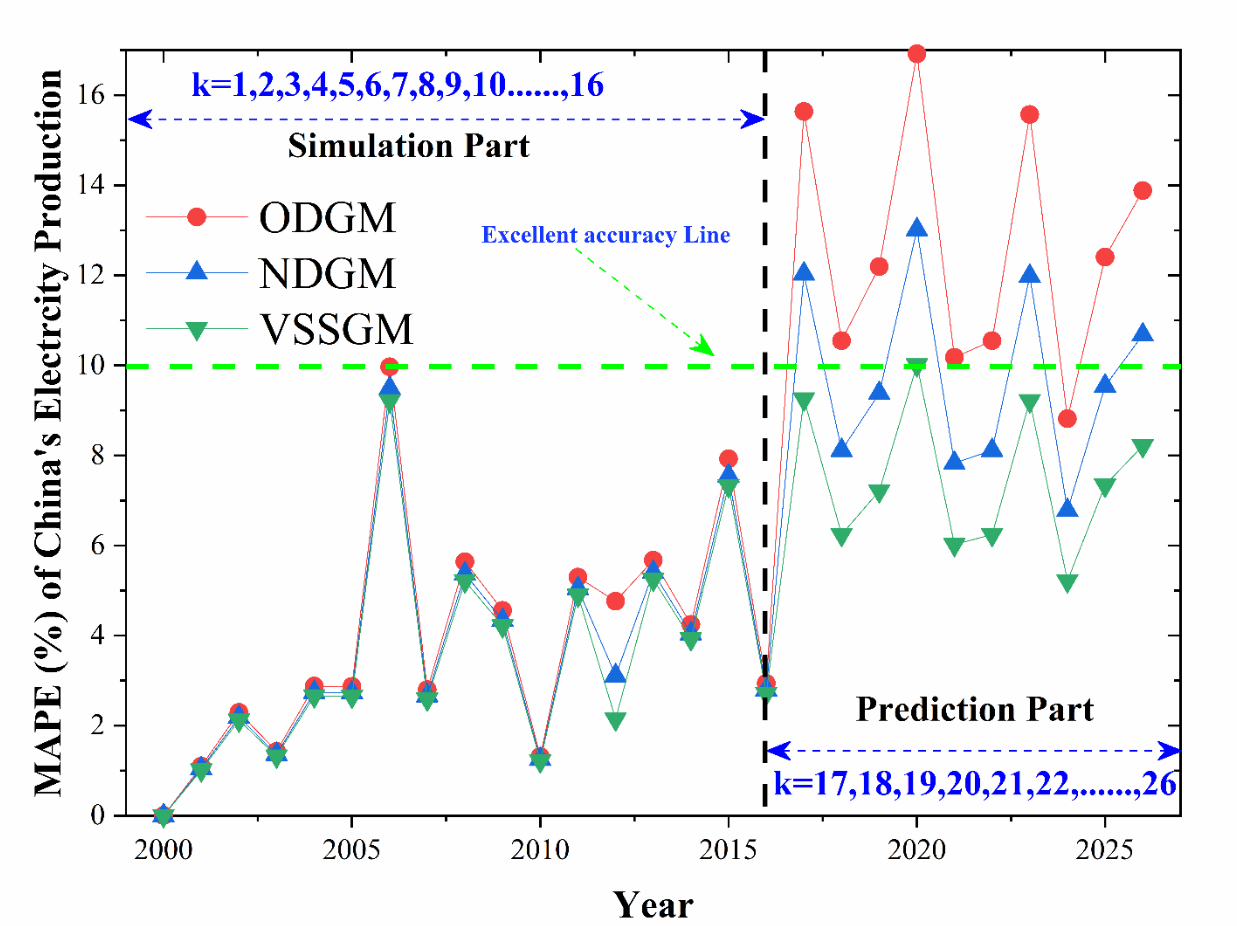


Figure 6: USA Simulation and predictive values of CO2 emission from 2000-2026



667

668 **Figure 7: China Simulation and predictive MAPE (%) of electricity production from 2000-2026**

