Energy-related CO_2 emission forecast for Turkey and Europe and Eurasia

A discrete grey model approach

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Abstract

Purpose – The global warming, caused by the anthropogenic greenhouse gases, has been one of the major worldwide issues over the last decades. Among them, carbon dioxide (CO_2) is the most important one and is responsible for more than the two-third of the greenhouse effect. Currently, greenhouse gas emissions and CO_2 emissions – the root cause of the global warming – in particular are being examined closely in the fields of science and they also have been put on the agenda of the political leaders. The purpose of this paper is to predict the energy-related CO_2 emissions through using different discrete grey models (DGMs) in Turkey and total Europe and Eurasia region.

Design/methodology/approach – The proposed DGMs will be applied to predict CO_2 emissions in Turkey and total Europe and Eurasia region from 2015 to 2030 using data set between 1965 and 2014. In the first stage of the study, DGMs without rolling mechanism (RM) will be used. In the second stage, DGMs with RM are constructed where the length of the rolling horizons of the respected models is optimised.

Findings – In the first stage, estimated values show that non-homogeneous DGM is the best method to predict Turkey's energy-related CO_2 emissions whereas DGM is the best method to predict the energy-related CO_2 emissions for total Europe and Eurasia region. According to the results in the second stage, NDGM with RM ($k=26$) is the best method for Turkey while optimised DGM with RM ($k=4$) delivers most reliable estimates for total Europe and Eurasia region.

Originality/value – This study illustrates the effect of different DGM approaches on the estimation performance for the Turkish energy-related CO_2 emission data.

Keywords Climate change, CO_2 emissions, Greenhouse gases, Discrete grey models, Grey forecasting

Paper type Research paper

1. Introduction

The global warming and climate change have become a worldwide problem over the last years. According to the experts, the root cause of the global warming is an upsurge in global economy, human consumption of energy, and the greenhouse effect from the emissions of six gases including carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), hydrofluorocarbons (HFCS), perfluorocarbons (PFCS), and sulphur hexafluoride (SF_6) that lead to the climate change in the Earth (Pao *et al.*, 2012). Hence, currently the greenhouse gas (GHG) emissions and global warming have become one of the most significant research subjects in the fields of science and politics (Wu *et al.*, 2015). GHG concentrations have severely increased in the Earth's atmosphere due to the pollution caused by fossil fuels, deforestation, and other various human activities since the beginning of the industrialisation (Abdul-Wahab *et al.*, 2015). The United Nations Framework Convention on Climate Change (UNFCCC), which was agreed upon in Rio de Janeiro, Brazil in 1992

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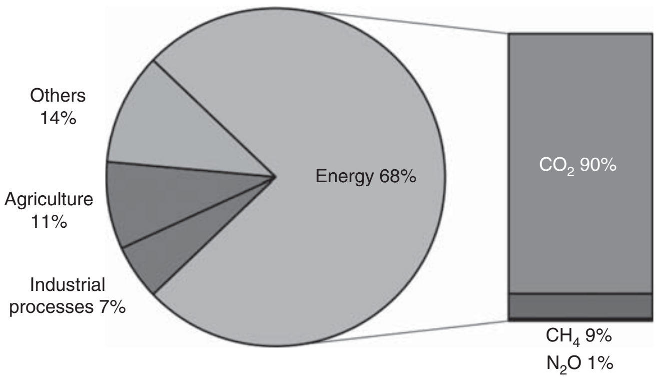
(Abdul-Wahab *et al.*, 2015), provides a structure for inter-governmental efforts to tackle the challenge posed by the climate change (International Energy Agency, 2015a, b). The Kyoto Protocol, which was enacted in 16 February 2005, can be cited as the most important agreement that intends to limit the countries' emissions within a time horizon (Tunç *et al.*, 2009; Köne and Büke, 2010). The Kyoto Protocol demanded a 5.2 per cent reduction of GHG emissions compared to the 1990 level between 2008 and 2012 (Pao *et al.*, 2012; Köne and Büke, 2010). The 37 industrialised countries and European community, which recognise the Kyoto Protocol, agreed that during the 2008-2012 period, each country would reduce anthropogenic GHG emissions such as CO_2, CH_4, N_2O, HFCS, PFCS, and SF_6 by an average of 5 per cent annually from 1990 levels (Lin *et al.*, 2011). CO_2 is responsible for 58.8 per cent of GHGs amongst the environmental pollutants causing the climate change (Pao and Tsai, 2011). Although CO_2 is a naturally occurring gas, it is also a by-product of burning fossil fuels such as coal, gas, and oil (Lin *et al.*, 2011). Among many human activities that produce GHGs, the use of energy represents the largest source of the emissions. The existing studies indicated that more than two-thirds of GHGs caused from fossil energy-related CO_2 emission (Wu *et al.*, 2015) depicted in Figure 1.

Taking place in a strategically geographic position between Asia and Europe, Turkey keeps its popularity as a growing country. However, this growth also causes a rapid growth in dangerous gas emissions over the 1980s (Keles and Bilgen, 2012). Turkey attended UNFCCC in May 2004 and recognised the Kyoto Protocol in February 2009 (Tunç *et al.*, 2009). According to the International Energy Agency (2015b) report, CO_2 emissions in Turkey has increased 123.3 per cent between1990 (127.1 $MtCO_2$) and 2013 (238.8 $MtCO_2$). The largest five emitting countries in the world in 2013 are China (27,1 per cent), the USA (16.9 per cent), India (5.5 per cent), Russian Federation (4.9 per cent), Japan (4 per cent), and Turkey is ranked in 23rd (0.937 per cent), respectively (British Petroleum, 2015).

