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# Forecasting of $CO_2$ emissions, energy consumption and economic growth in China using an improved grey model

Hsiao-Tien Pao [a,*], Hsin-Chia Fu [b], Cheng-Lung Tseng [c]

[a] Department of Management Science, National Chiao Tung University, Hsinchu, Taiwan
[b] College of Engineering, Huaqiao University, Quanzhou, China
[c] Department of computer science, National Chiao-Tung University, Taiwan

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ABSTRACT

Analyses and forecasts of carbon emissions, energy consumption and real outputs are key requirements for clean energy economy and climate change in rapid growth market such as China. This paper employs the nonlinear grey Bernoulli model (NGBM) to predict these three indicators and proposes a numerical iterative method to optimize the parameter of NGBM. The forecasting ability of NGBM with optimal parameter model, namely NGBM–OP has remarkably improved, compared to the GM and ARIMA. The MAPEs of NGBM–OP for out-of-sample (2004–2009) are ranging from 1.10 to 6.26. The prediction results show that China's compound annual emissions, energy consumption and real GDP growth is set to 4.47%, −0.06% and 6.67%, respectively between 2011 and 2020. The co-integration results show that the long-run equilibrium relationship exists among these three indicators and emissions appear to be real output inelastic and energy consumption elastic. The estimated values cannot support an EKC hypothesis, and real output is significantly negative impact on emissions. In order to promote economic and environmental quality, the results suggest that China should adopt the dual strategy of increasing energy efficiency, reducing the loss in power transmission and distribution and stepping up energy conservation policies to reduce any unnecessary wastage of energy.

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## 1. Introduction

"Climate Change 2007", the Fourth Assessment Report of the United Nations Intergovernmental Panel on Climate Change (IPCC), predicts that by 2100 global average temperature could rise 2–4.2°. Most experts have attributed the root causes of global warming to the rapid growth of the global economy, human consumption of large amounts of energy, and the greenhouse effect from emissions of six gases affecting Earth's climate changes. The 1997 Kyoto Protocol had the objective of reducing greenhouse gases (GHG), which cause climate change. It demanded a 5.2% reduction of GHG emissions compared to the 1990 level, between 2008 and 2012. The Protocol went into effect in 2005. Amongst several environmental pollutants that can cause climate change, carbon dioxide ($CO_2$) is responsible for 58.8% of all GHGs [1]. The combustion of fossil fuels is the largest single contributor to $CO_2$ and total GHG emissions, and of all the major sources, their impact has grown the most rapidly since 1970 because of the world's recent economic growth. Therefore, the analyses and forecasts of $CO_2$ emissions, energy consumption and economic growth constitute a vital part of clean energy economy.

In emerging markets such as China, although she signed the Kyoto protocol to curb emission, environmental concerns are still there, because of the country's large population, strong capital investment and urbanisation, and heavy reliance on coal. China is the biggest coal consumer in Asian region. For the trend of $CO_2$ emissions, increasing coal consumption brought China to overtake the United States in 2006 as the world's biggest emitter of carbon dioxide; China's $CO_2$ emissions were 25.43% of the world total in 2009 (EIA, Energy Information Administration). But the country's carbon dioxide emissions per capita are also relatively low compared to developed countries, and China has not contributed much to climate change because of its short history as an industrial nation. Figure for 2009 (EIA), per capita emissions were 5.82 tons in China, which is lower than 8.22 tons of the 15 nations in European Union, or 17.67 tons in United States, but it is larger than the world average figure of 4.47 tons. As shown in [2], in order to actively respond climate change and to develop clean energy economy, China has an ambitious goal to reduce carbon intensity by 40–45% by 2020, from 2005 levels.

* Corresponding author. Tel.: +886 3 5131578; fax: +886 3 5710102.
*E-mail address:* htpao@mail.nctu.edu.tw (H.-T. Pao).

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For the trend of energy consumption, in 2009, China became the world's largest energy consumer. In 2010, the country consumed 5.3% more coal, 12.9% more crude oil, 18.2% more natural gas and 13.1% more electricity than in 2009; however its energy intensity fell 4.01%. Based on data from 2008 (EIA), China's energy intensity was 11,086.80 Btu, which is higher than the 5278.14 Btu of the 15 nations in European Union, the 7602.96 Btu in USA or the 9798.42 Btu of the world average. China aims to reduce its energy intensity by as much as 17% by 2015 from current level, by closing enterprises that are heavy energy users. In the next five years, China aims to generate 11.4% of energy from non-fossil fuels, and to raise smart grid market from $22.3 billion to $61.4 billion [2]. The country's massive smart grid plans is to address issues in its power industry and to develop a lower-carbon economy. The plan will largely change the generation and the use of energy in China. In addition, Chinese government efforts to control inflation and restructure the economy will slow economic growth, which should also reduce the growth in energy use.

For the trend of economic growth, China ranks since 2010 as the world's second largest economy after the USA. It has been the world's fastest-growing major economy, with consistent growth rates of around 10.98% over the past 30 years. China is also the largest exporter and second importer of goods in the world. As China's economic importance has grown, so should be concerned about the economy's structure and health. Due to constantly pursuing rapid economic expansion in past years, China has brought unbalanced economic and social development. Therefore, the official target for average GDP growth over the next five years is set to 7% annually, which is 0.5% down from the past five years [3]. It reflects the government's determination to shift the economic focus from speed to quality.

The relationship between emissions and economic growth, as well as economic growth and energy consumption, has been intensively analysed over the past two decades. Recently, a combination of these two approaches has emerged, which facilitates the examination of the long-run relationship among economic growth, energy consumption and environmental pollutants. China's carbon dioxide emissions, energy consumption and economic growth rose sharply, the historical data for each series usually differ significantly from the actual growth. Therefore, an intelligent model with good adaptability and high forecasting accuracy to predict these time series is important for clean energy economy. This paper uses recent years' data in the grey prediction models for the multi-step forecasting of each series, with a forecast period between 2009 and 2020. The grey prediction model has good forecasting ability even if there are only four original data [4,5]. The co-integration technique is employed to examine the long-term relationship among emissions, energy consumption and economic growth.

The remainder of this paper is organised as follows: Section 2 presents a review of the literature; Section 3 outlines the models and both the GM and NGBM approaches are presented; Section 4 presents the data used and empirical findings. Section 5 discusses the prediction results. The last section summarises and concludes the paper.

## 2. Brief literature review

The relationship between economic growth and environmental pollution, as well as economic growth and energy consumption, has been intensively analysed over the past two decades. However, the empirical evidence remains controversial and ambiguous to date. The first nexus is closely related to testing the validity of the Environmental Kuznets Curve (EKC) hypothesis. The EKC hypothesis postulates that the relationship between economic development and the environment resembles an inverted U-shaped curve. That is, environmental pollution levels increase as a country develops, but started to decrease as rising incomes pass a turning point. This hypothesis was first proposed and tested by Grossman and Krueger [6]; recent examples are illustrated in articles [7,8]. However, a higher national income does not necessarily warrant greater efforts to contain the emissions of pollutants.

