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Forecasting of Turkey's greenhouse gas emissions using linear and nonlinear rolling metabolic grey model based on optimization

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ABSTRACT

This study aims to contribute to the development of energy policies for Turkey's greenhouse gas (GHG) emissions in the future. For this purpose, linear and nonlinear metabolic grey models are combined with the optimization technique to obtain more accurate forecasting results. Optimization technique provides estimation of the parameters in metabolic grey model (MGM(1,1)) and nonlinear metabolic grey model (NMGM(1,1)). In this study, MGM(1,1), NMGM(1,1), optimized metabolic grey model OMGM(1,1), and optimized nonlinear metabolic grey model (ONMGM(1,1)) are applied for prediction of Turkey's GHG emissions including the Land Use, Land Use Change and Forestry (LULUCF), excluding LULUCF and from the energy sector. The ONMGM(1,1) gives more accurate results than the others from 1995 to 2016. The MAPE values of the ONMGM(1,1) are 4.80%, 4.14% and 5.19% for Turkey's GHG emissions with LULUCF, without LULUCF and from the energy sector, respectively. On the other hand, results of the ONMGM(1,1) show that the annual growth rates are forecasted as 0.56%, 0.66% and 0.49% for Turkey's GHG emissions with LULUCF, without LULUCF and from the energy sector, respectively, from 2017 to 2025. Furthermore, Turkey's highest GHG emissions with LULUCF, without LULUCF and from the energy sector are estimated by MGM(1,1) as 606.9 Mt of CO_2 equivalent, 726.4 Mt of CO_2 equivalent and 585.2 Mt of CO_2 equivalent in 2025, respectively. According to Turkey's Intended Nationally Determined Contribution (INDC), target of its GHG emissions including LULUCF is estimated as 934 Mt of CO_2 equivalent in a Business-As-Usual scenario and 790 Mt of CO_2 equivalent in a Mitigation scenario for the year 2025. Therefore, this study presents lower values of Turkey's GHG emissions with LULUCF than the values of Turkey's INDC for the year 2025. Additionally, results of this study present that energy sector has the largest share of Turkey's GHG emissions from 2017 to 2025. Therefore, Turkish Government should develop policies to use energy more efficiently and to increase the capacity of renewable energy sources in electricity generation. Especially, Turkey's ambition to increase the share of renewable energy in total is very assertive. This can be seen from the Turkey's 11th Development Plan. According to the Plan, the share of total renewable energy and natural gas in total electricity generation is going to be increased from 32.5% in 2018 to 38.8% in 2023 and to be decreased from 29.85% in 2018 to 20.7% in 2023, respectively.

1. Introduction

Turkey has become a party to United Nations Framework Convention on Climate Change (UNFCCC) since 2004. In accordance with this agreement, Turkey has to develop and implement policies to combat climate change and is obliged to inform data on current greenhouse gas (GHG) emissions to the UNFCCC (MEU, 2013). Turkey has presented its First National Communication in 2007 and the last National Communication which was the 7th has presented in 2018. According to this latest report, Turkey's total GHG emissions reached 496.1 million tons of CO_2 equivalent without the Land Use, Land Use Change and Forestry (LULUCF) sector and 428.0 million tons (Mt) of CO_2 equivalent with LULUCF sector in 2016 which corresponds to about 135% increase to 1990 for both sector. Additionally, the energy sector had the largest share with 72.8% of GHG emissions without LULUCF in 2016. Turkey's energy sector has increased her GHG emissions from 134.33 Mt of CO_2 equivalent in 1990 to 360.98 Mt of CO_2 equivalent in 2016. Therefore, Turkey is in great efforts to reduce GHG emissions in the energy sector (MEU, 2018).