Under these circumstances, it becomes inevitable both to propose an effective tool that will help to track the emitting effect of the countries, as well as to benefit from it as an early warning system to prevent possible unexpected emission occurrences. Because of this reason, in this study, we present different discrete grey models (DGMs) to predict the energy-related CO_2 emissions amount in Turkey. Grey models (GM) are simple and powerful forecasting tools and used by many recent studies (Hamzacebi and Karakurt, 2015; Feng *et al.*, 2012; Akay and Atak, 2007). GM provides many advantages in terms of requiring few data to build forecasting models and yielding a higher forecasting accuracy compared with other forecasting techniques



Source: International Energy Agency (2015a)

Figure 1.
Shares of global anthropogenic GHG, 2010

(Pao and Tsai, 2011). We have developed six different discrete grey forecasting models such as: DGM, optimised discrete grey model (ODGM), non-homogeneous discrete grey model (NDGMG), discrete grey model with rolling mechanism (DGM-RM), optimised discrete grey model with rolling mechanism (ODGM-RM), and non-homogeneous discrete grey model with rolling mechanism (NDGM-RM), respectively (Kusakci and Ayvaz, 2017; Kusakci and Ayvaz, 2015). In order to predict CO_2 emissions, actual data of the time from 1965 to 2014 are utilised. With the aim of finding the best model, the various DGMs are developed to predict CO_2 emissions amount of the time between 2015 and 2030. A comparison of six DGMs is conducted by utilising three performance metrics: mean square error (MSE), mean absolute percentage error (MAPE), and root mean square error (RMSE).

Furthermore, the results obtained with the best method are compared with the results of the current state-of-the-art study which are conducted on the same data set. The contribution of this study is to illustrate the success of various DGM-based forecasting models on precision of the prediction process as well as to identify the best approach for revealing out Turkish energy-related CO_2 emissions. Additionally, this study indicates that as a relatively simple approach, GM has ability to produce highly precise and competitive estimates considering other complex methods introduced in the literature such as time series, artificial neural networks (ANNs), support vector machines, and genetic algorithms, etc.

The rest of the paper is organised as follows: a literature review is presented in Section 2. Section 3 is related to the methodology regarding GM-based forecasting models. The results are reported and discussed in Section 4 while the last section concludes the study and indicates some future research directions.

2. Literature review

CO_2 is the most important GHG emitted through human operations, and with the impact of the industrial revolution which was begun around 1,750, the climate has increasingly changed as a consequence of the increase in CO_2 caused from various human operations (EPA, 2014). By the effect of the growing attention on CO_2 emissions that results in climate changes, academic research works on modelling and forecasting CO_2 emissions have been improved in order to make the governments and societies be aware of its social, physical, financial, and cultural effects.

In the relevant literature, there are many valuable quantitative and qualitative studies on gas emissions forecasting, as seen in Table I. Chen (2005) developed MARKAL-MACRO, an integrated energy-environment-economy model, to generate future energy development and carbon emissions for China for through the year 2050. Sun (2006) forecasted the energy-related CO_2 emissions in the OECD countries based on GDP. It is agreed that CO_2 emissions intensity should be utilised as an indicator, and this agreement is proved with the help of statistical analysis and mathematical simulation. Köne and Büke (2010) used the trend analysis approach to the forecasting of the energy-related CO_2 emissions for the top-25 countries and the total global CO_2 emissions between 1971 and 2007 are identified. Lin *et al.* (2011) developed the grey forecasting model GM(1,1) to forecast future CO_2 emissions in Taiwan from 2010 until 2012. Pao and Tsai (2011) are determined to find the long-run equilibrium relationship among carbon emissions, energy consumption, and real output for Brazil between 1980 and 2007. The grey prediction model was used to predict three variables during 2008-2013. The forecasting ability of GM is compared with the autoregressive integrated moving average (ARIMA) model over the out-of-sample period between 2002 and 2007. Pao *et al.* (2012) employed the nonlinear grey Bernoulli model (NGBM) to forecast carbon emissions, energy consumption and real outputs and proposes a numerical iterative method to optimise the parameter of NGBM.

Study	Method	Forecasting issue
Chen (2005)	MARKAL-MACRO	Energy development and CO_2 emission for China
Sun (2006)	Statistical analysis, simulation	Energy-related CO_2 emissions
Köne and Büke (2010)	Trend analysis	Energy-related CO_2 emissions
Lin *et al.* (2011)	GM(1,1)	CO_2 emissions in Taiwan
Pao and Tsai (2011)	GM	CO_2 emissions, energy consumption, and real output for Brazil
Pao *et al.* (2012)	NGBM	CO_2 emissions, energy consumption
Liu (2013)	Grey neural network and input-output	Sector primary energy-related CO_2 emissions in China
Lotfalipour *et al.* (2013)	Grey system and autoregressive integrated moving average	CO_2 emissions
Radojević *et al.* (2013)	Neural network	Greenhouse gas emissions in European countries and the Republic of Serbia
Meng *et al.* (2014)	Non-homogeneous exponential equation and linear equation	Energy-related CO_2 emissions
Nabavi-Pelesaraei *et al.* (2014)	ANN	Yield and greenhouse gas emissions of watermelon production
Ge *et al.* (2017)	STIRPAT model, the logistic regression model, and the grey model	CO_2 emissions caused by industrial energy consumption of Tianjin
Hamzacebi and Karakurt (2015)	Grey prediction model	Energy-related CO_2 emissions in Turkey
Liu *et al.* (2015)	System dynamics simulation	Energy consumption, gross CO_2 emissions and CO_2 emission intensity in China
Perez-Suarez and Lopez-Menendez (2015)	Environmental Kuznets curve and the environmental logistic curve	Environmental forecasting
Özceylan (2015)	Particle swarm optimisation and artificial bee colony	CO_2 emission in Turkey

Table I.
Summary of literature review

The forecasting ability of NGBM with optimal parameter model, namely NGBM-OP has remarkably improved, compared to the GM and ARIMA. Liu (2013) presented a grey neural network and input-output combined forecasting model in order to forecast by sector primary energy-related CO_2 emissions in China. Lotfalipour *et al.* (2013) developed grey system and ARIMA to predict CO_2 emissions. The results show that the grey system forecasting is more accurate than the other methods of prediction. Radojević *et al.* (2013) developed neural network architecture to model, simulate, and predict GHG emissions in European countries and the Republic of Serbia. The share of renewable sources of energy, the gross domestic product, the gross energy consumption, and energy intensity was selected as the input parameters. Data for the selected European countries for the years 1999-2001 were used as a training set for the neural network and the data for the same countries for the years 2002-2007 were used as a test set.