The second strand is related to energy use and the real output nexus. This nexus suggests that higher economic growth requires more energy consumption. Likewise, more efficient energy use requires a higher level of economic development. Following the study by Kraft and Kraft [9], an increasing number of studies have assessed the empirical evidence by employing co-integration techniques and the Granger causality [10,11].

A recent and emerging line of literature has analysed both nexuses in the same framework. This approach facilitates the examination of the dynamic relationship between economic growth, energy consumption and environmental pollutants combined. Ang [12] and Soytas et al. [13] initiated this combined line of research. Recent work on this issue includes articles [14–19].

A sound forecasting technique is essential for accurate investment planning for energy production and distribution, environmental protection and economic development. Current forecasting methods can be divided into three categories: multivariate analysis, univariate time-series analysis, and non-linear intelligent models. Multivariate modelling and co-integrated techniques or regression analysis have been used in a number of studies to analyse and forecast energy consumption [20–22]. One limitation of multivariate models is that they depend on the availability and reliability of data on independent variables over the forecasting period, which requires further efforts in data collection and estimation. Univariate time-series analysis provides another modelling approach, which only requires the historical data for the variable of interest to forecast its future behaviour. The univariate Box–Jenkins ARIMA [23] analysis has been widely used for modelling and forecasting in many energy, environmental, financial, and engineering applications [24,25]. However, the need for a large number of observations to produce accurate forecasting results has usually been required. Due to fluctuations in energy consumption, some intelligent non-linear forecasting methods, namely artificial neural network (ANN) [26–28], fuzzy regression [29,30], and some hybrid models [31,32], have been employed to predict energy demand more efficiently. However, the forecasting results depend on the number of training data and their representativeness, and these limitations have not yet been overcome. In all of the above methods, the key element that affects the forecasting performance is the sample size, which limits their applicability to certain forecasting situations. Forecasting the energy demand, emissions and real GDP in rapidly developing countries are an example of this because the trend of each series may be changing rapidly over time. Therefore, the grey prediction model is an alternative forecasting tool for systems with complex, uncertain and chaotic structures because of their low data requirements to build forecasting models.

Grey theory was first proposed by Deng in 1989 [33] and has over 20 years of history. This theory does not rely on statistical methods to consider a grey quantity, but it uses, indirectly, original data and tries to identify its intrinsic regularity. Accumulated generating operation (AGO) is the main idea of Grey theory and originates from the cumulative distribution in elementary statistics. The aims of AGO are to reduce the randomness of raw data to a monotonically increasing series. Grey theory has been widely used in forecasting studies because of its higher forecasting accuracy when compared with other forecasting techniques [34,35]. For a time sequence that can be approximated by the exponential function curve, the forecasting accuracy can be improved to some degree using GM (1, 1), because the traditional grey model is constructed with an exponential function. However, the time sequence of the actual system will vary in waves, which do not always satisfy the above increasing rule. Therefore, many models have been proposed to increase this accuracy, such as the taguchi-grey [36], grey-fuzzy [37], trigonometric-grey [38], and other models [39–42]. These hybrid models include complex mathematics and are difficult to apply.

The nonlinear grey Bernoulli model (NGBM) was named by Chen et al. [43] and first appeared in the book by Liu et al. [44]. It is a simple modification of GM (1, 1) combined with the Bernoulli differential equation [45]. The advantage of this model is that the curvature of the solution curve can be adjusted to fit the result of the AGO of the raw data by adjusting variable parameters [46]. This paper proposes a numerical iterative method for choosing optimal parameter of NGBM to improve model accuracy, the improved NGBM with optimal parameter model is named NGBM-OP. The proposed iterative method is simple, easy to implement and has fast convergence.

## 3. Methodology

This section describes four prediction models: the Autoregressive Integrated Moving Average (ARIMA) linear model, the nonlinear grey prediction model (GM (1, 1)), NGBM$^{i}$ and the proposed NGBM −OP. All models are employed to forecast $CO_2$ emissions, energy consumption and real GDP for China from 2009 to 2020. The multi-step forecasting abilities of the NGBM−OP are compared with the GM and ARIMA models using actual data from the out-of-sample period between 2003 and 2008 for energy consumption, and 2004–2009 for both real GDP and emissions, where the in-sample period is 1980–2002 or 2003 for the ARIMA model, and 1997–2002 or 1998–2003 for the GM and the NGBM−OP, respectively. The co-integration technique is employed to analyse the long-run equilibrium relationship between the variables. If a co-integration relationship exists, predict all of them are an important part of the clean energy economy.

### 3.1. Model

Following the empirical literature in environmental economics, it is plausible to form a long-run relationship between $CO_2$ emissions, energy consumption, and economic growth in linear, logarithmic quadratic form to test the validity of the EKC hypothesis as follows:

$$\mathrm{LCO}_t = \beta_0 + \beta_1 \mathrm{LGDP}_t + \beta_2 \mathrm{LGDP}_t^2 + \beta_3 \mathrm{LEC}_t + u_t, \tag{1}$$

where LCO, LGDP and LEC represent the natural logarithms of $CO_2$ emissions, energy consumption and real GDP, respectively. The error term, $u_t$, is assumed to be independent and normally distributed with a zero mean and a constant variance. The expected sign of the energy consumption is positive because a higher level of energy consumption should result in greater economic activity and stimulate $CO_2$ emissions. Under the EKC hypothesis, the signs of $\beta_1$ and $\beta_2$ are expected to be positive and negative, respectively, to reflect the inverted U-shape pattern. The turning point occurs at an income level of $\beta_1/2\beta_2$ (in logarithms) [17]. That is, environmental pollution levels increase as a country develops but started to decrease as rising incomes pass this turning point.

To avoid both a spurious regression result and overestimating the importance of the independent variables, the nested linear models, with their $R^2$, adjusted $R^2$, and Jarque and Bera (JB) statistics [47], are used to evaluate how well the LEC, LGDP and LGDP$^2$ work together to accurately describe the LCO variable as follows:

$$\mathrm{LCO}_t = a_1 + b_1 \mathrm{LGDP}_t + u_t \tag{2-a}$$

$$\mathrm{LCO}_t = a_2 + b_2 \mathrm{LGDP}_t + c_2 \mathrm{LGDP}_t^2 + u_t \tag{2-b}$$

$$\mathrm{LCO}_t = a_3 + b_3 \mathrm{LGDP}_t + c_3 \mathrm{LEC}_t + u_t \tag{2-c}$$

$$\mathrm{LCO}_t = a_4 + b_4 \mathrm{LGDP}_t + c_4 \mathrm{LEC}_t + d_4 \mathrm{LGDP}_t^2 + u_t \tag{2-d}$$

If adding LGDP$^2$ provides an adjusted $R^2$ that is slightly larger ($<0.01$), we might decide that including LGDP$^2$ is not desirable. In Eq. (2-d), if LGDP$^2$ is not included, it indicates a monotonic relationship between emissions and income, when energy use does not change. Eq. (2) provides estimates of the long-run elasticities of energy use and income impacts on emissions.