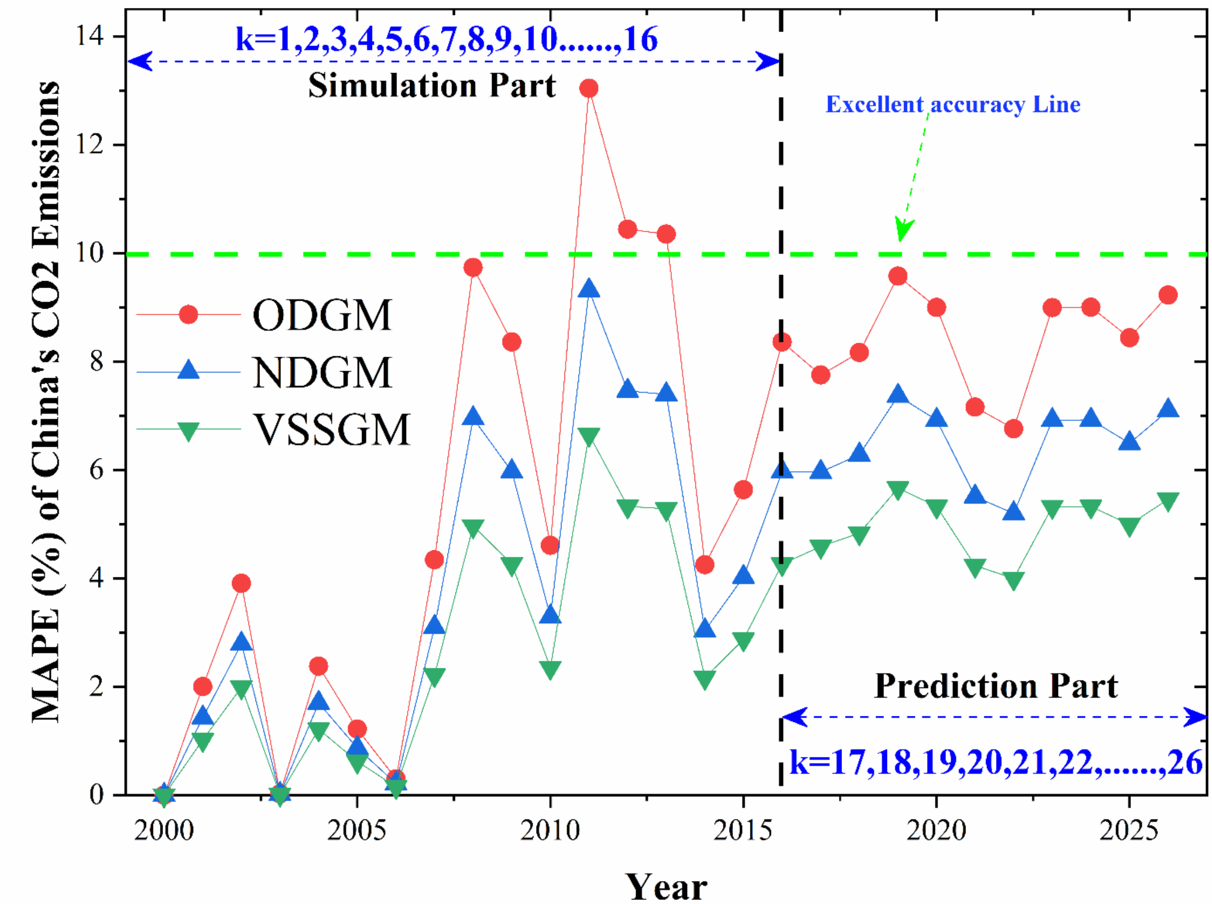


Figure 8: China Simulation and predictive MAPE (%) of CO2 emission from 2000-2026

