



# Forecasting Nitrous Oxide emissions based on grey system models

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**Abstract** Accurate forecasting is required to measure future national energy performance levels in order to establish clear policies for both monitoring and reducing Nitrous Oxide and other harmful emissions. Using the well-established and accepted measures, we predict the Nitrous Oxide emissions for the year 2030 based on actual data from the years 2000 to 2016 for six countries responsible for 61% of global emissions (China, Indonesia, India, Japan, Russia and the USA). Three advanced mathematical grey predictions models were employed, namely the Even Grey Model (1, 1), the Discrete Grey Model (1, 1) and the Non-homogeneous Discrete Grey Model, which is capable of working with poor or limited data. Results showed that the Non-homogeneous Discrete Grey

Model was a better fit and proved more effective in forecasting Nitrous Oxide emissions because it produced the lowest mean absolute percentage error for all countries when compared to the Even Grey Model (1, 1) and the Discrete Grey Model (1, 1). The mean absolute percentage error of the Even Grey Model (1, 1) was 2.4%, that of the Discrete Grey Model (1, 1) was 2.16%, and that of the Non-homogeneous Discrete Grey Model was 1.9%. Furthermore, the results show that China has the highest Nitrous Oxide emissions during the years studied (China 20,578,144, Russia 1,705,110, India 7,806,137, Indonesia 3,405,389, USA 8,891,219 and Japan 780,118). This study also suggests some implications for both academicians and practitioners in respect of reducing Nitrous Oxide emission levels.

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## Introduction

Global anthropogenic emissions cause major environmental issues, especially Nitrous Oxide (N<sub>2</sub>O) which is the crucial long-lived anthropogenic pollutant emission. Nitrous Oxide contributes to the damage of ozone layer. Rapidly growing economic development anthropogenic actions, and fossil fuel

combustion, considerably increase  $N_2O$  emissions (Pulido-Fernández et al. 2019). Furthermore, increasing concerns about climate change and the need to mitigate these impacts have led to a number of international agreements and policies designed to achieve this goal. For instance, in 2015, the Conference of Parties (COP) of the United Nations Framework Convention for Climate Change (UNFCCC) agreed to limit the increase in the global temperature to 2 °C above pre-industrial levels by 2100 (UNFCCC, 2015). Thus, this study is aiming to investigate Nitrous Oxide emissions forecasting based on grey system models.

Globally, Nitrous Oxide is one of the life-threatening pollutants as it affects agriculture products, the ecosystems and diverse human economic activities (Wang et al. 2019). China, India, Indonesia, the USA, Russia and Japan are responsible for approximately 61% of the total world emissions (Fufa et al. 2018). Increasing levels of  $N_2O$  can result in the following: (1) problems in the human respiratory system (Yodkhum et al. 2017); (2) harmful economic effects can destroy the components and the foundations of infrastructure projects (Dong et al. 2019) due to harmful reactions of  $N_2O$  with the ground surface of the earth (Meng et al. 2019); (3) Nitrous Oxide acts together with oxygen, water, nitrate particles and other toxic materials in the atmosphere to cause acid rain, and hazy air conditions, and it affects the environment with toxic particles and pollutants.

Due to these and many more harmful effects, there have been increasing studies on  $N_2O$  emission. However, what has not been given much attention is the prediction of Nitrous Oxide emission levels (Greuer et al. 2018). There has been considerable uncertainty about global  $N_2O$  emission estimates, which results in vagueness and ambiguity of the emission estimates. Rapid Nitrous Oxide emissions are also uncertain (Shi et al. 2019). Meanwhile, strong policies are needed to reduce the level of  $N_2O$  emissions (Chang et al. 2017). Although it is challenging to forecast future Nitrous Oxide concentrations, tracking future emissions is a crucial and meaningful path to follow (Kanter 2018; Xiao et al. 2018; Jiang and Ye 2019).

Therefore, to fill this gap in the literature, this study attempts to provide the following contributions: (1) to propose a new forecasting model for Nitrous Oxide emissions in a holistic way for the six selected

countries; (2) to present the policy guidelines that address the harmful effects of  $N_2O$  in societies; (3) to present the possible solutions that help managing  $N_2O$  emissions at different levels; (4) to present the guidelines for plant security by reducing plant damages. Several studies have attempted to forecast the Nitrous Oxide emission levels using soft computing approaches such as evolutionary algorithms (e.g., Roy et al. 2012; Wang et al. 2018; Luo et al. 2019; Wang et al. 2019), trend analysis, macroeconomic or input–output-based models, surveys (Zhang et al. 2017), machine learning algorithms, meta-heuristic algorithms and market-based models (Guo et al. 2016) and a grey-based harmony search optimization model (Sun et al. 2013). Despite these studies, insufficiencies and further uncertainties about these data/models remain. Furthermore, most of the previous methods' predictions showed a huge variation compared to the highest official forecasts (Gilmore and Patwardhan 2016), and uncertainties in these studies have also been ignored (Hao et al. 2017).

The accurate assessment of Nitrous Oxide emissions in countries where the emission rate is highly alarming is an absolute necessity in terms of the development of policy to protect vanishing species, deteriorating environmental quality as well as further environmental degradation (Pradhan et al. 2017). Knowing that the Nitrous Oxide emissions levels will help policymakers develop a clear policy direction that sets out steady targets to ensure evidential energy performance (Wesseh and Lin 2016).

There are numerous studies like Sun et al. (2019), Ye et al. (2019), Jiang et al. (2019), Mason et al. (2018), Nebenzal and Fishbain (2018) and Noorpoor and Feiz (2014) which usually emphasize the prediction of  $CO_2$  or  $SO_2$ , but the proposed technique forecasts the concentrations of Nitrous Oxide emissions with forecasting performance. Furthermore, the studies in this line of research lack the forecasting of Nitrous Oxide emissions, especially in the top six emitting countries. Therefore, in order to address the above-mentioned gap, we proposed the following study.

This paper's contribution is to propose a new forecasting model for Nitrous Oxide emissions in a holistic way for the six selected countries (China, Indonesia, India, Japan, Russia and the USA). These are the bigger economies on the bases of geographical reasons, economic conditions, political scenarios,

including CPEC development and maximum human resource availability in these contexts. This new model will provide an accurate prediction of Nitrous Oxide emissions for the year 2030 by taking regional characteristics into account including the consideration of total energy consumption, alongside the sector-specific econometric multiple-correlation forecasts models which require complicated effort, time and energy, which engender uncertainty both in terms of verbal ambiguity and numerical ranges. Consequently, a new prediction model will provide new insights into uncertainty reduction regarding Nitrous Oxide emissions and thereby increases the understanding of possible expected Nitrous Oxide emissions in the study countries. In addition, the study investigated the future trends in the level of Nitrous Oxide emissions so that policy makers could take actions based on future expected outcomes. Therefore, the proposed advance mathematics techniques, namely Grey models through good flexibility and high accuracy of forecasting is to predict the important pollutant Nitrous Oxide for clean energy economy.

The remainder of the paper is organized as follows. Section 2 outlines the background of the previous literature on forecasting Nitrous Oxide emissions, including a brief study rationale. The methodology used to predict future Nitrous Oxide emission trends is described in Sect. 3, and Sect. 4 presents the pertinent results. Finally, Sect. 5 contains the study's conclusions and policy implications, along with limitations and future research directions.