The co-integration test is performed in two steps. First, we verify the order of the integration of the variables, since various co-integration tests are only valid if the variables have the same order of integration. Three different unit root tests, including the Augmented Dickey–Fuller (ADF), the Phillips–Perron (PP) and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) [48–50] tests, are used to investigate the stationarity and the order of the integration of the variables. In terms of the literature, tests designed on the basis of the null hypothesis that a series is $I$ (1) have a low power of rejecting the null. Therefore, KPSS is sometimes used to complement the widely used ADF and PP tests to obtain robust results.

In the second step, when all of the series of the same order are integrated, the Johansen maximum likelihood method [51,52] is used to test the co-integration relationship between the variables in Eq. (1) or (2). If co-integration exists among the variables, OLS that is applied to the estimates from Eq. (1) or (2) does not lead to a spurious regression result. Furthermore, the parameters estimated by OLS are super-consistent. The existence of co-integration indicates that there are long-run equilibrium relationships among the variables. Therefore, the forecasts of $CO_2$ emissions, energy consumption and economic growth constitute a vital part of environmental energy policy.

### 3.2. ARIMA model

The ARIMA model analyses and forecasts equally spaced, univariate time series data. It predicts a value in a response time series as a linear combination of its own past values and past errors. The analysis performed by the ARIMA procedure is divided into three stages: identification, estimation and diagnostic checking, and forecasting, which correspond to the stages described by Box and Jenkins. Classical Box–Jenkins models describe stationary time series. Therefore, to tentatively identify a Box–Jenkins model, we must first transform the time series into a stationary time series by taking a pre-differencing transformation. The Box–Jenkins models, ARIMA ($p$,$d$,$q$), are expressed as follows:

$$\begin{aligned} & \phi_p(B)(1-B)^d y_t = \delta + \theta_q(B) a_t \\ \text{where} \quad & \phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p \\ & \theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q \end{aligned} \tag{3}$$

In this expression, the time series is $y_t$; $B$ is the backward shift operator; $d$ is the order of regular differences; and $a_t$, $a_{t-1}$,... are independent random shocks. The series $a_t$ is assumed to be a white noise process, and $\phi_p(B)$ and $\theta_q(B)$ are polynomials in $B$ of order $p$ and $q$, respectively. The roots of $\phi_p(B) = 0$ and $\theta_q(B) = 0$ should lie outside the unit circle.

### 3.3. Grey prediction model

The Grey theory was proposed by Deng [33]. A system is called "white" if all of the information about the system is known. On the other hand, a system is called "black" if nothing is known about it. Therefore, a grey system is one which is partially known. Grey prediction power comes from its ability to predict the future value with only a limited amount of data.

The grey prediction based on the grey model (GM) has three basic operations: accumulated generating operation (AGO), inverse accumulated generating operation (IAGO) and grey modelling. The GM (1, 1) model is the most commonly used model. The first '1' in GM (1, 1) indicates that there is only one variable, and the next '1' means that the first order grey differential equation is used to construct the model. The algorithm of the GM (1, 1) grey prediction model can be summarised as follows [35]:

Consider the non-negative time-sequence data;

$$\mathbf{u}^{(\mathbf{0})} = \left[u^{(0)}(0), u^{(0)}(1), \cdots, u^{(0)}(i), \cdots, u^{(0)}(n)\right]. \text{ where } n \geq 3. \quad (4)$$

Then, the GM (1, 1) is as follows:

$$u^{(0)}(k) + aZ^{(1)}(k) = b, \; k = 1, 2, \ldots, n, \quad (5)$$

where "$a$" is called "develop parameter" and "$b$" is called "grey input". The following procedures are then instituted:

1. Take AGO on $u^{(0)}$;

$$u^{(1)}(k) = AGO\left(u^{(0)}(k)\right) = \sum_{i=0}^{k} u^{(0)}(i), \; k = 1, 2, \cdots, n, \quad (6)$$

where $u^{(1)}(0) = u^{(0)}(0)$.

2. Find $Z^{(1)}(k)$;

$$Z^{(1)}(k) = 0.5\left[u^{(1)}(k) + u^{(1)}(k-1)\right], \quad k = 1, 2, \cdots, n. \quad (7)$$

3. Using the least square method, the parameters $[a\ b]^{\mathrm{T}}$ in Eq. (4) can be estimated as

$$[a, b]^T = \left[B^T B\right]^{-1} B^T y_n,$$

where

$$B = \begin{bmatrix} -Z^{(1)}(1) & 1 \\ -Z^{(1)}(2) & 1 \\ \cdots & \cdots \\ -Z^{(1)}(n) & 1 \end{bmatrix} \quad \text{and} \quad y_n = \begin{bmatrix} u^{(0)}(1) \\ u^{(0)}(2) \\ \cdots \\ u^{(0)}(n) \end{bmatrix}. \quad (8)$$

4. Find the response equation;

$$\hat{u}^{(1)}(k) = \left[u^{(1)}(0) - \frac{b}{a}\right] e^{-ak} + \frac{b}{a} = \left[u^{(0)}(0) - \frac{b}{a}\right] e^{-ak} + \frac{b}{a}, \; k = 0, 1, \ldots \quad (9)$$

5. By performing IAGO on $\widehat{u}^{(1)}(k+1)$, the predicted value of $\hat{u}^{(0)}(k+1)$ is

$$\begin{aligned} &\widehat{u}^{(0)}(k+1) = \widehat{u}^{(1)}(k+1) - \widehat{u}^{(1)}(k) \quad \text{or} \\ &\widehat{u}^{(0)}(k+1) = (1 - e^{a})\left(u^{(0)}(0) - \frac{b}{a}\right) e^{-a(k+1)}, \; k = 0, 1, \ldots, \end{aligned} \quad (10)$$

where $\widehat{u}^{(0)}(1), \widehat{u}^{(0)}(2), \ldots, \widehat{u}^{(0)}(n)$ are called the GM (1, 1) fitted sequence, while $\widehat{u}^{(0)}(n+1), \widehat{u}^{(0)}(n+2), \ldots$, are called the GM (1, 1) out-of-sample forecast values. The results of the grey prediction model are compared with the results of the ARIMA and NGBM-OP models.