Meng *et al.* (2014) proposed a small-sample hybrid model for forecasting the energy-related CO_2 emissions of developing countries. Because of the fact that the CO_2 emissions of these countries have not reached at the inflection point of the long-term S-shaped curve and usually present short-term linear or approximately exponential trends, they have presented a hybrid forecasting equation combined by a non-homogeneous exponential equation and a linear equation. To evaluate the performance of the hybrid model, the traditional linear model, GM(1,1), and the hybrid model were both used to forecast the CO_2 emissions of China from 1992 to 2011. In order to test the forecasting performance, the linear model GM(1,1) and the hybrid model are utilised to predict the CO_2 emissions of China from 1992 to 2011. Nabavi-Pelesaraei *et al.* (2014) applied ANNs to predict yield and GHG emissions in watermelon production in the Guilan province of Iran. Accordingly, several ANN models were presented and their prediction accuracies were evaluated in using quality parameters. Ge *et al.* (2017) predicted the CO_2 emissions caused by industrial energy consumption of Tianjin from 2005 to 2012 through using regression on population, affluence, and technology model, the logistic regression model and the GM. Hamzacebi and Karakurt (2015) proposed a grey prediction model to forecast the energy-related CO_2 emissions in Turkey considering for the period between 1965 and 2012. They predicted CO_2 emissions in Turkey up to year 2025. Liu *et al.* (2015) forecasted the energy consumption, gross CO_2 emissions, and CO_2 emission intensity in China from 2013 to 2020 through using system dynamics simulation. Perez-Suarez and Lopez-Menendez (2015) focused on environmental forecasting, based on the extended Environmental Kuznets Curve and the Environmental Logistic Curve. Considering a sample of 175 countries they made a comparison between methods in terms of their goodness of fitness and their forecasting accuracy. Özceylan (2015) proposed particle swarm optimisation and artificial bee colony techniques to forecast CO_2 emission in Turkey, based on socio-economic indicators such as energy consumption, population, gross domestic product, and number of motor vehicles data.

It should be noticed that grey forecasting model is still a popular forecasting tool. However, studies focusing on grey forecasting models have to be intensified on various GM variants and their performance on different data sets describing to energy-related CO_2 emissions dynamics of developing countries.

3. Methodology

As seen in the literature review section, the different methods were utilised to forecast the energy-related CO_2 emissions. Due to its success reported in the literature, this paper focuses on the recent powerful forecasting approach, GM (Akay and Atak, 2007; Bianco *et al.*, 2010; Feng *et al.*, 2012; Hamzacebi and Es, 2014). GM has been widely used in predicting because of its advantages of requiring sparse data to establish forecasting models with higher forecasting accuracy (Pao and Tsai, 2011). A brief introduction of the grey theory (GT) and three extensions of GM are given below.

3.1 GT and the conventional GM(1,1)

GT is first developed by Ju-Long (1982) as a system characterizing vagueness and incompleteness of the relations among system components. In recent years, GT has become an influential method in solving problems including high uncertainty (Ju-Long, 1989). In the information research field, deep or light colours represent clear or ambiguous information, respectively. Black represents that the researchers have no knowledge of the system structure, parameters, and characteristics, and white indicates that the information is completely clear. Colours between black and white indicate systems that are not clear, such as social, economic, or weather systems (Hsu, 2003).

The GM is a forecasting approach based on GT (Feng *et al.*, 2012). The most widely used grey prediction model is GM(1,1). The GM(1,1) uses a first-order differential equation to characterize an unknown system (Hamzacebi and Karakurt, 2015). GM(1,1) consists of three basic operations: accumulated generating operator (AGO), inverse accumulating operator, and GM (Ju-Long, 1989). The constructions of the GM(1,1) are described as follows (Hamzacebi and Karakurt, 2015; Liu and Lin, 2010).

Let $X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)$ given the original time series data set. By using AGO operator, the series $X^{(0)}$ is converted into series $X^{(1)} = (x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(n))$ as below:

$$x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i) \tag{1}$$

Then, GM(1,1) is built by a first-order grey differential equation:

$$x^{(0)}(k) + az^{(1)}(k) = b \tag{2}$$

Here, a denotes the development coefficient and b refers to the driving coefficient:

Theorem 1. Let $X^{(0)}$ and $X^{(1)}$ be the same as above. But $X^{(0)}$ is non-negative. The estimated coefficients, $[a, b]^T$, can be evaluated by the following equation:

$$\hat{a} = \begin{bmatrix} a \\ b \end{bmatrix} = \left(B^T B\right)^{-1} B^T Y \tag{3}$$

where:

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \ldots & \ldots \\ -z^{(1)}(n) & 1 \end{bmatrix}, \quad Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \ldots \\ x^{(0)}(n) \end{bmatrix} \tag{4}$$

and:

$$z^{(1)}(k) = 0.5\left(x^{(1)}(k) + x^{(1)}(k-1)\right) k = 2, 3, \ldots \tag{5}$$

then:

$$\frac{dX^1}{dt} + aX^1 = b \tag{6}$$

is referred to a whitenization equation of the GM(1,1) model in Equation (2):