## Review of literature and background

Several studies have tried to forecast CO<sub>2</sub> emission using soft computing approaches such as an evolutionary and artificial neural network algorithm (Behrang et al. 2011), trend analysis (Tang et al. 2016), computational inelegance macroeconomic or input–output-based models (Atsalakis 2016), surveys, a machine learning algorithm (Dai et al. 2018), a meta-heuristic algorithm and genetic algorithm (Yu et al. 2010) and a support vector machine (Guo et al. 2013). Sun et al. (2013) employed a grey-based harmony search optimization model to forecast CO<sub>2</sub> emissions in China. Unfortunately, an evolutionary algorithm causes the problem of premature convergence, while local extremism values may

be consequence of adverse configuration and does not yield a point near the standard extremism. In trend analysis, it is not easy to select the base year and it is hard to maintain the consistent accounting principle as it requires long-term data to conduct the analysis. Similarly, with surveys, it is often difficult to reach all the necessary respondents, respondents might not be fully aware of the subject matter of the survey, and simple yes/no question options may lead to flawed results. Moreover, the consistency, honesty and interpretation of the surveys can be compromised.

Using support vector machines is also problematic because it is a memory-intensive process, support vector machines are more difficult to set due to the importance of picking the right kernel, and they do not scale well larger datasets. Meta-heuristics provides biased and unfair results to compare with when you have evaluated the solution of one single run of the algorithm. Despite its highest performance in terms of long calculation in estimation, it lacks the transparency due to unnecessary complex and hurdles of acquisition in periodical variations and due to limited practical configuration option on ground bases.

Perhaps the biggest problem with a popular and reliable model is that it is unable to reflect regional characteristics of GHGs emission and, along with the methods for predictions mentioned above, shows a huge variation with high official forecasting. Meanwhile forecasting prediction of Nitrous Oxide emissions by 2030 having regional characteristics including the consideration of total energy consumption has been done in the present study. Also, the sector-specific econometric multiple-correlation forecasts forecasting models which require a complicated efforts, time and energy. Consequently, this study presents an advanced mathematical modeling technique for use in predicting Nitrous Oxide emissions. The advantage of the model is that whereas other traditional techniques are complicated in terms of evaluation and require several other parameters for forecasting, this model is simple to use and produces an accurate estimation based on whatever data are available. The study intends to adopt this technique to assess parameters which have effects on global warming and climate change.

China, Indonesia, India, Japan, Russia and the USA are the regions with highest producing economies in the world. They are also the regions that are highest in terms of emissions, and increasing environmental

problems in these regions, making life unsustainable. Nitrous Oxide damages the ozone layer, which ultimately increases global temperatures which, in turn, causes rising sea levels, floods, hurricanes, heatwaves and tsunamis, especially in India, Indonesia and the USA. Nitrous Oxide also causes the combustion process of the combination of oxygen and nitrogen, and it contributes to the vulnerability of the ozone layer in the atmosphere.

These environmental problems, compounded by the impacts of population explosion, economic production and industrialization, are exposing the regions to climate change disasters (Kakakhel 2012) such as flash floods, droughts, glacial lake outburst floods, sand storms, landslides, epidemics, cyclones, avalanches, extreme weather events and forest fires. Among GHG emissions, Nitrous Oxide is the most dangerous element for humans, plants and the environment in general (Abas et al. 2017; Ye et al. 2019). For example, increasing levels of Nitrous Oxide can have serious effects on the human respiratory system, and higher Nitrous Oxide levels can cause severe damage to plants by destroying foliage and reducing crop yields (Hasanuzzaman et al. 2018). Furthermore, Nitrous Oxide causes acid rain and this acid rain, mixed with moisture at high concentration, can be detrimental to buildings, can fade the furnishings and foundation structure of constructive projects, decrease visibility and react harmfully with the ground surface of the Earth. Consequently, these six countries are more likely to face the destructive effects of climate change.

These six countries are responsible for 61% of total global emissions, with 85% of the GHGs emissions being associated with fossil fuel consumption. These countries are the largest energy consumers in the world, and according to the National Bureau of Statistics (NBS), in China, total energy consumption in 2017 increased by 2.9%, in 2016 figures, from 4.36 Gigatonne (billion tonnes of standard coal equivalent) (Reuters 2018). India's net imports of crude oil are nearly 198.8 million tons which, along with liquefied natural gas (LNG) at 25.7 Mtoe, and coal at 129.8 Mtoe, means a total of 354.3 Mtoe of primary energy, which is equal to 47% of the total primary energy consumption in 2017, (Sukumaran et al. 2017).

Moreover, about 75% of India's electricity is generated using fossil fuels (mainly coal and imported oil) and it was also a marginal exporter of electricity in

2017 (International Energy Agency 2017). Indonesia's primary energy supply mainly depends on fossil fuels like oil, coal and gas, of which 41% of energy consumption was from oil, 29% from coal, and 24% from natural gas in 2015 (Ministry of Energy and Mineral Resources Republic of Indonesia 2017). Although Japan's electricity production in 2015 was fossil fuel based, currently, Japan produces about 10% of its electricity from renewable sources (Wong 2018). The Russian economy is highly dependent on its oil, hydrocarbons and natural gas revenues, which account for more than one-third of the federal budget revenues (Rutland 2018). For all types of energy used in the USA, about 82% is derived from fossil fuels (British Petroleum 2017).

## Methodology

### Even Grey Model GM (1, 1)

The advanced mathematical model, the grey system, was first introduced by Deng Julong in the 1980s. Currently, it is considered as a means of forecasting in an uncertain system by using small amounts of data and poor data (Zhao and Guo 2016). The advantage of this model is that it forecasts the system whatever the data are poorly available or uncertain (Javed et al. 2018; Javed and Liu 2018). GM (1, 1) is a fundamental and key component of an advanced mathematical modeling system being used for making a prediction based on incomplete information with incomplete and uncertain data. The applications of the grey mathematical forecasting modeling system of GM (1, 1) have been used in several studies in various fields such as wind speed (El-Fouly et al. 2006), industrial output (Wang and Hsu 2008), rural household net income (Zhao et al. 2012), electricity demand forecasting in China (Zhou et al. 2006) and, recently, output growth (Javed and Liu 2018). GM (1, 1) contains one variable having first-order grey model to obtain forecasting information from beginning to end the pile up by means of original sequence of data. Further, GM (1, 1) consists of four fundamental kinds of forecasting models. The Even Grey Model is considered to be more reliable and symmetric in nature having non-exponential increasing sequence highlighted by Liu et al. (2017a, b) shown in Eq. 1.

$$\hat{x}^{(0)}(N) = (1 - e^a) \left( x^{(0)}(1) - \frac{b}{a} \right) e^{-a(N-1)}, \quad (1)$$

$N = 1, 2, \dots, n$

$x^{(0)}$  symbolizes the original sequence of actual data in the above equation, while the additional parameter  $a$  shows the development index and reflects the trend of  $\hat{x}^{(0)}$  and  $\hat{x}^{(1)}$ , whereas  $b$  represents the grey actuating quantity. The prediction is most suitable in a data sequence for the first two data values after the last origin value.