### 3.4. NGBM–OP model

The forecasting model NGBM (1, 1) was named by Chen [43] and first appeared in the book by Liu et al. [44]. Based on the ordinary nonlinear differential Bernoulli equation [45], the NGBM$^i$ (1, 1) is as follows [53]:

$$\text{where } \begin{aligned} &u^{(0)}(k) + aZ^{(1)}(k) = b\left[Z^{(1)}(k)\right]^i, \; i \in R, \\ &Z^{(1)}(k) = 0.5\left[u^{(1)}(k) + u^{(1)}(k-1)\right], \; k = 1, 2, \ldots, n \end{aligned} \quad (11)$$

The optimal value of power $i$ is determined by the minimum mean absolute percentage error (MAPE) of the forecasting model. The solution of Eq. (11) reduces to Eq. (5) when $i = 0$, and it reduces to the Grey–Verhust equation when $i = 2$ [44]. The parameters $a$ and $b$ can be estimated as follows:

$$\begin{aligned} &[a, b]^T = \left[B^T B\right]^{-1} B^T y_n \\ &\text{where} \quad B = \begin{bmatrix} -Z^{(1)}(1) & \left[Z^{(1)}(1)\right]^i \\ -Z^{(1)}(2) & \left[Z^{(1)}(2)\right]^i \\ \vdots & \vdots \\ -Z^{(1)}(n) & \left[Z^{(1)}(n)\right]^i \end{bmatrix} \quad \text{and} \quad y_n = \begin{bmatrix} u^{(0)}(1) \\ u^{(0)}(2) \\ \\ u^{(0)}(n) \end{bmatrix}, \; i \in R \end{aligned} \quad (12)$$

The alternative form of parameters $a$ and $b$ are shown below:

$$\begin{bmatrix} a \\ b \end{bmatrix} = \frac{\begin{bmatrix} \sum_{k=1}^{n}\left[Z^{(1)}(k)\right]^{i+1} \sum_{k=1}^{n}\left\{u^{(0)}(k)\left[Z^{(1)}(k)\right]^{i}\right\} - \sum_{k=1}^{n}\left[Z^{(1)}(k)\right]^{2i} \sum_{k=1}^{n} u^{(0)}(k) Z^{(1)}(k) \\ \sum_{k=1}^{n}\left\{u^{(0)}(k)\left[Z^{(1)}(k)\right]^{i}\right\} \sum_{k=1}^{n}\left[Z^{(1)}(k)\right]^{2} - \sum_{k=1}^{n}\left\{u^{(0)}(k) Z^{(1)}(k)\right\} \sum_{k=1}^{n}\left[Z^{(1)}(k)\right]^{i+1} \end{bmatrix}}{\sum_{k=1}^{n}\left[Z^{(1)}(k)\right]^{2i} \sum_{k=1}^{n}\left[Z^{(1)}(k)\right]^{2} - \left(\sum_{k=1}^{n}\left[Z^{(1)}(k)\right]^{i+1}\right)^{2}} \quad (13)$$

The response equation is the following:

$$\widehat{u}^{(1)}(k) = \left[\left(u^{(0)}(0)^{(1-i)} - \frac{b}{a}\right)e^{-a(1-i)k} + \frac{b}{a}\right]^{1/(1-i)}, \quad i \neq 1 \text{ and } k = 0, 1, \cdots, \tag{14}$$

By performing IAGO on $\widehat{u}^{(1)}(k+1)$, the predicted value of $\hat{u}^{(0)}(k+1)$ is

$$\widehat{u}^{(0)}(k+1) = \widehat{u}^{(1)}(k+1) - \widehat{u}^{(1)}(k), \ k = 0, 1, \ldots, \tag{15}$$

where $\widehat{u}^{(0)}(1), \widehat{u}^{(0)}(2), \ldots, \widehat{u}^{(0)}(n)$ are called the NGBM$^i$ (1, 1) fitted sequence, and $\widehat{u}^{(0)}(n+1), \widehat{u}^{(0)}(n+2), \ldots,$ are called the NGBM$^i$ (1, 1) out-of-sample forecast values.

The parameter $i$ in NGBM serves as the adjustable parameter, this paper proposes a numerical iterative method with MAPE value to optimize this parameter. In the next section, the iterative results will show parameter $i$ is efficient in improving the model precision, and the prediction results of NGBM with optimal parameter $i$ model (NGBM–OP) are compared with the results of the ARIMA and GM (1, 1) models.

For the purpose of evaluating the out-of-sample forecast capability, the forecasting accuracy is examined by calculating three different evaluation statistics: the root mean square error (RMSE), the mean absolute error (MAE) and the mean absolute percentage error (MAPE). These are expressed as follows:

$$\begin{aligned} \text{RMSE} &= \sqrt{\sum_{i=1}^{n} (P_i - A_i)^2 \Big/ n}, \\ \text{MAE} &= \sum_{i=1}^{n} |P_i - A_i| \Big/ n, \\ \text{MAPE} &= \sum_{i=1}^{n} |(P_i - A_i)/A_i| \Big/ n*100, \end{aligned} \tag{16}$$

where $P_i$ and $A_i$ are the $i$th forecasting and actual values, respectively, and $n$ is the total number of predictions. Lewis [54] interprets the MAPE results as way to judge the accuracy of the forecast, where less than 10% is a highly accurate forecast; 10%–20% is a good forecast; 20%–50% is a reasonable forecast; and more than 50% is an inaccurate forecast.

## 4. Data and forecasts

### 4.1. Data analysis

This study collected annual data on energy consumption for 1980–2008, and the $CO_2$ emissions, energy intensity and carbon intensity for 1980–2009, from the EIA. The real GDP from 1980 to 2009 was collected from the World Development Indicators (WDI). $CO_2$ emissions are measured in metric tons of carbon dioxide based on the energy consumption and flaring of fossil fuels. Real GDP is measured in US dollars at 2000 prices. Total energy consumption is measured in quadrillion Btu (British thermal unit). The energy intensity in Btu is measured by the total primary energy consumption per dollar of GDP. The carbon intensity in metric tons is measured by the total carbon dioxide emissions from the consumption of energy per dollar of GDP. Table 1 displays the summary statistics associated with the five variables.