Theorem 2. Let B, Y, and $\hat{a}$ be the same as in Theorem 1. If $\hat{a} = \begin{bmatrix} a \\ b \end{bmatrix} = (B^T B)^{-1} B^T Y$ then, grey forecasting equation blow is obtained by grey differential equation:

$$\hat{x}^{(1)}(k+1) = \left[x^{(0)}(1) - \frac{b}{a}\right] e^{-ak} + \frac{b}{a} \text{ for } k = 1, 2, \ldots, n \tag{7}$$

Here, $\hat{x}^{(1)}(k+1)$ shows the forecasting of x at time $k+l$. The initial condition is given as:

$$x^{(1)}(1) = x^{(0)}(1) \tag{8}$$

The last step is applied as follows in order to acquire predicted values:

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) = (1 - e^{a})\left(x^{(0)}(1) - \frac{b}{a}\right) e^{-ak} \quad k = 1, 2, \ldots, n \tag{9}$$

3.2 Grey prediction with rolling mechanism (GPRM)

GPRM is a variant of GM(1,1) (Kumar and Jain, 2010). The all data sets are used for forecasting in GM(1,1). In order to improve forecasting accuracy, it is, however, using only recent data that are recommended (Akay and Atak, 2007). To avoid the accumulation of historical data as well as keeping a constant number of data points and adopting the recent data for model construction, the GPRM (1,1) model has developed to modify the traditional GM(1,1) (Hsu, 2011). In GPRM, $x^{(0)}(k+1)$ is forecasted through implementing GM(1,1) to the original sequence $x^{(0)} = (x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(k))$, where $k < n$ and $k \geqslant 4$. The procedure is repeated, but the new forecasted data $x^{(0)}(k+1)$ are added to the end of the original data while the previous first data $x^{(0)}(1)$ are extracted. This procedure creates a new sequence of $x^{(0)} = (x^{(0)}(2), x^{(0)}(3), \ldots, x^{(0)}(k+1))$. So, following GM(1,1) of the forecasting process, the predictive value of $x^{(0)}(k+2)$ can be obtained. This is called the GPRM (1,1) (Akay and Atak, 2007; Hsu, 2003; Hsu, 2011). Here, the length of the sequence, k, is an important parameter that effects directly the forecasting accuracy.

3.2.1 DGM. DGM, $\hat{x}^{(1)}(k+1) = \beta_1 x^{(1)}(k) + \beta_2$, is developed to cope with the limitations of the continuous approach (Liu and Lin, 2010). Same as in Equation (3), the least square estimates for the two parameters satisfy:

$$\hat{\beta} = \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix} = \left(B^T B\right)^{-1} B^T Y \tag{10}$$

where:

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

Letting $x^{(1)}(1) = x^{(0)}(1)$, the estimate of the $(k+1)^{th}$ observation is given as $\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k)$.

3.2.2 ODGM. Liu and Lin (2010) presented that different initial values $\hat{x}^{(1)}(1)$ lead to different results, where small changes in the initial value $\hat{x}^{(1)}(1)$ might cause a drastically different simulation sequence. To eliminate this, they suggested adding a small adjustment, β_3, to $x^{(1)}(1)$. Thus, the following model can be constructed:

$$\begin{cases} \hat{x}^{(1)}(k+1) = \beta_1 \hat{x}^{(1)}(k) + \beta_2 \\ \hat{x}^{(1)}(1) = x^{(1)}(1) + \beta_3 \end{cases} \tag{11}$$

where β_1, β_2, and β_3 are model parameters to be determined, and $\hat{x}^{(1)}(1)$ is the basis of iteration. This model is expressed to the optimised GM with fixed starting point, ODGM (Liu and Lin, 2010).

As mentioned before, β_1 and β_2 will be determined with Equation (16). The optimal value of β_3 is obtained by minimising the sum of mean squared errors of the estimation (MSE) (Liu and Lin, 2010):

$$\beta_3 = \frac{\sum_{k=1}^{n-1} \left[x^{(1)}(k+1) - \beta_1 x^{(1)}(1) - \frac{1-\beta_1^k}{1-\beta_1} \beta_2 \right] \beta_1^k}{1 + \sum_{k=1}^{n-1} \left(\beta_1^k \right)^2} \tag{12}$$

Similar to DGM, $x^{(1)}(1)=x^{(0)}(1)$ and the estimation of the $(k+1)^{\text{th}}$ observation is given as $\hat{x}^{(0)}(k+1)=\hat{x}^{(1)}(k+1)-\hat{x}^{(1)}(k)$.

3.2.3 NDGM. The grey prediction models described above based on the assumption that the original data, $X^{(0)}$, satisfies the law of homogeneous exponential growth that is $x^{(0)}(k)\approx ac^k$, $k=1, 2, \ldots, n$. NDGM expands the model to cope with the non-homogeneous samples as follows (Liu and Lin, 2010):

$$\begin{cases} \hat{x}^{(1)}(k+1)=\beta_1\hat{x}^{(1)}(k)+\beta_2 k+\beta_3 \\ \hat{x}^{(1)}(1)=x^{(1)}(1)+\beta_4 \end{cases} \tag{13}$$

where β_1, β_2, and β_3 are to be determined by the method of the least squares estimate:

$$\hat{\beta}=\left[\beta_1,\beta_2,\beta_3\right]^T=\left(B^TB\right)^{-1}B^TY \tag{14}$$