$$\hat{x}^{(1)}(N) = \left( x^{(0)}(1) - \frac{b}{a} \right) e^{-a(N-1)} + \frac{b}{a}, \quad (2)$$

$N = 1, 2, \dots, n$

### Discrete Grey Model GM (1, 1)

Although outcomes obtained from EGM modeling are satisfactory, acceptable and reliable, better and improved results are required. In order to achieve this, we employed a DGM model to assess the accuracy of forecasted results by using actual data (Liu et al. 2017a, b). The accuracy in estimation by using GM (1, 1) is a significant problem that has been addressed by several researchers who have attempted to solve this problem of obtaining more accurate results and minimizing errors. Xie and Liu (2009) undertook an in-depth study in which they measured the relationship between the EGM and DGM models using the Maclaurin formula. They proved that the accuracy level of DGM and its optimization model is better results than GM (1, 1). In our case, the mean absolute percentage error (MAPE) of the DGM is shown to be significantly better than even GM (1, 1) as indicated in Table 5. If  $x^{(0)}$  represents the actual data sequence and  $x^{(1)}$  indicates the general accumulated sequences, then the Discrete Grey Model is given (Liu et al. 2017a, b, chapter 7).

$$\hat{z}^{(1)}(N) = \left[ x^{(0)}(1) - \frac{\beta_2}{1 - \beta_1} \right] \beta_1^N + \frac{\beta_2}{1 - \beta_1} \quad (3)$$

### Non-homogeneous Discrete Grey Model (NDGM)

The Discrete Grey Model is well accepted due to its popularity in forecasting fields, but, in order to ensure more reliable analysis, the mechanism of Non-

homogeneous Discrete Grey Model (NDGM) is more appropriate. NDGM follows the law of approximation non-homogenous exponential growth (Wu et al. 2014), and it is based on the assumption of a sequence of actual data. Xie et al. (2013) recommended that the sequence in the original data is an agreement with a homogenous trend like GM (1, 1). They also concluded that the Non-homogeneous Discrete Grey Model’s accuracy level is much better than DGM (1, 1) and GM (1, 1)’s in terms of mean sequence value and value set of the interval (Xie and Liu 2015). In our case, Table 5 indicates that the overall accuracy level of NDGM is 95.47% among five countries, which is higher than DGM and EGM. The Non-homogeneous Discrete Grey Model has been applied in different fields like Pirthee (2017), who predicted tourism in Mauritius and showed that Non-homogeneous Discrete Grey Model’s forecasting accuracy level is better than any other grey models. Moreover, Ayvaz and Kusakci (2017) predicted the electricity consumption in Turkey and demonstrated that the homogeneous Discrete Grey Model performs better than other grey forecasting models. If the same sequence follows the Non-homogenous Discrete Grey Model  $x^{(0)}$  and  $x^{(1)}$  as above in EGM (1, 1), DGM (1, 1) in Eqs. 1–3.

$$\hat{x}^{(1)}(N + 1) = \beta_1 \hat{x}^{(1)}(N) + \beta_2 \cdot N + \beta_3 \quad (4)$$

$$\hat{x}^{(1)}(1) = x^{(1)}(1) + \beta_4 \quad (5)$$

$\hat{x}^{(1)}(N)$  is the simulated value of  $x^{(1)}$  with four parameters  $\beta_1, \beta_2, \beta_3$  and  $\beta_4$ . We can rewrite the equation in matrix form. If  $N = 1, 2, 3, \dots, n - 1$

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

To input data, the following matrix equation satisfies parameters  $\beta_1, \beta_2, \beta_3$  and  $\beta_4$  by applying the following relation in Eq. 6 (Zhou and He 2013). The solution can be acquired by using the least-squares method which is given as,

$$\hat{\beta} = (B^T B)^{-1} B^T Y = [\beta_1, \beta_2, \beta_3]^T \quad (6)$$

where

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

By using the following formula to calculate  $\beta_4$  for minimizing the sum of square error

$$\beta_4 = \frac{\sum_{N=1}^{n-1} \left[ x^{(1)}(N+1) - \beta_1^N x^{(1)}(1) - \beta_2 \sum_{j=1}^N j \beta_1^{N-j} - \frac{1-\beta_1^N}{1-\beta_1} \cdot \beta_3 \right] \cdot \beta_1^N}{1 - \sum_{N=1}^{n-1} (\beta_1^N)^2} \tag{7}$$

$$\hat{x}^{(1)}(N+1) = \beta_1^N \hat{x}^{(1)}(1) + \beta_2 \sum_{j=1}^N j \beta_1^{N-j} + \frac{1-\beta_1^N}{1-\beta_1} \cdot \beta_3; \tag{8}$$

$N = 1, 2, \dots, n-1$

Hence, the predicted series is intended to calculate the future values and it works with sequence of following the formula,

$$X_{\text{forecast}}(1) = x^{(0)}(1), X_{\text{forecast}}(k) = \hat{x}^{(1)}(k) - \hat{x}^{(1)}(k-1), \tag{9}$$

where  $k = 1, 2, \dots, n$ .

Liu and Forrest (2010) can be consulted for more details about NDGM and its properties and parameters. Environmental sustainability indexes contain mostly highest emitting countries, so we have selected highest emitting countries worldwide which are responsible for huge amounts of emissions. The data for the years 2001 to 2016 used in this paper was run by Grey System software v 8.0 developed by Nanjing University of Aeronautics and Astronautics (NUAA), China, which is used to forecast emissions by using the actual data. Furthermore, Even Grey Model GM(1, 1) and Discrete Grey Model GM (1, 1) were used according to Liu et al. (2017a, b) and NDGM (1, 1) solved with the help of v8.0, MATLAB and Excel.

Performance criterion approach

Mean absolute percentage error (MAPE) represents the performance criteria for comparative analysis between the three grey models. Error measurement information is essential to measure forecasting accuracy and for benchmarking the prediction process.

Explanation of these figures can be complicated, especially when forecasting is done using incomplete information or accuracy assessment across multiple elements. Many institutions focus on the mean absolute percentage error when assessing the predictive accuracy of certain predicted items, and stakeholders feel reassured by taking decisions based upon the predicted accuracy using mean absolute percentage error (Zhou et al. 2006).

$$\text{MAPE}(\%) = \frac{1}{n} \sum_{N=1}^n \left| \frac{x^{(0)}(N) - \hat{x}^{(0)}(N)}{x^{(0)}(N)} \right| \times 100\% \tag{10}$$

Here,  $x^{(0)}(k), \hat{x}^{(0)}(k)$  represent forecasting data values (Chen and Wang 2012).

Lastly, mean absolute percentage error is a statistical tool indicator to confirm the disparity between the forecast and actual values in terms of percentage. The smaller the mean absolute percentage error value, the greater the accuracy of the forecast model. The present study adopted a forecasting model estimating the Nitrous Oxide emissions in 2030 by country.