**Table 1**
Summary statistics for China, 1980–2008.

| $CO_2$ emissions (billion metric tons) | | | Energy consumption (quadrillion Btu) | | | Real GDP (constant 2000 US$ billion) | | |
|---|---|---|---|---|---|---|---|---|
| Mean | S.D. | CV (%) | Mean | S.D. | CV (%) | Mean | S.D. | CV (%) |
| 3.04 | 1.48 | 48.68 | 37.32 | 18.89 | 50.62 | 927.89 | 713.18 | 76.86 |

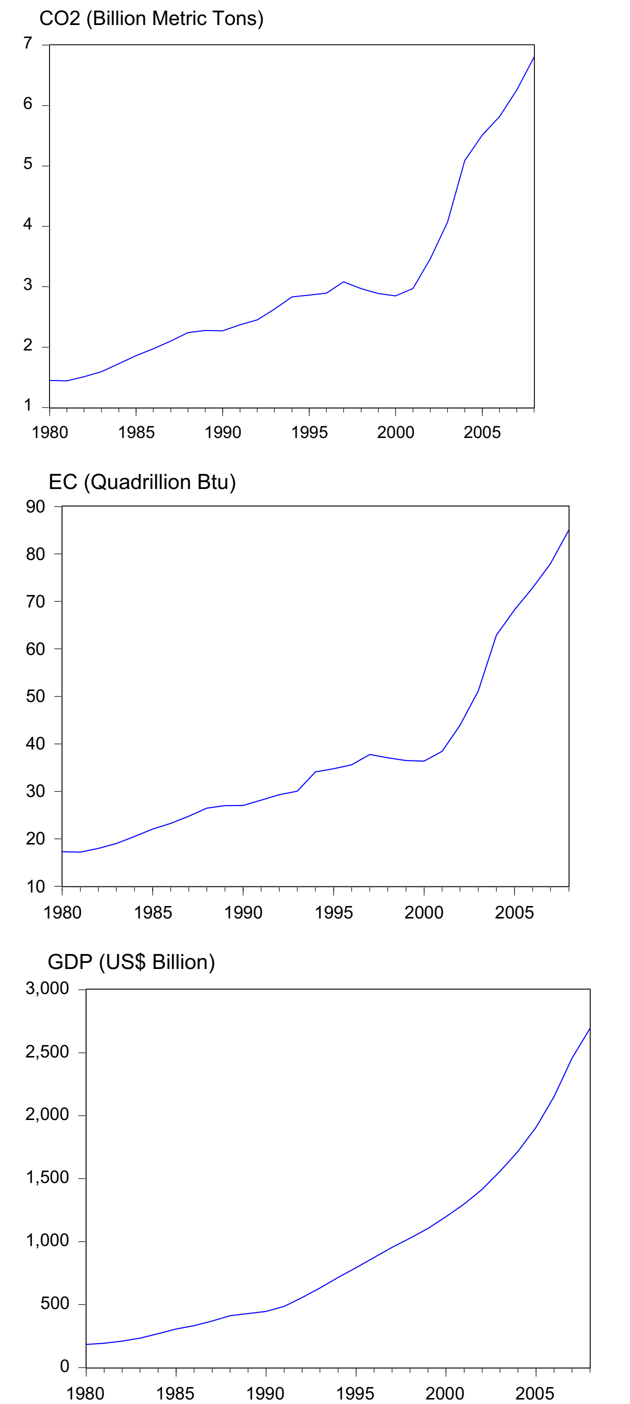


**Fig. 1.** Time series plots of the emissions, energy consumption and real GDP, 1980–2008.

Fig. 1 shows the change trend of each series for China. All variables increased over time, with real GDP exhibiting the most related variation (defined by the coefficient of variation (CV)), and emissions the least related variation (Table 1). Table 2 shows the annual average percentage growth rates in the years to 2008 of each variable. Fifteen-, ten-, and five-year growth rates were calculated as the growth between 1993 and 2008, 1998–2008, and 2003–2008, respectively. In the most recent five years

**Table 2**
Average growth rates in percentages to 2008 for each variable.

| Growth rate | China | | | | | World | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $CO_2$ emissions | Energy consumption | Real GDP | Energy intensity | Carbon intensity | $CO_2$ emissions | Energy consumption | Real GDP | Energy intensity | Carbon intensity |
| 15-year | 6.55 | 7.19 | 10.14 | −2.68 | −3.26 | 2.30 | 2.41 | 3.11 | −0.71 | −0.81 |
| 10-year | 8.65 | 8.67 | 10.11 | −1.31 | −1.33 | 2.83 | 2.57 | 3.09 | −0.60 | −0.33 |
| 5-year | 10.82 | 10.71 | 11.57 | −0.77 | −0.67 | 3.26 | 2.97 | 3.43 | −0.60 | −0.20 |

**Table 3**
Coefficients of Eq. (2) for $CO_2$ emissions.

| | Independent variables | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | LGDP | $LGDP^2$ | LEC | Intercept | Adj-$R^2$ | $R^2$ | JB | p val. |
| Eq. (2-a) | 0.520*** (19.046) | | | −2.385*** (−13.264) | 0.9282 | 0.9307 | 1.877 | 0.391 |
| Eq. (2-b) | −0.790* (−1.853) | 0.100*** (3.079) | | 1.827 (1.327) | 0.9453 | 0.9492 | 4.085 | 0.130 |
| Eq. (2-c) | −0.081*** (−75.10) | | 1.095*** (1186.64) | −2.308*** (−312.59) | 0.9983 | 0.9985 | 0.233 | 0.890 |
| Eq. (2-d) | 0.193*** (52.69) | −0.026*** (−28.69) | 1.196*** (99.71) | −3.338*** (−115.72) | 0.9991 | 0.9992 | 139.584 | 0.000 |

Figures in parentheses indicate *t*-statistics.
* and *** indicate the rejection of a null hypothesis at 10% and 1% level of significance, respectively.

(2003–2008), the average growth rate in real GDP was 11.57%, which is almost 3.4 times higher than the world growth rate of 3.43%; the growth rate in energy consumption was 10.71%, which is almost 3.6 times higher than the world growth rate of 2.97%; and the emissions growth rate was 10.82%, which is almost 3.3 times higher than the world growth rate of 3.26%. These indicate that China is a very fast growing market. The five-year growth rate in emissions is almost 1.7 times higher than the fifteen-year growth rate, but it is only 1.1 times higher than the fifteen-year growth rate in real GDP. For the ten-year and fifteen-year growth rates, energy consumption was greater than emissions, but emissions were greater than energy consumption for the five-year growth rate. These results show that China has no intention of capping its emissions, even as authorities are committed to realising the nation's target to reduce carbon intensity through new policies and measures. Additionally, the fifteen-year decline rate of carbon intensity and energy intensity shown in Table 2 were 3.26% and 2.68%, respectively, which is almost 4.0 and 3.8 times higher than the world decline rate of 0.81% and 0.71%, respectively. These numbers show that China has made significant gains in reducing carbon intensity and energy intensity in the fifteen-year period, despite an increase in both emissions and energy consumption; however, developing countries have a long way to go to improve people's lives and eliminate poverty. Despite these challenges, China has pledged to reach their goal of cutting carbon intensity per GDP unit by 40–45% by 2020 [2].