Similar to the previous model, B, and Y are defined as follows:

$$B=\begin{bmatrix} x^{(1)}(1) & 1 & 1 \\ x^{(1)}(2) & 2 & 1 \\ \vdots & \vdots & \vdots \\ x^{(1)}(n-1) & n-1 & 1 \end{bmatrix}, \quad Y=\begin{bmatrix} x^{(1)}(2) \\ x^{(1)}(3) \\ \cdots \\ x^{(1)}(n) \end{bmatrix} \tag{15}$$

For the estimation of the parameter, β_4, an optimisation model without any constraint can be solved so that the sum of squared errors is minimised, that is, $\min\limits_{\beta_4} \sum_{k=1}^{n}[\hat{x}^{(1)}(k)-x^{(1)}(k)]^2$ (Liu and Lin, 2010). Solving this model leads to:

$$\beta_4=\frac{\sum_{k=1}^{n-1}\left[x^{(1)}(k+1)-\beta_1^k x^{(1)}(1)-\beta_2\sum_{j=1}^{k}j\beta_1^{k-j}-\frac{1-\beta_1^k}{1-\beta_1}\beta_3\right]\beta_1^k}{1+\sum_{k=1}^{n-1}\left(\beta_1^k\right)^2} \tag{16}$$

3.3 Evaluation of the forecasting accuracy

To evaluate the forecasting performance, three metrics, mean absolute percentage error (MAPE), MSE, and root mean square error (RMSE) are used as indicators to compare the performance of different forecasting models. Performance metrics that are used are defined as (Kaytez *et al.*, 2015):

$$\text{MAPE}(\%)=100\times\frac{\sum_{k=1}^{N}\left|\left(x^{(0)}(k)-\hat{x}^{(0)}(k)\right)/(y_r)\right|}{N} \tag{17}$$

$$\text{MSE}=\frac{1}{N}\sum_{k=1}^{N}\left(x^{(0)}(k)-\hat{x}^{(0)}(k)\right)^2 \tag{18}$$

$$\text{RMSE}=\sqrt{\frac{\sum_{k=1}^{N}\left(x^{(0)}(k)-\hat{x}^{(0)}(k)\right)^2}{N}} \tag{19}$$

The performance of the forecasting models can be grouped into four categories in terms of MAPE criterion as depicted in Table II (Sun *et al.*, 2016).

4. Application

4.1 Data gathering

To determine the data set of the energy-related CO_2 emissions, it is compared with different data set in terms of sources, update frequency, starting and latest year, and countries. Table III shows the comparison of six data sets for the energy-related CO_2 emissions (Olivier *et al.*, 2015).

In this section, Turkish energy-related CO_2 emissions between 2015 and 2025 are forecasted through using discrete grey forecasting techniques based on the historical data from 1965 to 2014 reported by British Petroleum (2015), are depicted in Figure 2. Turkey, as a developing country, tries to deal with increased demand of energy and growing CO_2 emissions. Growing population and increasing GDP make Turkey face with increased energy demand in the recent decades. Installed electricity capacity reached a level of 64,000 MW in 2013, 12 times more than the capacity level of 1980 Turkish Electricity Transmission Corporation (TEIAS 2013). The Ministry of Energy and Natural Resources forecast that per capita energy use increased from 1,276 kgoe (kilograms of oil equivalent) in 2005 to 1,663 kgoe in 2013. Total energy demand currently stands at 135.3 million toe (Acar *et al.*, 2015). Turkey does not have its own oil or gas reserves that make it depend on

Forecasting performance	MAPE (%)
Excellent	< 10
Good	10-20
Reasonable	20-50
Incorrect	> 50

Table II. The performance of the forecasting models

Source	EDGAR[a]	IEA[b]	CDIAC[c]	EIA[d]	BP[e]	UNFCCC[f]
Update frequency	Annual	Annual	Annual	Annual	Annual	Annual
Start-latest year	1970-2008	1971-2014	1751-2010 (2012 for 67+5 other)	1980-2012	1965-2014	1990-2012
Countries in data set	2014	137 + 3	224	224	67 + 5 other	44

Notes: [a]http://edgar.jrc.ec.europa.eu/; [b]www.iea.org/statistics/topics/co2emissions/; [c]http://cdiac.ornl.gov/trends/emis/meth_reg.html; [d]www.eia.gov/cfapps/ipdbproject/IEDIndex3.cfm?tid=90&pid=44&aid=8; [e]www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy.html; [f]http://unfccc.int/ghg_data/items/3800.php
Source: Olivier *et al.* (2015)

Table III. Comparison of six data sets for CO_2 emissions

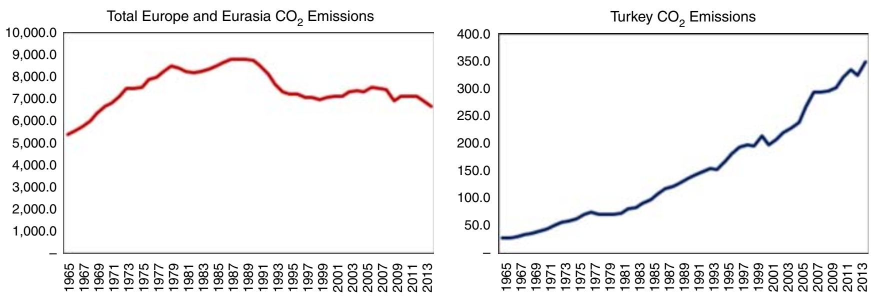


Figure 2. Total Europe and Eurasia and Turkey CO_2 emissions (1965-2014)

imports. The country is struggling to conduct a cheap energy supply and reducing CO_2 emissions. Since 1990, CO_2 emissions have increased by 2.8 times in average. And in 2010 it reaches the level of 403.55 million tons of CO_2.