Nitrous Oxide emissions growth and doubling time analysis

Doubling time is the quantity of time which takes into account for a amount to be doubled in value with a constant growth rate. Actually, it determines the exponential growth in order to double the time of a simulated variable. Growth can be explained as an exponential once the rise of an amount is proportional to the value of the quantity. Exponential growth is low in the early phases, while it rapidly increases. The properties of the doubling time analysis show that the greater the growth rate ( $r$ ), the faster the doubling time. Secondly, growth rate varies significantly among growing organisms and population. Various phenomena cannot be doubled, for example the resistance variables like natural reserve constraints over time. Here, in our case if the population and industrial development continuously grow, the doubling growth rate may occur in future. The doubling time ( $D_t$ ) and relative growth rate (RGR) were calculated by following Javed and Liu (2018). They applied two parameters ( $D_t$  and RGR) to predict certification growth of four countries by using EGM and NDGM models.

The formula of RGR is given by,

$$RGR = (\ln K_2 - \ln K_1) / (\ln N_2 - \ln N_1)(t_2 - t_1) \tag{11}$$

where  $K_2$  and  $K_1$  represent the cumulative number of certifications in a respective year  $t_2$  and  $t_1$ . In our case, the above equation can be rewritten because  $t_2 - t_1$  is 1 year.

$$RGR = \log \left( \frac{K_2 - K_1}{N_2 - N_1} \right) \tag{12}$$

Doubling time ( $D_t$ ) indicates time needed to become double in terms of numbers in specified RGR. The ( $D_t$ ) is given by:

$$D_t = (t_2 - t_1) \ln \left( \frac{2}{2(\ln K_2 - \ln K_1)(\ln N_2 - \ln N_1)} \right). \tag{13}$$

In this study, we used the World Bank data from 2000 to 2016 to calculate simulated values by using advanced mathematical modeling such as Even Grey Model GM (1, 1), Discrete Grey Model GM (1, 1) and Non-homogeneous Discrete Grey Model NDGM performance criteria approach together with growth and doubling time analysis to forecast Nitrous Oxide emissions among the six countries. The World Bank provides a wide-ranging worldwide emissions data while our approximations are varying from the quantification from World Bank, but we have used the Nitrous Oxide emissions data to forecast the future Nitrous Oxide emissions. By using the given data set from 2000 to 2016, it is possible to apply the proposed models to calculate simulated values. Table 7 shows the Nitrous Oxide emissions MAPE a and b for EGM, DGM and NDGM growth/output for selected countries. All three grey models are tested successfully, and results reveal that the NDGM model shows MAPE % overall accuracy results are better than both DGM and EGM. Nevertheless, in the case of India, Japan and China, results reveal that accuracy level is better when compared to other countries in all cases including EGM, DGM and NDGM, respectively. NDGM was a better fit and proved more effective in forecasting of Nitrous Oxide emissions among the three grey models.

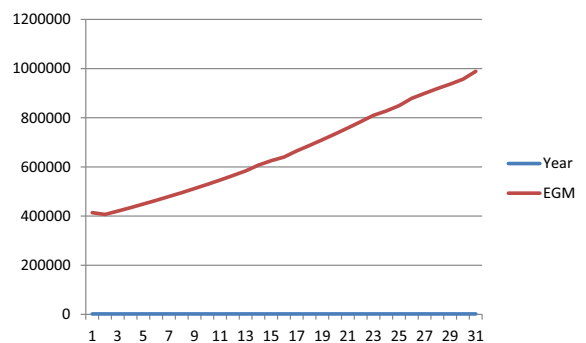
### Results and discussion

This section deals with the presentation of the results on the bases of methodology and data sets obtained for analysis. The section presents the brief results with advanced mathematical tool, namely grey mathematical system. Moreover, this section also clarifies the findings of the study on the bases of study model used during conceptualization.

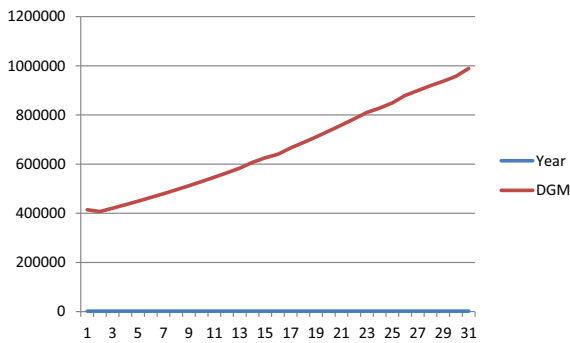
China’s future Nitrous Oxide emission shows an increasing trend with the passage of time. In spite of China’s 2030 renewable ambitious energy metrics plan, our results show a contrary Nitrous Oxide emissions path (Figs. 1, 2). China’s highest Nitrous Oxide emissions are 988,979.6 and minimum Nitrous Oxide emissions are 406,932.3, while the total Nitrous Oxide emissions are 20,578,144 and average value is 663,811.1. Mean absolute percentage error (MAPE) assesses the criteria performance to measure the comparative analysis among the three advanced mathematical models.

Error measurement information is necessary to evaluate forecasting accuracy by using the Even Grey Model, Discrete Grey Model and Non-homogeneous Discrete Grey Model, allowing for benchmarking of the prediction process of Nitrous Oxide emissions during the years 2000 to 2030. The MAPE value of EGM model for China is 1.04%, which implies that the accuracy path in the proposed model is greater than 98%. For NDGM, from 2016 to 2030 simulated values and for the next 2030 years forecasting values were calculated (Fig. 3).

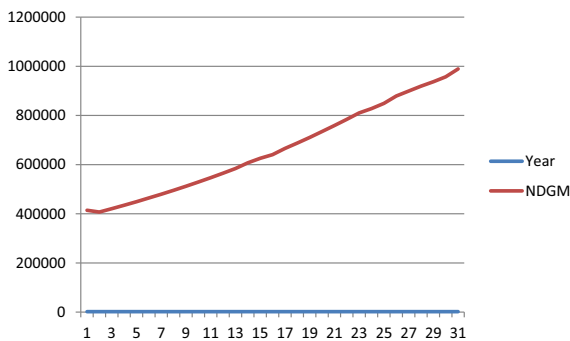
The comparison between actual data and simulated/forecasting data is shown in Table 1. Table 2 shows the results for Indonesia. Using the Even Grey



**Fig. 1** China’s Nitrous Oxide emissions based on EGM (2000–2030)



**Fig. 2** China's Nitrous Oxide emissions based on DGM (2000–2030)



**Fig. 3** China's Nitrous Oxide emissions based on NDGM (2000–2030)

Model GM (1, 1), Discrete Grey Model GM (1, 1) and Non-homogeneous Discrete Grey Model NDGM performance criteria approach and growth and doubling time analysis to forecast Nitrous Oxide emission similarly, almost the same results were obtained, while the Non-homogeneous Discrete Grey Model NDGM shows slightly more better results compared to EGM and DGM.

Indonesia's highest Nitrous Oxide emissions are 136,819.4 and minimum Nitrous Oxide emissions are 91,548.24, while the total Nitrous Oxide emissions are 3,405,388.7 and average value is 109,851.3. The MAPE value for Indonesia is 4.79%, which implies that the accuracy path in the proposed model is greater than 95%. Table 3 presents the results for India, where MAPE accuracy is obtained by using NDGM, DGM and EGM. Here, NDGM is a slightly more useful forecasting model than DGM and EGM.

India has a population of approximately 1.4 billion and has some of the world's most congested cities like Bombay, New Delhi, Kolkata and Ahmadabad.