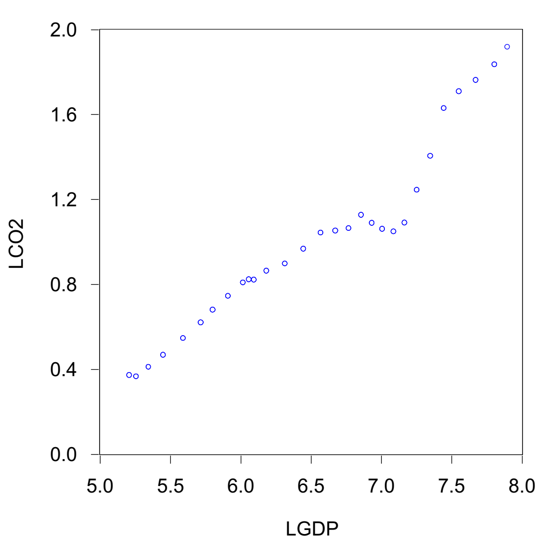


**Fig. 2.** The ln($CO_2$ emissions)–ln(GDP) plot for China, 1980–2008.

### 4.2. Co-integration test

The annual data from 1980 to 2008 were used to estimate Eqs. (1,2), and the time series properties of the variables were checked using three different unit root tests, including the ADF, PP, and KPSS. The coefficients of Eq. (2-b) shown in Table 3 indicate that the relationship between income and emissions resembles a U-shape; therefore, the estimates cannot support an EKC hypothesis. The turning point of the U-shape occurs at an income level of 3.95 (=0.79/(2*0.10), in logarithm). Because the value of the turning point (3.95) is less than the minimum value (5.21) of the LGDP in China for the period 1980–2008, the relationship between income and emissions shown in Fig. 2 presents a monotonic increase. The values of the $R^2$, adjusted $R^2$ and JB-statistic from Eq. (2) shown in Table 3 indicate that Eq. (2-d) is inappropriate because adding $LGDP^2$ results in an adjusted $R^2$ that is slightly larger (<0.001), and the *p-value* of the JB-statistic is less than 0.01. The comprehensive results of Eq. (2-b) with turning point and Eq. (2-d) imply that Eq. (2-c) is appropriate to describe the relationship among variables.

All of the series in Eq. (2-c) appear to contain a unit root in their levels but are stationary in their first difference, indicating that they are integrated at order one, i.e., *I* (1). The results are displayed in

**Table 4**
Results of the unit roots tests.

| | ADF | | PP | | KPSS | |
|---|---|---|---|---|---|---|
| | Level | 1st diff. | Level | 1st diff. | Level | 1st diff. |
| LCO | −0.07 | −2.64* | 0.96 | −2.72* | 0.67** | 0.20 |
| LEC | 0.30 | −2.93* | 1.25 | −2.96* | 0.68** | 0.24 |
| LGDP | −0.48 | −3.92*** | 0.30 | −3.29** | 0.70** | 0.06 |

All unit roots (except the KPSS) have a null hypothesis in that the series has a unit root against the alternative of being stationary. The null of KPSS states that the variable is stationary. Individual intercepts are included in test regressions.
*, ** and *** mean that the null of the unit root test is rejected at a 10%, 5% and 1% level. The lag lengths are selected using AIC.

**Table 5**
Results of the Johansen co-integration test.

| Eigenvalue | Trace Stat. | 5% critical value | Max Eigen. Statistic | 5% critical value | Number of co-integrations |
|---|---|---|---|---|---|
| Panel C: Eq. (4) | | | | | |
| Variable: LCO, LEC and LGDP; lag = 1 | | | | | |
| 0.941 | 92.10* | 35.19 | 79.33* | 22.30 | None |
| 0.286 | 12.78 | 20.26 | 9.44 | 15.89 | At most 1 |
| 0.113 | 3.34 | 9.17 | 3.34 | 9.17 | At most 2 |

The optimal lag lengths are selected using AIC.
* indicates the rejection of a null hypothesis at a 5% level of significance.

Table 4. The next step is to test whether the variables in Eq. (2-c) are co-integrated; therefore, Table 5 shows the results of the Johansen test. The trace and eigenvalue tests reject the hypothesis of no co-integrating equation at a 5% or better level of significance and indicate at least one co-integration equation with no lags. Therefore, there is a long-run equilibrium relationship between emissions, energy consumption and real GDP, and the OLS applied to the estimated Eq. (2-c) does not lead to a spurious regression result. The results of Eq. (2-c) indicate that a 1% increase in energy usage increases emissions by 1.095% when the real GDP does not change, and a 1% increase in real output decreases emissions by 0.081% when energy consumption does not change. Therefore, emissions appear to be real output inelastic and energy consumption elastic, and energy consumption is a more important determinant of emissions than real output in China. In addition, results indicate that when the energy consumption does not change, real output is significantly negative impact on emissions. In order to enhance economic growth and reduce emissions, it is suggested that China should increase both energy supply investment and energy efficiency, and step up energy conservation policies to reduce unnecessary wastage of energy. Based on long-run equilibrium relationship, forecasts of $CO_2$ emissions, energy consumption and economic growth are a vital part of green energy policy.

### 4.3. Forecasting results

The multi-step forecasting abilities of the NGBM-OP models were compared with the ARIMA and GM (1, 1) models using actual data over the six-year, out-of-sample period between 2003 and 2008 for energy consumption, and 2004–2009 for the $CO_2$ emissions and the real GDP variables. For each variable, the GM models used six-year (GM-6, 1997–2002 or 1998–2003), five-year (GM-5, 1998–2002 or 1999–2003) and four-year (GM-4, 1999–2002 or 2000–2003) data as the in-sample period, and the ARIMAs used only one in-sample period from 1980 to 2002 or 1980–2003. This in-sample period was used to build the models, and the out-of-sample period was used to evaluate the prediction accuracy by using the RMSE, MAE and MAPE statistics. For each variable, the best GM model was determined by the smallest MAPE value. The original data set for the best GM-$k$ ($k = 6, 5$ or $4$) model was employed to build the NGBM–OP model, where the parameter $i$ was determined using the numerical iterative method with the MAPE value. Figs. 3–5 show the impact on the results of the MAPE in the NGBM when the parameters $i$ are set to −0.2 to 0.2, with 0.01 increments, for emissions, energy consumption and output, respectively. They show that the numerical iterative method is an effective optimisation algorithm that is suitable for the parameter $i$ selection of the NGBM. In particular, for all tested $i$, 0.1, −0.1 and −0.08 resulted in the smallest MAPE values in the NGBM$^i$ model for emissions, energy consumption and real GDP, respectively.