Turkey needs to improve its sustainable economic growth which needs to focus on greening industry through using sustainable technologies, sustainable raw material, and sustainable techniques. Sustainable economic growth can be succeeded by the help of policies such as fossil energy reduction, promoting decentralised energy production, using renewable energy, etc. (Apak and Atay, 2013). The application of these policies can decrease the negative impact of industrialisation in Turkey by the help of maintaining environmentally friendly practices. In order to provide a basis for environmental policies, there is a need for the utilisation of decision support tools and analytical models. By the help of these approaches, the inputs of environmental policies, such as evaluation of investment alternatives for sustainable technologies, forecasting gas emissions, procurement types of raw materials, etc. can be revealed out. Because Turkey, as a potential candidate country of the European Union accession, is obliged to satisfy the responsibilities on CO_2 emissions, therefore it is required to track the amount of CO_2 emissions in a proper manner in order to give answer the question "How is the potential of Turkey in CO_2 emissions?" We believe that the proposed forecasting approach is able to make decision makers have effective foresights for the future of CO_2 emissions that can help to revise and develop policy alternatives in order to help the greening of the economy. As a result, need for green technologies, need for green employment, and need for sustainable growth patterns can be effectively exposed.

4.2 The solutions of DGMs

By using the data set from 1965 to 2014, different types of DGMs are generated. The first model corresponds to the DGM, the second and third models are extensions of DGM, ODGM, and NDGM, respectively. The results of applying the three versions are given in Table IV.

To identify the best method, the historical data are simulated with three GMs. When compared with the actual time series with simulated values, the following MSE, RMSE, and MAPE values in Table V are obtained. The results show that NDGM gives the best performance measures among these three methods for Turkey and DGM gives the best performance measures among these three methods for total Europe and Eurasia region.

The forecasted values for 2015-2030 period with the best method for Turkey and total Europe and Eurasia region are presented in Table VI and Figure 3.

4.3 The solutions of DGMs with RM

Using the data set from 1965 to 2014, DGM-RM, ODGM-RM, and NDGM-RM are developed and tested for various k values ($k = 4, 5, \ldots, 30$). Analysing the DGM-RM, ODGM-RM, and NDGM-RM with various rolling lengths, we obtained MAPE values depicted in Figure 4.

Table IV.
Comparison of six data sets for energy-related CO_2 emissions

Method	Turkey	Total Europe and Eurasia
DGM	$\hat{x}^{(1)}(k+1) = 1.0449x^{(1)}(k)+45{,}1870$	$\hat{x}^{(1)}(k+1) = 0.99998x^{(1)}(k)+7489$
ODGM	$\begin{cases}\hat{x}^{(1)}(k+1) = 1.0449^{(1)}(k)+45{,}1870\\ \hat{x}^{(1)}(1) = x^{(1)}(1)-45{,}7540\end{cases}$	$\begin{cases}\hat{x}^{(1)}(k+1) = 0.99998x^{(1)}(k)+7489\\ \hat{x}^{(1)}(1) = x^{(1)}(1)-39.141\end{cases}$
NDGM	$\begin{cases}\hat{x}^{(1)}(k+1) = 1.0319\hat{x}^{(1)}(k)+1{,}9924k+26{,}6109\\ \hat{x}^{(1)}(1) = x^{(1)}(1)+0{,}6546\end{cases}$	$\begin{cases}\hat{x}^{(1)}(k+1) = 0.97448\hat{x}^{(1)}(k)+197.82k+7261.8\\ \hat{x}^{(1)}(1) = x^{(1)}(1)-854.08\end{cases}$

The comparison of MAPE values obtained with three methods for different k values show that DGM-RM and ODGM-RM give more precise and accurate forecasting results than NDGM-RM for short periods (k values ranging from 4 to 7) whereas for the long term the accuracy of the DGM-RM and NDGM is better than ODGM-RM with k values

Country	Method	Performance measures for models MSE	RMSE	MAPE
Turkey	DGM	178.723	13.369	10.955
	ODGM	112.249	10.595	9.2482
	NDGM	63.414	7.9633	4.6304
Total Europe and Eurasia	DGM	6.006e + 05	774.98	8.421356
	ODGM	6.006e + 05	774.98	8.421358
	NDGM	5.917e + 05	769.21	8.8055

Table V. Performance measures obtained for GMs and performance measures for models

Year	Turkey NDGM	Total Europe and Eurasia DGM
2015	365,922	7,482,465
2016	379,578	7,482,333
2017	393,668	7,482,201
2018	408,208	7,482,069
2019	423,211	7,481,937
2020	438,693	7,481,805
2021	454,667	7,481,673
2022	471,151	7,481,540
2023	488,160	7,481,408
2024	505,712	7,481,276
2025	523,823	7,481,144
2026	542,511	7,481,012
2027	561,794	7,480,880
2028	581,693	7,480,748
2029	602,225	7,480,616
2030	623,412	7,480.484

Table VI. Forecasted values of energy-related CO_2 emissions

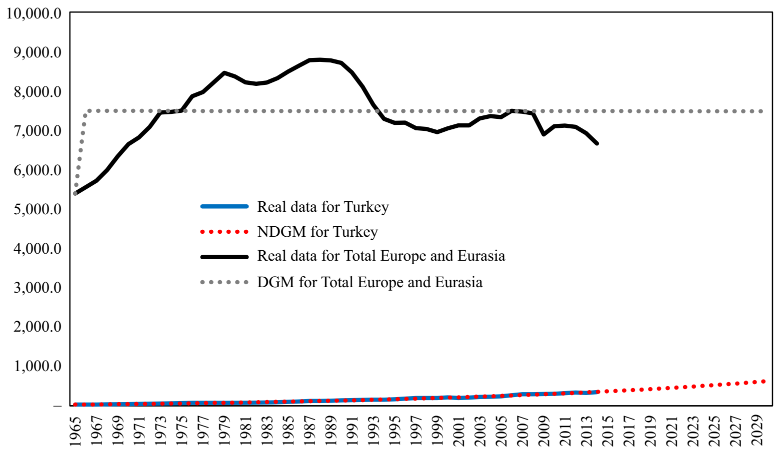


Figure 3. Comparison of the forecasts with three methods and real data from 1965 to 2030

ranging from 5 to 30 for Turkey. This is due to the relative complexity of NDGM-RM compared to the other two methods as it requires more data to capture the underlying dynamic. However, ODGM-RM is better than the other methods with $k = 30$ for total Europe and Eurasia.