Forecasting of GHG emissions plays an important role in

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developing of energy policies and maintaining the international agreement to combat climate change for the countries (Hamzacebi and Karakurt, 2015). Accurate prediction of GHG emissions level is one of the main issues in the target of GHG emissions reduction. Therefore, forecasting of GHG emissions is a necessary and important issue (Fang et al., 2018). There are many studies about forecasting of Turkey's greenhouse gas emissions. Köne and Büke (2010) forecasted Turkey's CO_2 emissions from fuel combustion using trend analysis. They showed that CO_2 emissions from fuel combustion was estimated as 351.09 Mt in 2030, which corresponds to average annual growth rate of 1.79% from 2015 to 2030. Özer et al. (2013) used the Long-range Energy Alternatives Planning system (LEAP) model, based on Business As Usual (BAU) and Mitigation scenarios, to forecast CO_2 emissions in the Turkish electricity sector from 2006 to 2030. According to the results of the BAU and Mitigation scenario, CO_2 emissions in the Turkish electricity sector was estimated as 425.15 Mt and 321.15 Mt in 2030 with the annual growth rate of 6.98% and 5.8%, respectively. Aydin (2015) developed a model based on multiple linear regression analysis (MLRA) and trend analysis (TA) to predict energy-related CO_2 emissions (ERCDE) in Turkey from 1971 to 2010. The developed model was used to forecast ERCDE in Turkey from 2010 to 2025. The results showed that ERCDE was estimated as 335.41 Mt for 2025, which corresponds to average annual growth rate of 1.25% from 2010 to 2025. Hamzacebi and Karakurt (2015) used grey prediction model to forecast energy-related CO_2 emissions in Turkey from 2013 to 2025. They found that energy-related CO_2 emissions would reach up to 496.4 Mt in 2025, which is equal to average annual growth rate of 3.45% from 2013 to 2025. Ayvaz et al. (2017) forecasted Turkey's energy related CO_2 emissions using non-homogeneous discrete grey model (NDGMG) and non-homogeneous discrete grey model with rolling mechanism (NDGM-RM). According to the NDGM results, energy related CO_2 emissions were estimated as 623.4 Mt in 2030 with the annual growth rate of 3.62% from 2015 to 2030. Additionally, results of the NDGM-RM model showed that energy related CO_2 emissions was estimated as 607.9 Mt in 2030 which is equal to the annual growth rate of 3.45% from 2015 to 2030. Şahin (2019) forecasted Turkey's CO_2 emissions from electricity generation in estimated capacity factor using trend analysis. Results showed that total CO_2 emissions from electricity generation were estimated as 199.2 Mt and 187.1 Mt tons in 2021 according to the optimistic and pessimistic scenario, respectively.

One of the forecasting techniques of GHG emissions of countries is Grey prediction model (GM), firstly proposed by Deng. In the GM theory, “white”, “black” and “grey” defines the known information, unknown information and partially known information about the system, respectively (Deng, 1982). The advantages of the GM are; the next unknown data can be produced by a few past data and the GM can use a first order differential equation to characterize the unknown system behavior (Huang and Huang, 1997).

The GM(1,1), is the most widely used among other grey prediction models, implies a first-order single variable prediction model (Hamzacebi and Karakurt, 2015; Hamzacebi and Es, 2014). One of the considerable advantages of the GM(1,1) is requiring only recent year's data for accuracy prediction (Akay and Atak, 2007). In literature, there are many studies that GM(1,1) has been applied for prediction of GHG emissions of countries such as Taiwan (Lin et al., 2011), Brazil (Pao and Tsai, 2011), China (Pao et al., 2012; Meng et al., 2014) and Turkey (Hamzacebi and Karakurt, 2015). Also, Dengiz et al. (2019) used GM(1,1) to forecast CO_2 emissions of seven developed countries; Australia, China, Italy, Spain, Turkey, United Kingdom and United States. Sometimes the GM(1,1) cannot be successful to fit the actual data very well in such a case improving techniques can be used with grey prediction models (Akay and Atak, 2007).

The technique of “rolling” or named “metabolism” is using to improve the accuracy of grey prediction (Akay and Atak, 2007; Wang et al., 2018a). The basic advantage of rolling grey model or rolling metabolic grey model (MGM(1,1)) is reconstructing itself by using the latest data (Chang et al., 2005). Ma et al. (2013) showed that the MGM(1,1) had more accuracy than the GM(1,1) for the prediction of iron ore import and consumption of China. Zhao et al. (2016) predicted electricity consumption of Inner Mongolia. They obtained that MAPE value of the MGM(1,1) is 9.55% when this value was 25.01% for the GM(1,1). Ayvaz et al. (2017) improved the accuracy of grey prediction models by using rolling mechanism to predict the energy related CO_2 emissions of Turkey, Europe and Eurasia. In addition, Akay and Atak (2007) predicted Turkey's total and industrial electricity consumption using MGM(1,1). Results showed that mean absolute percentage error (MAPE) was below than 5% for both prediction of total and industrial electricity consumption. Boran (2015) found the prediction accuracy of the MGM(1,1) for Turkey's natural gas consumption was 93.5% during 1995–2012.