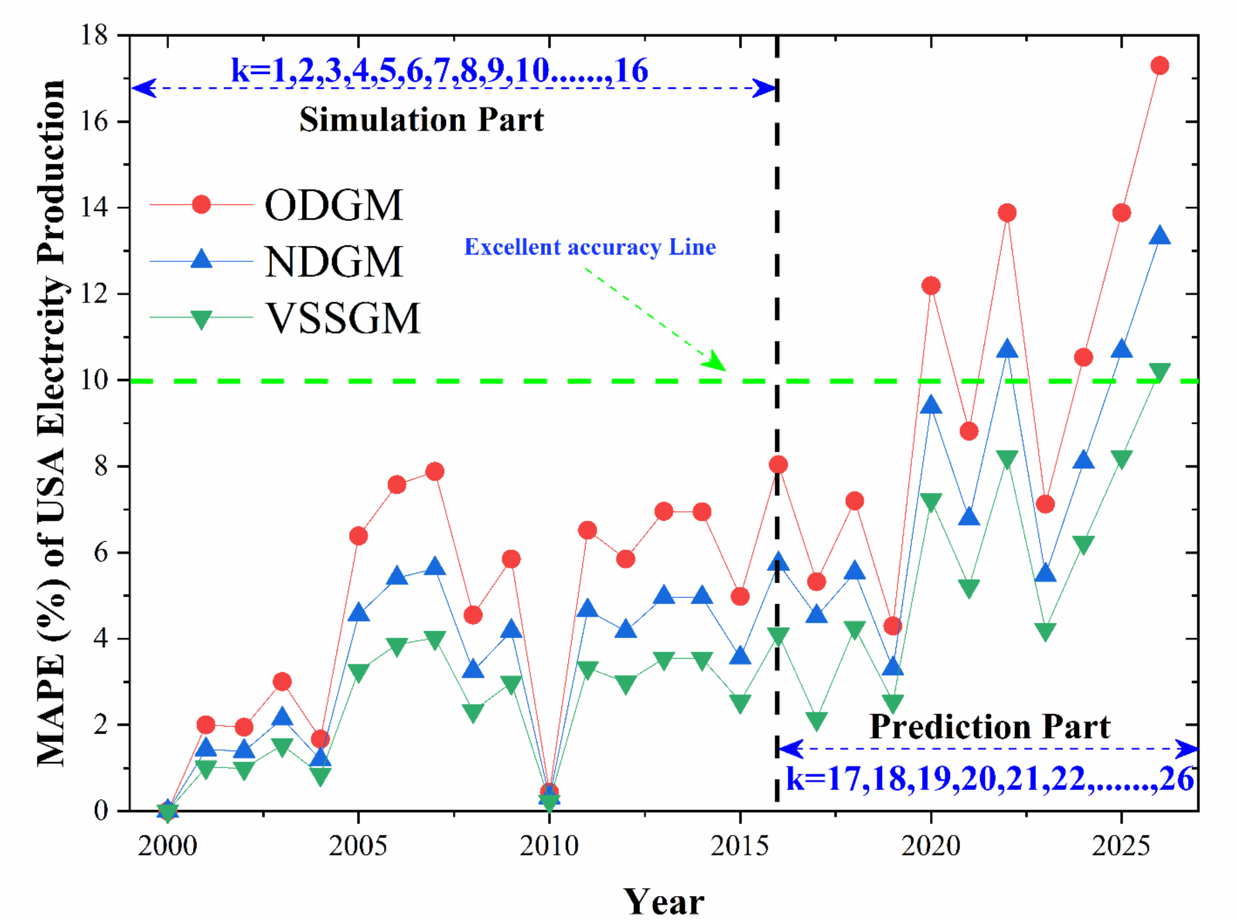


Figure 9: USA Simulation and predictive MAPE (%) of electricity production from 2000-2026