**Table 1** Nitrous Oxide emissions of China

Year	Actual	EGM	DGM	NDGM
2000	414,138.3	414,138.3	414,395.9	414,539.6
2001	421,934.8	406,932.3	407,189.9	407,222.1
2002	421,934.8	420,492.6	420,750.2	420,782.4
2003	423,618.1	434,504.8	434,762.4	434,794.6
2004	450,616.0	448,984.0	449,241.6	449,273.8
2005	460,545.3	463,945.6	464,203.2	464,235.4
2006	478,878.7	479,405.8	479,663.4	479,695.6
2007	492,159.1	495,381.2	495,638.8	495,671
2008	502,550.3	511,889.0	512,146.6	512,178.8
2009	527,747.1	528,946.8	529,194.4	529,236.6
2010	550,296.5	546,573.1	546,820.7	546,862.9
2011	568,731.4	564,786.7	565,034.3	565,076.5
2012	587,166.4	583,607.3	583,854.9	583,897.1
2013	607,176.6	607176.6	607,424.2	607,466.4
2014	625,392.8	625,392.8	625,640.4	625,682.6
2015	640,051.7	640,051.7	640,299.3	640,341.5
2016	665,373.7	665,373.7	665,621.3	665663.5
2017		687,546.2	687,843.8	687,836
2018		710,457.5	710,755.1	710,747.3
2019		734,132.3	734,429.9	734,422.1
2020		758,596.3	758,894.5	758,885.8
2021		783,875.5	784,173	784,164.8
2022		809,996.3	810,293.9	810,286.1
2023		827,694.6	827,996.5	827,983.1
2024		848,962.7	849,264.5	849,252.5
2025		878,959.3	879,256.9	879,249.1
2026		898,968.3	899,262.5	899,252
2027		918,944.3	919,244.8	919,235.1
2028		936,724.3	937,024	937,019.7
2029		956,724.9	957,021.9	957,011.3
2030		988,979.6	989,274	989,268.2

Moreover, another major issue is India's reliance on imported crude oil from OPEC and other international oil exporters in the world, even though India is trying to incorporate a renewable energy metrics roadmap in their national energy consumption roadmap. The MAPE value for India is 1.01%, which means that the accuracy path in the forecasting model is greater than 98%. Meanwhile, the results reveal that the following EGM-based forecasting equations help out to measure the parameters *a* and *b* for Nitrous Oxide emissions. Table 4 represents a list of results for Japan. The results show that, as with other countries,



**Table 2** Nitrous Oxide emissions of Indonesia

Year	Actual	EGM	DGM	NDGM
2000	94,932.85	94,932.85	95,234.7	95,253.65
2001	96,600.65	136,819.4	137,121.3	137,140.2
2002	151,117.9	134,307.5	134,609.4	134,628.3
2003	103,095.2	131,841.7	132,143.6	132,162.5
2004	120,281.6	129,421.1	129,723.7	129,741.9
2005	162,715.6	127,045.0	127,346.9	127,365.8
2006	243,198.7	124,712.6	125,014.5	125,033.4
2007	98,407.02	122,422.9	122,724.8	122,743.7
2008	97,405.72	120,175.3	120,477.2	120,496.1
2009	134,060.4	117,969.0	118,270.9	118,289.8
2010	91,312.67	115,803.1	116,105.5	116,123.9
2011	92,225.80	113,677.0	113,978.9	113,997.8
2012	93,138.92	111,590.0	111,891.9	111,910.8
2013	109,541.3	94,932.85	95,234.75	95,253.65
2014	107,530.2	136,819.4	137,121.3	137,140.2
2015	105,556.0	134,307.5	134,609.4	134,628.3
2016	103,618.0	131,841.7	132,143.6	132,162.5
2017		101,716.4	102,055.8	102,036.5
2018		99,848.24	100,150.8	100,169.3
2019		98,015.12	98,316.44	98,335.87
2020		96,215.98	96,556.55	96,536.37
2021		94,476.11	94,751.01	94,769.91
2022		92,715.09	93,094.99	93,035.89
2023		92,212.54	93,034.21	9542.031
2024		92,791.11	92,733.01	92,431.91
2025		91,985.76	91,924.99	92,218.89
2026		91,666.28	92,079.13	92,098.08
2027		91,548.24	92,001.44	91,993.23
2028		91,712.34	91,863.79	91,882.14
2029		91,893.98	91,734.79	91,753.78
2030		99,972.56	100,274.6	100,293.5

**Table 3** Nitrous Oxide emissions of India

Year	Actual	EGM	DGM	NDGM
2000	207,700.0	207,700.0	207,989.8	207,999.8
2001	202,543.2	196,504.8	196,794.6	196,804.6
2002	196,076.9	200,073.6	200,363.4	200,373.4
2003	203,758.4	203,707.2	203,997	204,007.2
2004	209,205.1	207,406.9	207,696.7	207,706.7
2005	209,587.6	211,173.7	211,463.5	211,473.5
2006	213,150.1	215,008.9	215,298.7	215,308.7
2007	216,862.4	218,913.8	219,203.6	219,213.6
2008	219,944.4	222,889.6	223,179.4	223,189.4
2009	226,562.0	226,937.6	227,227.4	227,237.4
2010	234,135.9	231,059.1	231,348.9	231,358.9
2011	236,945.5	235,255.5	235,545.3	235,555.3
2012	239,755.1	239,528.1	239,817.9	239,827.9
2013	243,878.2	207,700.0	207,989.8	207,999.8
2014	248,307.4	196,504.8	196,794.6	196,804.6
2015	252,817.1	200,073.6	200,363.4	200,373.4
2016	257,408.6	203,707.2	203,997.5	257,708.4
2017		262,083.5	262,322.7	262,383.3
2018		266,843.3	267,159.4	267,143.1
2019		271,683.6	271,529.4	271,989.4
2020		276,659.9	276,982.7	276,923.7
2021		281,698.8	281,932.9	281,947.6
2022		286,764.9	287,052.1	287,062.7
2023		298,839.5	299,157.1	299,173.1
2024		296,729.3	297,035.2	297,098.2
2025		306,746.5	307,068.7	307,062.3
2026		308,778.8	309,033.4	309,099.6
2027		318,896.3	319,135.6	319,199.1
2028		318,748.9	319,065.8	319,086.3
2029		338,734.1	339,058.6	339,099.6
2030		348,785.1	349,076.7	349,010.9

the NDGM is slightly more useful and showed better forecasting results than EGM and DGM.

The MAPE value for Japan is 0.84%, which means that the accuracy path in the forecasting model is greater than 99%. Meanwhile, the EGM-based forecasting equation shows that the values of parameters  $a = 0.015$  and  $b = 30,583.59$  for Japan. Table 5 shows the results for USA using the Even Grey Model EGM (1, 1), Discrete Grey Model DGM (1, 1) and Non-homogeneous Discrete Grey Model NDGM performance criteria approach and growth and doubling time

analysis to forecast Nitrous Oxide emissions. Again, almost the same results were obtained, although the Non-homogeneous Discrete Grey Model NDGM shows slightly more effectiveness compared with EGM and DGM.