On the other hand, the accuracy of grey prediction models can be improved by optimization of the horizontal adjustment value (λ), which is the range of 0–1. In traditional grey model GM(1,1), λ is equal to 0.5 (Ma et al., 2013). Researchers showed that optimization of λ increases the accuracy of grey model. Chang et al. (2005) predicted Taiwan's semiconductor industry production using the MGM(1,1) model. They optimized variable horizontal adjustment value and correlated this value for forecasting. They showed that the average residual percentage error of the MGM(1,1) with variable λ was maximum 12.55% while this error was 30.24% for the MGM(1,1) with λ is equal to 0.5. Additionally, Ma et al. (2013) and Wang et al. (2017) showed that using optimization of λ gave more accuracy prediction for both GM(1,1) and MGM(1,1). They used particle swarm optimization (PSO) algorithm to optimize λ. Hamzacebi and Es (2014) used optimized grey model OGM(1,1) for prediction and forecasting of Turkey's annual electricity consumption. They optimized the horizontal adjustment value (λ) and length of subsequence (k). They found that the best λ and k were 0.45 and 4, respectively with having MAPE which is equal to 3.28%. Xu et al. (2019) used a novel model, namely adaptive grey model with buffered rolling mechanism (BR-AGM(1,1)) to predict and forecast Chinese coal-related and total energy-related greenhouse gas emissions. In the new improved model, a relationship between parameters development coefficient (a), driving coefficient (b) and horizontal adjustment value (λ) was established. Results showed that MAPE values of the proposed model were in the range 2.81–2.94% when the others were in the range 3.12–7.58%.

In traditional MGM(1,1), the power coefficient value (α) is equal to 1 and the method is called also “linear MGM”. If this coefficient is different from 1, the method is named “nonlinear MGM” or “NMGM”. In the NMGM(1,1), α denotes the degree of nonlinearity (Wang and Hung, 2003). Using only linear grey model in the prediction can affect the predictive accuracy because of short-term fluctuations in the middle part of the year. In nonlinear grey model, the power coefficient value can overcome this handicap (Wang et al., 2018b). Recently, researchers focused on the NMGM(1,1) for the forecasting of China's and India's energy demand (Wang et al., 2018b), China's foreign oil dependence (Wang et al., 2018c), shale oil production of United States (Wang et al., 2018a), coal consumption in South Africa (Ma et al., 2018).

As mentioned above, forecasting of greenhouse gas (GHG) emissions plays an important role for decision makers to develop countries' energy policies, because of the obligations imposed by international agreements. The use of linear and nonlinear grey prediction models for forecasting of Turkey's GHG emissions is almost no in literature therefore, it is believed that this study will fill the gap in the literature. Additionally, rolling mechanism technique was used to make more accurate estimation using current data.

This study aims to predict and forecast Turkey's greenhouse gas emissions. To achieve this, the accuracy of linear and nonlinear rolling metabolic grey model on prediction was performed and then Turkey's greenhouse gas emissions was forecasted using best model. The main frame of this study can be summarized as below.

The prediction models are: (1) MGM(1,1), (2) MGM(1,1) based on optimized horizontal adjustment value (λ) or briefly as OMGM(1,1), (3) Nonlinear MGM(1,1) based on optimized power coefficient value (α) or briefly as NMGM(1,1), (4) Nonlinear MGM(1,1) based on optimized power coefficient value (α) and horizontal adjustment value (λ) or briefly as ONMGM(1,1).

The subjects are: (1) Turkey's total GHG emissions with LULUCF. (2) Turkey's total GHG emissions without LULUCF. (3) Turkey's GHG emissions from the energy sector.

The prediction and forecasting procedure is applied from 1995 to 2016 and from 2017 to 2025, respectively.

The novelty of this study is in traditional NMGM(1,1) model only power coefficient value (α) is optimized but in this study the horizontal adjustment value (λ) is also optimized and the improved model is given as briefly ONMGM(1,1). Additionally, nonlinear generalized reduced gradient (GRG) algorithm method is preferred instead of the fourth-order Runge-Kutta method for the optimization of α and λ in this study.

The contributions of this study can be given as: (1) Linear and nonlinear rolling metabolic grey models based on optimization have compared for the prediction of Turkey's GHG emissions. (2) Results of this study can give valuable information to the decision makers to set strategic plans for achieving the target of Turkey's GHG emission reduction arising from international agreement. (3) Projections of Turkey's GHG emissions including LULUCF, excluding LULUCF and from the energy sector are given from 2017 to 2025 by using rolling mechanism and optimization technique in linear and nonlinear grey prediction models. Thus, these techniques have been used as far as it is known in prediction and forecasting of Turkey's GHG emissions with LULUCF, without LULUCF and from the energy sector.