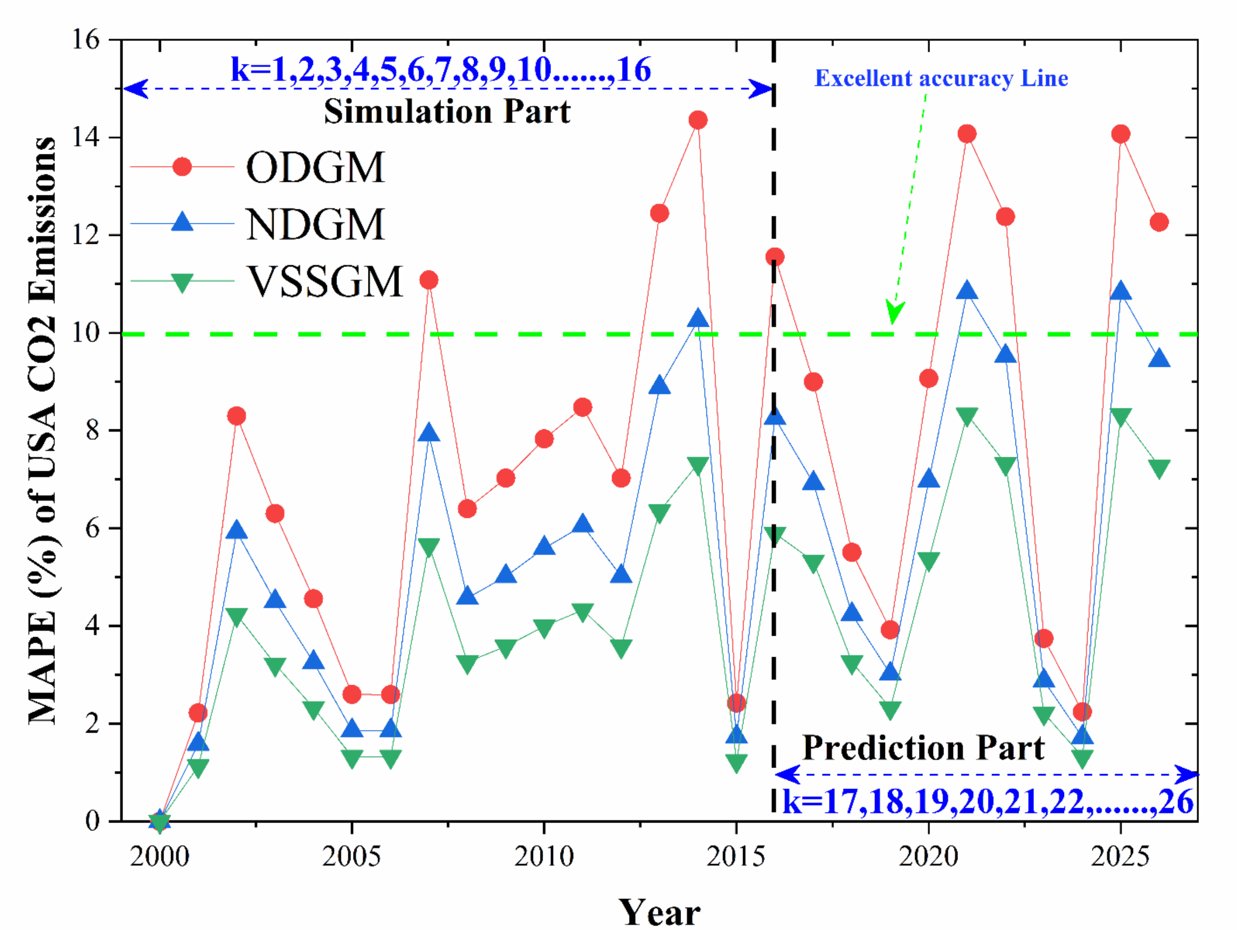


Figure 10: USA Simulation and predictive MAPE (%) of CO2 emission from 2000-2026

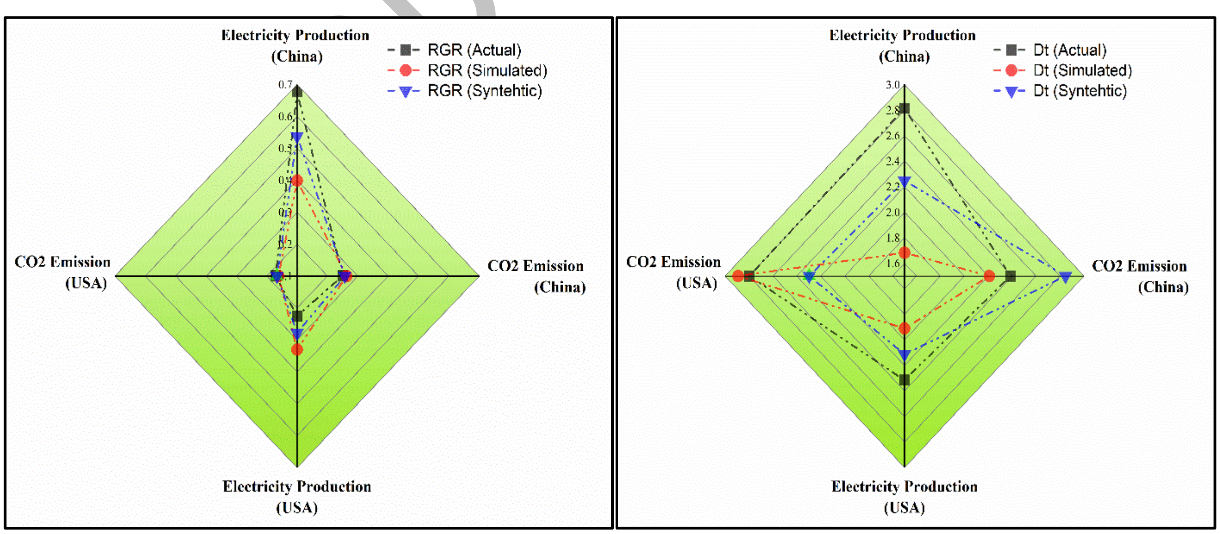


Figure 11(a):Relative Growth Rate (RGR) of China Vs. USA **Figure 11(b): Doubling Time (Dt) of China Vs. USA**