Table VII demonstrates that k and MAPE values are for each grey method. It can be stated that the proposed models are highly precise and accurate tools for conducting forecasting based on the underlying data set as MAPE values are in the range of 4.2380-4.6786 per cent.

Therefore, we can conclude that NDGM-RM is a highly competitive forecasting tool with 26 parameters to be determined for Turkey and ODGM-RM is a highly competitive forecasting tool with only four parameters to be determined for total Europe and Eurasia. The energy-related CO_2 emissions forecasting for Turkey and total Europe and Eurasia is conducted through performing GMs from 2015 to 2030. The results are shown in Table VIII.

The forecasted CO_2 emissions for Turkey and total Europe and Eurasia values are illustrated in Figure 5.

CO_2 emissions of total Europe and Eurasia are expected to decrease forcefully. On the other hand because Turkey is an industrialising country; increase in CO_2 emissions is an expected result. Some policies should be developed in order to take precautions on dangerous effects of energy usage, for instance less carbon intensive energy (such as natural gas) should be used and produced. Moreover, possible mitigation alternatives should be taken into consideration. The sector-based emission mitigation policy can be improved and renewable energy sources can be increased. Renewable energy usage (such as hydro, geothermal, wind, biomass) is significant for the mitigation of CO_2 emissions. Due to weather conditions and geographic location, Turkey has a high solar power potential. However, in Turkey, price of electricity obtained from solar power facilities is so low and applications for having license are not satisfactory. The government can increase usage of renewable energy by offering attractive incentives.

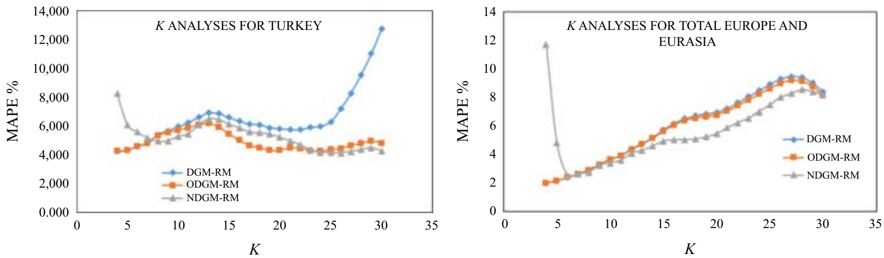


Figure 4.
Comparison of MAPE values obtained with three methods for different k values

Table VII.
Performance measures and the best rolling period length for proposed models

Country	Method	Best MAPE values and corresponding k's MAPE (%)	k
Turkey	DGM-RM	4.2812	4
	ODGM-RM	4.2789	4
	NDGM-RM	4.1376	26
Total Europe and Eurasia	DGM-RM	2.0256	4
	ODGM-RM	2.0253	4
	NDGM-RM	2.5395	6

Year	Turkey NDGM-RM ($k = 26$)	Total Europe and Eurasia ODGM-RM ($k = 4$)
2015	365,390	6,472,747
2016	378,892	6,245,579
2017	392,679	6,057,897
2018	406,990	5,854,768
2019	421,630	5,672,469
2020	437,865	5,486,485
2021	454,255	5,312,830
2022	470,333	5,140,515
2023	485,672	4,976,558
2024	500,975	4,815,983
2025	517,204	4,661,821
2026	531,953	4,511,772
2027	549,372	4,367,100
2028	567,875	4,226,703
2029	587,085	4,091,062
2030	607,880	3,959,612

Table VIII. Forecasted values for three DGMs with RM

5. Discussion

In order to reveal out the performances of proposed model, RM effect is measured and then the values of performance metrics of the best approach are compared with the study of Hamzacebi and Karakurt (2015) which use the same data for forecasting.

5.1 The effect of RM

The effect of RM on the forecasting accuracy is revealed out by comparing best solutions of the proposed GMs and GMs with RM.

For Turkey, NDGM delivered a MAPE value of 4.6304 per cent and NDGM-RM ($k = 26$) delivered a MAPE value of 4.1376 per cent as shown in Table IX. The result of this experiment obviously highlights the positive effect of RM embedded into NDGM.

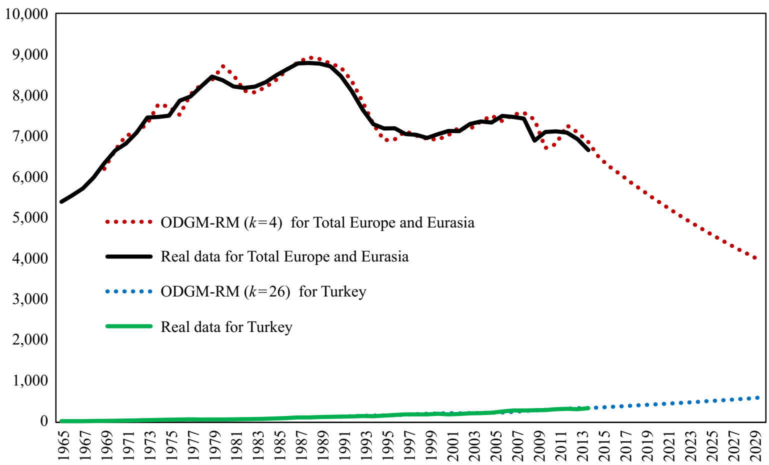


Figure 5. The forecasted CO_2 emission for Turkey and total Europe and Eurasia and real data between 1965 and 2030

For total Europe and Eurasia, DGM delivered a MAPE value of 8.4213 per cent and ODGM-RM ($k = 4$) delivered a MAPE value of 2.0253 per cent as shown in Table IX. The result of this experiment obviously highlights the positive effect of RM embedded into ODGM.