The structure of this study is given as follows: Section 2 presents the methodology of the MGM(1,1), OMGM(1,1), NMGM(1,1) and ONMGM(1,1). In section 3, application and comparison of these models are presented for the prediction and forecasting of Turkey's greenhouse gas emissions with LULUCF, without LULUCF and from the energy sector. The fourth section denotes summary, limitations and suggestions.

2. Methodology

2.1. The rolling metabolic grey model

In traditional grey model GM(1,1), the first "1" and the second "1" indicates that there is only one variable and the first order differential equation is used to construct the model, respectively (Pao and Tsai, 2011). The algorithm of the GM(1,1) model can be expressed by the following procedure (Liu et al., 2016).

Non-negative varying sequence $X^{(0)}$ with n length of the sequence are presented by actual data:

$$X^{(0)} = \left\{X^{(0)}(1), X^{(0)}(2), X^{(0)}(3), \;……..,X^{(0)}(n)\right\} \tag{1}$$

First-order accumulated generating operation $x^{(1)}$ is obtained to the original series $X^{(0)}$:

$$X(k) = \left\{X^{(1)}(1), X^{(1)}(2), X^{(1)}(3), \;……..,X^{(1)}(n)\right\} \tag{2}$$

where,

$$X^{(1)}(k) = \sum_{i=1}^{k} X^{(0)}(i) \qquad k = 1,2,3…..,n \tag{3}$$

First-order grey differential equation of the GM(1,1) is obtained as:

$$X^{(0)}(k) + a\left(z^{(1)}(k)\right)^{\alpha} = b \qquad k = 2,3……,n \tag{4}$$

where, a is the development coefficient, b is the driving coefficient and α is the power coefficient. In traditional grey model the power coefficient value is equal to 1 and in this case $z^{(1)}(k)$ is calculated by the following equation:

$$z^{(1)}(k) = \lambda * X^{(1)}(k) + (1-\lambda) * X^{(1)}(k-1) \qquad k = 2,3,4,…..,n \tag{5}$$

where λ is horizontal adjustment value in the range of 0–1. In traditional GM(1,1), λ is equal to 0.5 (Ma et al., 2013).

a and b coefficients are calculated by employing the least squares method:

$$[a\ b]^T = \left[B^T B\right]^{-1} B^T Y \tag{6}$$

where, Y is the constant vector,

$$Y = \begin{bmatrix} X^{(0)}(2) \\ X^{(0)}(3) \\ X^{(0)}(4) \\ \vdots \\ X^{(0)}(n) \end{bmatrix} \tag{7}$$

And B is the accumulated matrix,

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ -z^{(1)}(4) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix} \tag{8}$$

The initial condition is:

$$X^{(1)}(1) = X^{(0)}(1) \tag{9}$$

After obtaining of a and b coefficients, the GM(1,1) model can be established as:

$$X_P^{(0)}(k+1) = X_P^{(1)}(k+1) - X_P^{(1)}(k) = (1-e^{a})\left(X^{(0)}(1) - \frac{b}{a}\right)e^{-a*k} \quad k = 1,2,..,n \tag{10}$$

The data, which is used in prediction, may show different characteristics at different times. To success these differences, rolling mechanism (RM) technique is recommended for use in the GM(1,1). Rolling or metabolism mechanism, which is an efficient technique to improve prediction accuracy of the GM(1,1) in the case of having chaotic data, is based on rolling steps that uses recent data by removing old data for each loop (Akay and Atak, 2007). In rolling metabolic grey model MGM(1,1) process, at least four oldest actual data ($X^{(0)}(1)$, $X^{(0)}(2)$, $X^{(0)}(3)$, $X^{(0)}(4)$, $X^{(0)}(5)$) is used by the GM(1,1) to predict the value of the next data ($X^{(0)}(6)$) at the first rolling stage. In the next rolling stage, the oldest value is changed by the latest value and the new five oldest data ($X^{(0)}(2)$, $X^{(0)}(3)$, $X^{(0)}(4)$, $X^{(0)}(5)$, $X^{(0)}(6)$) is set to predict the value of the next data ($X^{(0)}(7)$). This process is repeated until the prediction is finished.