The results show that USA’s highest Nitrous Oxide emissions are 325,500 and minimum Nitrous Oxide emissions are 247,671.5, while the total Nitrous Oxide emissions are 8,891,219 and the average value is 286,813.5. The MAPE value for USA is 1.16%, which means that the accuracy path in the forecasting model

**Table 4** Nitrous Oxide emissions of Japan

Year	Actual	EGM	DGM	NDGM
2000	30,411.00	30,411.00	30,411.00	30,411.00
2001	29,488.32	29,689.07	29,689.07	29,689.07
2002	28,920.24	29,253.67	29,253.67	29,253.67
2003	28,660.46	28,824.65	28,824.65	28,824.65
2004	28,474.96	28,401.92	28,401.92	28,401.92
2005	28,427.28	27,985.39	27,985.39	27,985.39
2006	27,837.81	27,574.97	27,574.97	27,574.97
2007	27,770.11	27,170.57	27,170.57	27,170.57
2008	26,747.20	26,772.10	26,772.10	26,772.10
2009	26,287.19	26,379.47	26,379.47	26,379.47
2010	25,761.62	25,992.60	25,992.6	25,992.60
2011	25,599.34	25,611.41	25,611.41	25,611.41
2012	24,911.49	25,235.81	25,235.81	25,235.81
2013	24,865.71	30,411.00	30,411.00	30,411.00
2014	24,501.04	29,689.07	29,689.07	29,689.07
2015	24,141.72	29,253.67	29,253.67	29,253.67
2016	23,787.67	28,824.65	28,824.65	28,824.65
2017		23,436.24	23,591.81	23,438.81
2018		23,092.50	23,248.07	23,095.07
2019		22,753.80	22,909.37	22,756.37
2020		22,420.07	22,575.64	22,422.64
2021		22,091.23	22,246.80	22,093.80
2022		21,767.21	21,922.78	21,769.78
2023		21,562.21	21,717.78	21,564.78
2024		21,449.79	21,605.36	21,452.36
2025		21,347.21	21,502.78	21,349.78
2026		21,231.90	21,387.47	21,234.47
2027		20,184.90	20,340.47	20,187.47
2028		20,540.41	20,695.98	20,542.98
2029		20,390.25	20,545.82	20,392.82
2030		20,369.64	20,525.21	20,372.21

**Table 5** Nitrous Oxide emissions of USA

Year	Actual	EGM	DGM	NDGM
2000	325,500.0	325,500.0	325,500.0	325,500.0
2001	319,346.5	319,346.5	319,346.5	319,346.5
2002	317,486.5	317,486.5	317,486.5	317,486.5
2003	318,013.5	318,013.5	318,013.5	318,013.5
2004	321,857.5	321,857.5	321,857.5	321,857.5
2005	320,397.4	320,397.4	320,397.4	320,397.4
2006	311,987.1	311,987.1	311,987.1	311,987.1
2007	311,664.7	311,664.7	311,664.7	311,664.7
2008	302,405.0	302,405.3	302,476.9	302,414.7
2009	304,609.1	304,609.1	304,609.1	304,609.1
2010	304,082.1	304,082.1	304,082.1	304,082.1
2011	296,743.5	296,743.5	296,743.5	296,743.5
2012	288,878.0	288,878.1	288,823.0	288,845.0
2013	293,020.2	293,020.2	293,020.2	293,020.2
2014	290,541.1	290,541.1	290,541.1	290,541.1
2015	288,082.9	288,082.9	288,082.9	288,082.9
2016	285,645.5	285,645.5	285,645.5	285,645.5
2017		283,226.2	283,226.2	283,226.2
2018		280,829.9	280,829.9	280,829.9
2019		278,453.8	278,453.8	278,453.8
2020		276,097.9	276,097.9	276,097.9
2021		273,761.9	273,761.9	273,761.9
2022		271,445.7	271,445.7	271,445.7
2023		264,240.5	264,240.5	264,240.5
2024		256,191.6	256,191.6	256,191.6
2025		251,231.0	251,231.0	251,231.0
2026		259,523.1	259,523.1	259,523.1
2027		250,521.0	250,521.0	250,521.0
2028		248,341.8	248,341.8	248,341.8
2029		249,422.3	249,422.3	249,422.3
2030		247,671.5	247,671.5	247,671.5

is about 98%. Similarly, NDGM showed slightly better forecasting results over DGM and EGM. Meanwhile, the EGM-based forecasting equation measures the values for USA by using the parameters  $a$  and  $b$  for three models. Table 6 shows the result for Russia: the accuracy level of EGM, DGM and NDGM, respectively.

The results reveal that the Russia's highest Nitrous Oxide emissions are 119,441.5 and minimum Nitrous Oxide emissions are 31,779.66, while the total Nitrous Oxide emissions are 1,705,110 and the average value is 55,003.56. The MAPE value for Russia has been

noted as 5.56%; it implies that the accuracy path in the forecasting model was found near about greater than 94%. Similarly, NDGM showed slightly better forecasting results over DGM and EGM. Meanwhile, the following EGM-based forecasting equation for Russia by using the parameters  $a$  and  $b$ .

As far as the three prediction grey models used in forecasting of Nitrous Oxide emissions are concerned, in each of the six countries, NDGM accuracy level seems more better than EGM and DGM as presented in Table 7. These results showed satisfactory results;

**Table 6** Nitrous Oxide emission of Russia

Year	Actual	EGM	DGM	NDGM
2000	93,000.00	93,000.00	93,009.99	930,067.9
2001	90,116.38	90,116.38	90,116.38	90,116.38
2002	108,805.7	108,805.7	108,805.7	108,805.7
2003	119,441.5	119,441.5	119,441.5	119,441.5
2004	77,519.22	77,519.22	77,519.22	77,519.22
2005	77,471.17	77,471.17	77,471.17	77,471.17
2006	65,002.04	65,002.04	65,002.04	65,002.04
2007	65,020.33	65,020.33	65,020.33	65,020.33
2008	62,545.60	62,545.60	62,523.72	62,545.6
2009	64,810.77	64,810.77	64,810.77	64,810.77
2010	63,728.25	63,728.25	63,728.25	63,728.25
2011	64,461.12	64,461.12	64,461.12	64,461.12
2012	65,194.00	65,194.00	65,123.21	65,194.02
2013	52,888.30	52,888.30	52,865.31	52,888.45
2014	50,060.53	50,060.53	50,060.53	50,060.53
2015	47,383.95	47,383.95	47,383.95	47,383.95
2016	44,850.47	44,850.47	44,850.47	44,850.47
2017		42,449.89	42,605.46	42,452.46
2018		40,180.09	40,335.66	40,182.66
2019		38,031.65	38,187.22	38,034.22
2020		35,998.07	36,153.64	36,000.64
2021		35,220.23	35,375.8	35,222.8
2022		34,982.86	35,138.43	34,985.43
2023		34,431.64	34,587.21	34,434.21
2024		34,118.64	34,274.21	34,121.21
2025		33,829.55	33,985.12	33,832.12
2026		33,551.30	33,706.87	33,553.87
2027		33,741.30	33,896.87	33,743.87
2028		32,245.24	32,400.81	32,247.81
2029		31,779.66	31,935.23	31,782.23
2030		32,250.95	32,406.52	32,253.52

Non-homogeneous Discrete Grey Model was a better fit and proved more effective in forecasting of Nitrous Oxide emissions because using the Non-homogeneous

**Table 7** MAPE, *a* and *b* for EGM, DGM and NDGM

Country	EGM (%)	DGM (%)	NDGM (%)	<i>a</i>	<i>b</i>
China	1.04	1.00	0.91	− 0.032	380,453.8
Indonesia	4.79	4.11	3.62	0.009	141,153.8
India	1.01	0.97	0.86	− 0.018	189,294.8
Japan	0.84	0.77	0.63	0.015	30,583.59
Russia	5.56	4.98	4.42	0.026	113,295.7
USA	1.16	1.11	0.98	0.009	330,018.9

Discrete Grey Model the mean absolute percentage error of all countries has lowest values as compared to Even Grey Model (1, 1) and Discrete Grey Model (1, 1).