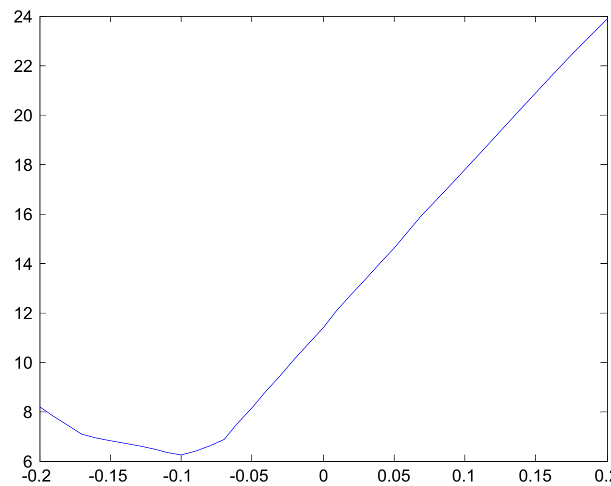

**Fig. 4.** The results of the MAPE with different power $i$ in the NGBM$^i$ (1, 1) for energy consumption over the out-of-sample period between 2003 and 2008.

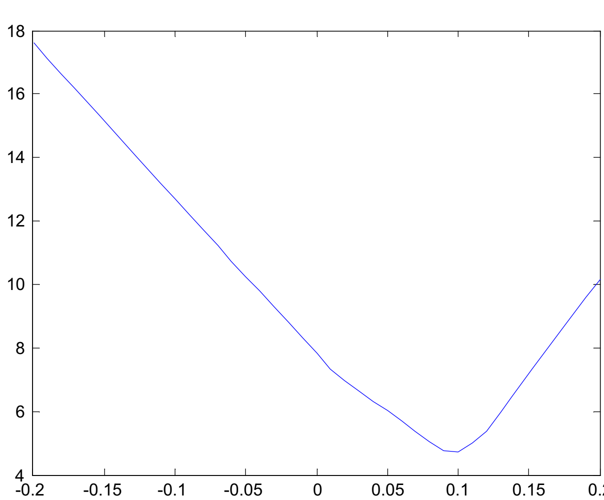

**Fig. 3.** The results of the MAPE with different power $i$ in the NGBM$^i$ (1,1) for emissions over the out-of-sample period between 2004 and 2009.

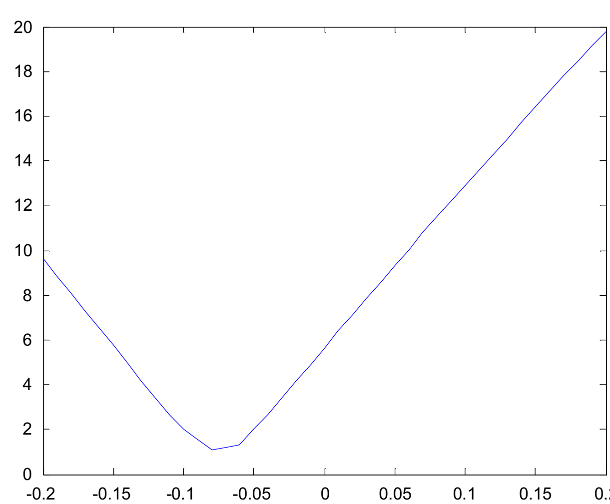

**Fig. 5.** The results of the MAPE with different power $i$ in the NGBM$^i$ (1, 1) for real GDP over the out-of-sample period between 2004 and 2009.

**Table 6**
Out-of-sample comparisons among the NGBM–OP, GM and ARIMA models.

| | ARIMA | GM-4 | GM-5 | GM-6 | NGBM–OP |
|---|---|---|---|---|---|
| Forecasts of $CO_2$ emissions (billion metric tons) (2004–2009) | | | | | $i = 0.1$, $n = 5$ |
| RMSE | 1.53 | 1.55 | 0.57 | 0.68 | 0.35 |
| MAE | 1.68 | 1.21 | 0.50 | 0.67 | 0.26 |
| MAPE | 23.74% | 17.91% | 7.84% | 11.08% | 4.72% |
| Forecasts of energy consumption (Quadrillion Btu) (2003–2008) | | | | | $i = -0.1$, $n = 4$ |
| RMSE | 21.45 | 8.30 | 16.87 | 22.47 | 4.97 |
| MAE | 19.57 | 7.96 | 16.04 | 21.20 | 4.17 |
| MAPE | 26.64% | 11.42% | 22.33% | 29.36% | 6.26% |
| Forecasts of real GDP (Constant 2000 US$ Billion) (2004–2009) | | | | | $i = -0.08$, $n = 4$ |
| RMSE | 331.18 | 172.05 | 209.12 | 230.97 | 40.15 |
| MAE | 264.08 | 143.59 | 176.66 | 196.31 | 27.45 |
| MAPE | 10.18% | 5.65% | 6.98% | 7.78% | 1.10% |

**Table 7**
The parameters $a$ and $b$ in both the GM and NGBM–OP models.

| Parameter | Emissions | Energy consumption | Real GDP | Emissions | Energy consumption | Real GDP |
|---|---|---|---|---|---|---|
| | GM-5 | GM-4 | GM-4 | NGBM–OP | NGBM–OP | NGBM–OP |
| $a$ | −0.1277 | −0.0969 | −0.0914 | −0.0994 | −0.1279 | −0.1186 |
| $b$ | 2.1837 | 30.5185 | 1127.1 | 1.9728 | 43.1760 | 1971.5 |

Five observations can be made. First, the NGBM–OP have a strong forecasting performance because all of the MAPE values are ranging from 1.10% to 6.26%, while the ARIMA and GM models have a good or reasonable forecasting performance [54]. The results are shown in Table 6. Second, the optimal GM (1, 1) models for emissions, energy consumption and real GDP are GM-5 (MAPE = 7.84%), GM-4 (MAPE = 11.42%) and GM-4 (MAPE = 5.65%), respectively, which have the smallest values of MAPE among the GM-$k$ models. The estimated values of parameters $a$ and $b$ for each GM are shown in Table 7. Third, Figs. 3–5 show that the proposed numerical iterative method is an effective optimization algorithm for choosing optimal parameters $i$ in the NGBM to improve the accuracy of the model. Fourth, the NGBM–OP for emissions, energy consumption and real GDP are NGBM-0.1 (MAPE = 4.72%), NGBM-0.1 (MAPE = 6.26%) and NGBM–-0.08 (MAPE = 1.10%), respectively. The estimated values of parameters $a$ and $b$ for each NGBM–OP are shown in Table 7. Finally, this study uses the proposed NGBM–OP models to forecast three variables for China from 2009 to 2020. The forecast data, together with the actual data, are presented in Table 8. The prediction results show that China's emissions, energy consumption and real GDP will grow at a compound annual growth rates (CAGRs) of 4.47%, −0.06% and 6.67%, respectively in the next decade to 2020.