5.2 A comparison of two approaches

After the best approach to forecast the energy-related CO_2 emission is determined in previous section, we compared the proposed NDGM-RM model for Turkey with a recent study aiming to offer an effective forecasting model for Turkish energy-related CO_2 emission. The model generated by Hamzacebi and Karakurt (2015) was optimised by GM(1,1) that includes the forecast for 2013-2025, and they obtained a MAPE value of 4.900 per cent. As it can easily be noticed, NDGM-RM, which is presented in this study, has lower MAPE value (4.1376 per cent) than Hamzacebi and Karakurt (2015) as can be seen in Table X.

Comparison results highlight that proposed model is successful on forecasting the energy-related CO_2 emissions because it has the lowest MAPE value. The proposed model identifies the best solution among different grey forecasting techniques.

Newly available data for 2015 and 2016 also provides additional clues on the success of the proposed approach. Table XI summarises these findings.

6. Conclusion

In recent years, the global warming and climate change has become vital problem across the world. According to the experts, one of the root causes of the global warming is GHGs. Hence, recently GHGs and the global warming have become one of the most significant research areas in science and global politics. CO_2 is responsible for 58.8 per cent of GHGs amongst environmental pollutants causing climate change.

Table IX. Comparison of the forecasting performances of NDGM and ODGM-RM

Country	Methods	MSE	RMSE	MAPE
Turkey	NDGM	63.414	7.9633	4.6304
	NDGM-RM ($k = 26$)	189.28	13.758	4.1376
Total Europe and Eurasia	DGM	6.006e + 05	774.98	8.4213
	ODGM-RM ($k = 4$)	36,234	190.35	2.0253

Table X. Comparison with Hamzacebi and Karakurt (2015)

Years	Paper	Method	MAPE (%)
1965-2012	Hamzacebi and Karakurt (2015)	GM(1,1)	4.9000
1965-2014	Our Study	NDGM-RM ($k = 26$)	4.1376

Table XI. Comparison with realized values of 2015 and 2016

Region	Method	Year	Real data	Estimate
Turkey	ODGM-RM ($k = 26$)	2015	342,998	365,390
		2016	361,782	378,892
Total Europe and Eurasia	ODGM-RM ($k = 4$)	2015	6,240,730	6,472,747
		2016	6,258,527	6,245,579

The existing literature indicates that more than two-thirds of GHG caused from the energy-related CO_2 emissions.

In this study, we developed different DGMs in different forms to model and forecast the energy-related CO_2 emissions in Turkey and Europe and Eurasia region. GM has been commonly utilised in forecasting due to its advantages of needing sparse data to establish models with higher forecasting accuracy. This study presents six different grey forecasting models in two stage: DGM, ODGM, NDGM, DGM-RM, ODGM-RM, and NDGM-RM, respectively.

In the first stage of the study, we compared DGMs without RM using historical energy-related CO_2 emissions data from 1965 to 2014 in order to determine the best forecasting method which has the smallest MAPE (per cent) values. In the second stage of the solution, we compared DGM, ODGM, and NDGM with RM by analysing which k (the length of the sequence) is the best for the addressed method. After determining the best method with RM, we conducted a comparison in order to reveal out the best forecasting method to model and to predict the energy-related CO_2 emissions from 2015 to 2030 for Turkey and total Europe and Eurasia. Furthermore, the results obtained with the best method introduced in this work are compared with the current state-of-the-art study on the same data set. In the first stage, results show that NDGM is the best method to predict the energy-related CO_2 emissions for Turkey with minimum MAPE (4.630 per cent), and DGM is the best method to predict the energy-related CO_2 emissions for total Europe and Eurasia with minimum MAPE (8.4213 per cent).

According to the second stage results, NDGM-RM ($k = 26$) is the best method for Turkey with minimum MAPE (4.238 per cent) and ODGM-RM ($k = 4$) is the best method to predict the energy-related CO_2 emission for total Europe and Eurasia with minimum MAPE (2.0253 per cent). In addition, it is also validated that the best method for Turkey (NDGM-RM ($k = 26$)) gives better solution in comparison with the result of the study of Hamzacebi and Karakurt (2015).

The contribution of this study is to illustrate the effect of the different DGMs on the accuracy of the CO_2 emissions prediction as well as to identify the best approach for the Turkish energy-related CO_2 emissions. Turkey is a fast growing economy and due to the increase in energy-related-based sectors, CO_2 emissions are raising. Therefore, it is needed to take into consideration CO_2 emissions for the improvement of energy policies. For instance, it is vitally needed to make strict environmental regulations come into force in order to decrease the dangerous effects of industrialisation on environment. Moreover, it is also required to make changings on the energy mixes, use cleaner fuels and reduce reliance on coal in order to reduce CO_2 emissions. In the light of these, this study explains comparative results for decision makers to improve energy strategies for reducing CO_2 emissions in Turkey. Decision makers from governments, energy institutions, environmental institutions, and/or research centres, etc. can easily benefit from this system as a supportive tool to forecast the emissions, and can have foresight about the riskiest situations on environment. Effective tools enable decision makers to have managerial and operational foresights about unexpected situations, and to take necessary actions against risk. In the near future, the proposed model might be compared with the heuristic and/or metaheuristic methods such as ant colony, particle swarm optimization, and neural networks.

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