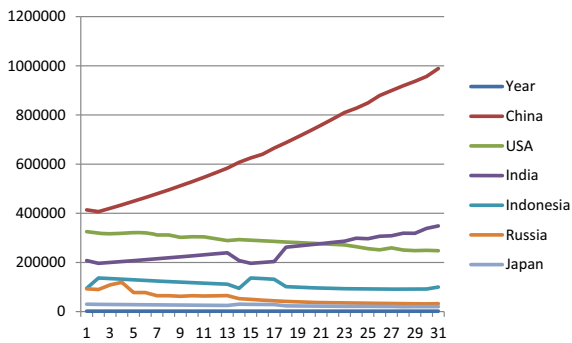
The above results show that China has the highest growth rate followed by India and Indonesia, while Japan, Russia and USA have the negative growth rate. The results also show that in developing countries like China and India, Nitrous Oxide emissions are increasing but decreasing in developed countries (Fig. 4). Using the Even Grey Model forecasted/simulated based data to predict the future trend of Nitrous Oxide emissions among six countries, according to the total emissions the following sequence was obtained:

$$\begin{aligned} & \text{China}_{(20,578,144)} > \text{USA}_{(8,891,219)} > \text{India}_{(7,806,137)} \\ & > \text{Indonesia}_{(3,405,389)} > \text{Russia}_{(1,705,110)} \\ & > \text{Japan}_{(780,118)} \end{aligned}$$

These interesting results show that India is expecting a higher growth rate in the coming years followed by Indonesia and Japan. Similarly, based on relative growth rate, India required almost several years to double Nitrous Oxide emissions. By using the actual and forecasting data, this study proposes a novel grey synthetic model of both doubling time and relative growth rate (RGR). Liu et al. (2017a, b) developed two synthetic grey indices: synthetic relative growth and synthetic doubling time. By using the actual data and forecasted/simulated data, based on relative growth rate the synthetic relative growth rate equation is given by:

$$\text{RGR}_{\text{synthetic}} = \alpha(\text{RGR}_{\text{actual}}) + (1 - \alpha)(\text{RGR}_{\text{simulated}}) \tag{14}$$

Hence,  $\alpha$  represents the coefficients of relative weights and values of  $\alpha$  can be taken as 0.5. If the decision makers in decision making take the relative growth rate of actual data more important, then



**Fig. 4** Level of Nitrous Oxide emissions (2000–2030)

$1 - \alpha < \alpha$ . Furthermore, by using the actual data and forecasted/simulated data, based on doubling time the synthetic doubling time equation is given by:

$$D_{\text{synthetic}} = \alpha(D_{\text{actual}}) + (1 - \alpha)(D_{\text{forecasted}}) \quad (15)$$

Here,  $D_{\text{actual}}$  indicates the doubling time from actual data,  $D_{\text{forecasted}}$  shows the doubling time from simulated/forecasted data, and  $\alpha$  shows the coefficient of relative weights. By using the synthetic grey model based on relative growth rate at  $\alpha = 0.5$ , the following sequence of the result was obtained: Likewise, by using the synthetic grey model based on doubling time at  $\alpha = 0.5$ , the following sequence of the result was obtained. By successfully applying the two synthetic grey indices, synthetic RGR and synthetic doubling time, we obtained similar sequence from simulated data, and the results are aligned with forecasting data.

## Discussion

Indonesia has the highest renewable energy consumption share contributing to 37.45% of its total final energy consumption, while China has the medium ratio of renewable energy consumption share contributing to 12.22% of its total final energy consumption. China has the highest CO<sub>2</sub> emissions of 10877.2 million tons, while Indonesia has the lowest CO<sub>2</sub> emissions (511.3 million ton) contributing 1.38% of the total world's CO<sub>2</sub> emissions. Every country in the world is making efforts to reduce emissions to adapt to climate change. It is a global problem which is not restricted to a specific area. People from all over the world are in a danger due to the continuous rise in the earth's temperature which is causing melting of the permafrost and polar ice cap, and this will certainly affect the planet's ecosystems. Unfortunately, in the

past few decades the undue fossil fuel consumption and deforestation have aggravated the situation. The atmosphere holds approximately 44% more dangerous emitting molecules as compared to the level of 1750 in the previous time. This problem has led to the global warming at 0.8 °C since 1880 through continuous increase rate of nearly 0.15–0.20 °C/decade. Share of renewable sources in USA's energy mix is 8.75% of the national energy mix and Japan having 3.42% in its national energy mix. Even though these figures are continuously rising with passage of time, but according to the Paris agreement it requires a substantial improvement to increase the clean energy mix in order to cope with controlling the global temperature (Tables 8, 9).

This is why China's Nitrous Oxide emission shows a rising (with decreasing) trend during this period. It means that China's actual performance toward emission reduction with the Paris Agreement shows a close semblance to increase the renewable energy sources as well. The renewable energy consumption share of Russia accounts for only 3.42% of its total final energy consumption, while its emission contribution toward world total emission is 4.76%. Russia's emissions and renewable energy share scarcely have increased which is beyond the expectation that the Russian can increase its renewable figure by 5% in near future, to match with the ratio of pollution emissions.

Regarding India's emission, it is 6.62% while its renewable consumption is 36.65% which seems better than Russia. Similarly, Japan's situation is the same as India's, but for Indonesia, it is leading in renewable (including hydro) energy sources. China's current environmental situations showed that the status ([http://www.gov.cn/xinwen/2017-06/06/content\\_5200281.htm](http://www.gov.cn/xinwen/2017-06/06/content_5200281.htm)), with regard to air quality in the 338 prefecture-level cities, 84 cities, attained the standard of environmental air quality which accounted for 24.9%, while 254 urban air quality indexes surpassed the desired standard, which accounted for 75.1%. Through the involvement of policies of national government in 2016, the concentration of Nitrous Oxide varied from 9 to 61 µg/m<sup>3</sup>; through an average value of 30 µg/m<sup>3</sup>, this value was equal to 2015' value (Feng et al. 2019). But it is still far from the Paris Agreement's goal.

**Table 8** Global contribution of CO<sub>2</sub> emission level of 2017 (Mt/yr)

Country	Contribution in global emission (%)	Total emission
China	29.34	10877.2
Indonesia	1.38	511.3
India	6.62	2454.8
Japan	3.56	1320.8
Russia	4.76	1764.9
USA	13.78	5107.4

**Table 9** Renewable energy consumption in 2014

Country	Renewable energy consumption share (% of total final energy consumption)	Energy use (kg of oil equivalent per capita)
China	12.22	2236.7
Indonesia	37.45	883.9
India	36.65	636.6
Japan	5.63	3470.8
Russia	3.42	4942.9
USA	8.75	6960.7

**Sensitivity analysis**

We have conducted sensitivity analysis to measure the robustness of the employed methodology. Since poorly developed methodology may lead to a misleading and non-robust policy, we have undertaken this task. The results in Table 10 obviously demonstrate the effect of data variation on the overall results. The sampling variation and the uncertainty are not objectives of the paper, while still the data accuracy is one more important task. In the case of Nitrous Oxide data, as suggested by Zhou et al. (2016) the level of uncertainty in measuring the accuracy of the data formed the forecasting of Nitrous Oxide emissions.