## 5. Discussion

This study employs univariate multi-period forecasting approach to predict variables about the green energy system for China. The employed approach includes three models, namely, ARIMA, GM and NGBM–OP. For the out-of-sample period 2004–2009, the MAPE values of NGBM–OP are ranging from 1.10% to 6.26%. The results are compared with leading research in the areas of energy forecasting, e.g., Wang et al. [39], Lee and Tong [40] and Pi et al. [41] for China, and Kumar and Jain [42] for India. Wang et al. used three univariate models, namely, discrete grey model (DGM), rolling DGM (RDGM) and $p$ value RDGM to forecast coal production in China. During the out-of-sample period 2006–2010, the MAPE values of Wang et al. range from 1.28% to 14.52%, and their $p$ value RDGM model has the best forecasting performance, e.g., MAPE = 1.28%. Lee and Tong proposed an improved grey forecasting model that combines residual modification with genetic programming sign estimation to forecast energy consumption in China. For the out-of-sample period 2004–2007, Lee and Tong's MAPE value is 20.23%. Pi et al. used three univariate models, namely, GM, Remnant GM and improved GM to forecast China's electricity demand and energy production. For the out-of-sample period 1990–2006, the MAPE values of Pi et al. are ranging from 2.7% to 8.6%, where the improved GM shows the best forecasting performance, e.g., the MAPE values are 2.7% and 4.6% for electricity and energy production, respectively. Additionally, Kumar and Jain applied three univariate models, namely, Grey-Markov, Grey-Model with rolling mechanism and singular spectrum analysis to forecast consumption of conventional energy (petroleum, coal, electricity and nature gas) in India. For two out-of-sample forecasts (2006–2007), the MAPE values of Kumar and Jain's models are ranging from 1.6% to 3.4%.

According to Lewis's criteria [54] and the above discussion, the proposed NGBM–OP presents a highly accurate forecast for clean energy economy (emissions, energy consumption and real GDP) in rapid growth market such as China. As we can see that the predicted MAPE values are lesser than or equal to 6.26%, which is much

**Table 8**
Forecasts of emissions, energy consumption and GDP for China, 2009–2020.

| Year | Emissions (billion metric tons) | | Energy consumption (quadrillion Btu) | | GDP (constant 2000 US$ billion) | |
|---|---|---|---|---|---|---|
| | Actual | NGBM–OP | Actual | NGBM–OP | Actual | NGBM–OP |
| 2005 | 5.51 | 5.51 | 68.25 | 68.25 | | |
| 2006 | 5.82 | 5.59 | 72.89 | 71.58 | | |
| 2007 | 6.26 | 6.36 | 78.00 | 79.29 | 2456.68 | 2456.68 |
| 2008 | 6.80 | 6.98 | 85.06 | 84.26 | 2692.53 | 2668.87 |
| 2009 | 7.71 | 7.54 | | 87.62 | 2940.23 | 2961.37 |
| 2010 | | 8.05 | | 89.93 | 3243.07 | 3226.91 |
| 2011 | | 8.53 | | 91.46 | | 3484.94 |
| 2012 | | 9.00 | | 92.42 | | 3743.48 |
| 2013 | | 9.45 | | 92.93 | | 4006.85 |
| 2014 | | 9.89 | | 93.08 | | 4277.81 |
| 2015 | | 10.32 | | 92.95 | | 4558.36 |
| 2016 | | 10.75 | | 92.57 | | 4850.08 |
| 2017 | | 11.18 | | 92.00 | | 5154.33 |
| 2018 | | 11.61 | | 91.27 | | 5472.36 |
| 2019 | | 12.03 | | 90.41 | | 5805.33 |
| 2020 | | 12.46 | | 89.43 | | 6154.37 |

lesser than Lewis's criteria, 10%. However, due to the recent uncertain global economics, high-tech progresses and changing social structures in a country, for each five year period, it is strictly recommended revising the results using NGBM−OP to obtain more accurate outcomes.

## 6. Conclusions

In this paper, it is attempted to model and forecast $CO_2$ emissions, energy consumption and real GDP for China based on co-integration technique and intelligent grey prediction model. Using recent four- to six-year historical data, the proposed univariate NGBM−OP obtained robust results in terms of MAPE, RMSE and MAE, when compared with both ARIMA and GM models. All of the MAPEs of NGBM−OP for out-of-sample are ranging from 1.10% to 6.26%. Performance evaluation results clearly show that NGBM−OP can be used safely for future projection of these indicators in clean energy economy. Future projections have also been carried out for these indicators using NGBM−OP for the period between 2009 and 2020. The prediction results show that China's emissions, energy consumption and real GDP will grow at a compound annual growth rates (CAGRs) of 4.47%, −0.06% and 6.67%, respectively in the next decade to 2020. The CAGRs over the next decade (2011–2020) are lower than the CAGRs (8.65%, 8.67% and 10.11%, respectively) over the past decade. It indicates that China will effectively conserve resources, protect the environment and respond actively to climate change.

Based on co-integration technique, the estimated values showed that there was a long-run equilibrium relationship between emissions, energy consumption and real GDP, and emissions appeared to be real output inelastic and energy consumption elastic over the period 1980–2008 in China. Therefore, energy consumption was a more important determinant of emissions than real output, and the estimates did not support an EKC hypothesis. In addition, estimated results indicate that when energy consumption does not change, real output is significantly negative impact on emissions. During the period 1980–2008, the correlation coefficient between carbon emissions and energy efficiency (GDP/Energy ratio, PPP $ per kg of oil equivalent) [55] is −91.67%, and the correlation coefficient between energy efficiency and real GDP is 96.52%. Therefore, economic growth has a negative impact on emissions in China. Figure for 2008 shows that China's GDP/Energy ratio is 3.88, which is lower than 6.26 in USA or 5.54 in India. However, the ten-year average growth rate in GDP/Energy ratio is 11.27%, which is higher than the 9.05% in USA or 9.46% in Germany. Additionally, China's energy intensity fell 19.1% over the past five years [2]. The results indicate that the government made vast gains in increasing energy efficiency, although China has relatively low energy efficiency. Therefore, we suggest that China should adopt the dual strategy of increasing investment in energy infrastructure, reducing the loss in power transmission and distribution and stepping up energy conservation policies to reduce any unnecessary wastage of energy. In other words, energy conservation is expected to increase the efficient use of energy, thus promoting economic growth and environmental quality.

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