On the other hand, using the grey mathematical models, the sensitivity analysis for data can be theoretically checked. In the current study, the sensitivity analysis of Nitrous Oxide emission has been carried out, by using the newly developed data with ± 10% variation in the original data sets, which generating the random numbers within the range of interval [− 10%, 10%]. Results show that the impact of forecasted values of Nitrous Oxide emission is comparatively similar to results generated by original data which may indicate the robustness of the

methodology in terms of accurate assessment of predicting capacity.

**Conclusion and policy implication**

We forecasted the Nitrous Oxide emissions levels for some selected countries—China, Indonesia, India, Japan, Russia and the USA for the year 2030 based on actual data from 2000 to 2016. The forecast is done using the best and well-accepted methods that provides specific measurement criteria at micro- and macro-level. Further, the outcomes provide a feasible solution, whereas clarity makes things easier for policy and decision makers and makes it role play to reduce the Nitrous Oxide emissions. The results presented that all three grey predictions models, Even Grey Model (1, 1), Discrete Grey Model (1, 1) and Non-homogeneous Discrete Grey Model NDGM, were tested successfully and showed satisfactory results; Non-homogeneous Discrete Grey Model was a better fit and proved more effective in forecasting of Nitrous Oxide emissions. Results shows that by using the Non-homogeneous Discrete Grey Model the mean absolute percentage error of all countries has lowest values as compared to Even Grey Model (1, 1) and Discrete Grey Model (1, 1).

Mean absolute percentage error of Even Grey Model (1, 1) is 2.4%, that of Discrete Grey Model (1, 1) is 2.16%, and that of Non-homogeneous Discrete Grey Model is 1.9%. Further, the results show that China has highest Nitrous Oxide emissions during the years, i.e., China 20,578,144, USA 8,891,219, India 7,806,137, Indonesia 3,405,389, Russia 1,705,110 and Japan 780,118 Nitrous Oxide emissions. Nitrous Oxide emissions projections are predisposed by various parameters such as technological advances, types of fuel consumptions, political initiatives and economic growth rates. For attainment of more realistic

**Table 10** Sensitivity analysis of Nitrous Oxide emissions of China

Year	Actual	EGM	DGM	NDGM
2000	414,138.3	414,422.3	414,567.9	414,567.6
2001	421,934.8	406,821.3	407,630.9	407,682.1
2002	421,934.8	420,492.6	420,750.2	420,782.4
2003	423,618.1	434,504.8	434,762.4	434,794.6
2004	450,616.0	448,984.0	449,241.6	449,273.8
2005	460,545.3	463,945.6	464,203.2	464,235.4
2006	478,878.7	479,405.8	479,663.4	479,695.6
2007	492,159.1	495,381.2	495,638.8	495,671
2008	502,550.3	511,889.0	512,146.6	512,178.8
2009	527,747.1	528,946.8	529,194.4	529,236.6
2010	550,296.5	546,573.1	546,820.7	546,862.9
2011	568,731.4	564,786.7	565,034.3	565,076.5
2012	587,166.4	583,607.3	583,854.9	583,897.1
2013	607,176.6	607,176.6	607,424.2	607,466.4
2014	625,392.8	625,392.8	625,640.4	625,682.6
2015	640,051.7	640,051.7	640,299.3	640,341.5
2016	665,373.7	665,373.7	665,621.3	665,663.5
2017		687,375.2	687,983.8	687,826.4
2018		710,983.5	710,432.1	710,983.3
2019		734,436.3	734,984.9	734,432.1
2020		758,732.3	758,455.5	758,671.8
2021		783,963.5	784,542.9	784,198.8
2022		809,964.3	810,234.9	810,298.1
2023		827,635.6	827,996.5	827,989.1
2024		848,963.7	849,298.5	849,100.6
2025		878,959.3	879,256.9	879,249.1
2026		898,968.3	899,262.5	899,420.5
2027		918,944.3	919,409.8	919,235.1
2028		936,724.3	937,024	937,019.7
2029		956,762.8	957,856.4	957,395.3
2030		988,458.6	989,745.3	989,345.8

and successful results, projections should be done together with additional factors of technological advances, types of fuel consumptions, and political initiatives and economic growth rates. The detailed study can be done for developing countries because these countries are more vulnerable to climate change. Globally, every country is trying its best to solve the problem of greenhouse gas emissions. This study suggests some implications for both academicians and practitioners. From an academic point of view, the application of NDGM grey prediction models showed

overall better results than other grey models used in the analyses of future trends in different countries and sectors. Based on Discrete Grey Model and Non-homogeneous Discrete Grey Model technique, the projected values showed that there is a direct relationship between energy consumption, Nitrous Oxide emissions and real GDP for economic development. Consequently, energy consumption is a crucial element of Nitrous Oxide emissions. In order to decrease the Nitrous Oxide emissions, there is the need to control the chemical wastage during industrial production.

- Undertake the execution of tighter less emission vehicle standards and promote the awareness of zero emission vehicles to manage environmental protection.
- Construction of national environment protection precautionary measures against fossil fuel to overcome harms of GHGs emissions.
- Increase the level of renewable energy in total national energy mix. This will enhance green environmental productivity and sustainability including environmental cleanliness and availability of hygienic system for social stakeholders.
- There should be development of emissions and pollution forecasting systems for highly congested societies to reduce GHGs issues for society.
- Use bicycle and electric vehicles for near commuting to reduce environmental pollution.
- Get rid of coal power plants and thermal plants for power production so that air pollution and environmental dehydration may reduce.
- There should be subsidy on renewable energy in total energy mix.
- There should be proper underground system of industrial chemical waste management.
- There should be a special percentage of forest land in the country for generation of green oxygen to combat with harms of GHGs emission.
- Green mutual fund should be established to continuously monitor the environmental degradation and other harmful effects.
- The targets of sustainable development policies and sustainable development achievement play a major role in growth rate, while it decreases the depletion of natural resources possible by the above-mentioned environment protection strategies.

- There should be a balanced equilibrium approach among population growth and economic development in order to control the environmental degradation.
- The irreparable severe impacts of Nitrous Oxide need a worldwide joint effort to deal with these worst situations to maintain sustainable development.

**Limitations** There is little or no other way out for environmental diversification. Moreover, some rare studies, however, have found evidence of investigating environmental diversification portfolios to overcome GHGs issues, but these concepts have not assessed comparatively. This is the major limitation that is faced by researchers to operationalize recent investigation. Due to the study’s entire focus on Nitrous Oxide emissions assessment and national peculiarities/characteristics presenting less support to society, more work needs to be done in the practical implementation. Due to time and data constraints, macroeconomic environmental factors were not incorporated in the investigation model. This could be included in future studies for a more in-depth analysis.

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