$$B=\begin{bmatrix} -\left(z^{(1)}(2)\right)^{\alpha} & 1 \\ -\left(z^{(1)}(3)\right)^{\alpha} & 1 \\ -\left(z^{(1)}(4)\right)^{\alpha} & 1 \\ \vdots & \vdots \\ -\left(z^{(1)}(n)\right)^{\alpha} & 1 \end{bmatrix} = \begin{bmatrix} -\left(\lambda * X^{(1)}(2)+(1-\lambda) * X^{(1)}(1)\right)^{\alpha} & 1 \\ -\left(\lambda * X^{(1)}(3)+(1-\lambda) * X^{(1)}(2)\right)^{\alpha} & 1 \\ -\left(\lambda * X^{(1)}(4)+(1-\lambda) * X^{(1)}(3)\right)^{\alpha} & 1 \\ \vdots & \vdots \\ -\left(\lambda * X^{(1)}(n)+(1-\lambda) * X^{(1)}(n-1)\right)^{\alpha} & 1 \end{bmatrix} \tag{11}$$

Fig. 1 shows the flow chart of the MGM for this study. First sequence, which is established by the actual data from the year 1990–1994, is used to predict the data for the year 1995. In the next sequence, the oldest data is removed and the new following actual data, which is for the year 1995, is added into this sequence. Thus, other next data is predicted for the year 1996. This process is continued until the last data is predicted for the year 2016, thus prediction process from the year 1995–2016 is finished. At this stage, predicted data are compared with the actual data for measuring of accuracy of the prediction model. The next stage denotes the forecasting process. In this process, the oldest data is removed from the sequence and the forecasted value is added as the newest data into the sequence. This loop is repeated until the last data is forecasted for the year 2025. In this way, forecasting process contains data from the year 2017–2025.

2.2. Nonlinear metabolic grey model

The nonlinear metabolic grey model NMGM(1,1) is different from the rolling metabolic grey model MGM(1,1). Because of this difference is the power coefficient (α) in the Equation (4). The power coefficient, which is the degree of the nonlinearity, is not equal to 1 in the NMGM(1,1) (Wang and Hung, 2003). In the NMGM(1,1), the accumulated matrix in Equation (8) can be revised as:

In the NMGM(1,1), the horizontal adjustment value (λ) is equal to 0.5. Additionally, the power coefficient value (α) can be considered as dynamically to get the ideal value for making minimum average percentage error (APE) between the actual data. To achieve this, the optimal value of α can be calculated by iterative computation (Wang et al., 2018a).

2.3. Optimization of the model parameters

In this section, optimization technique of rolling metabolic grey

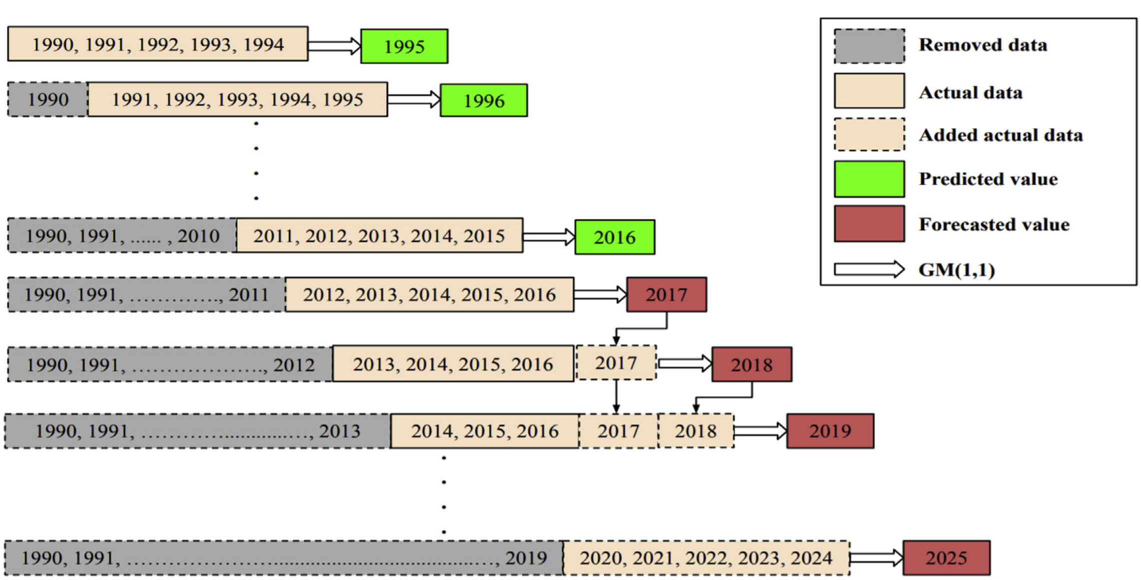

Fig. 1. The flow chart of the MGM(1,1) for this study.

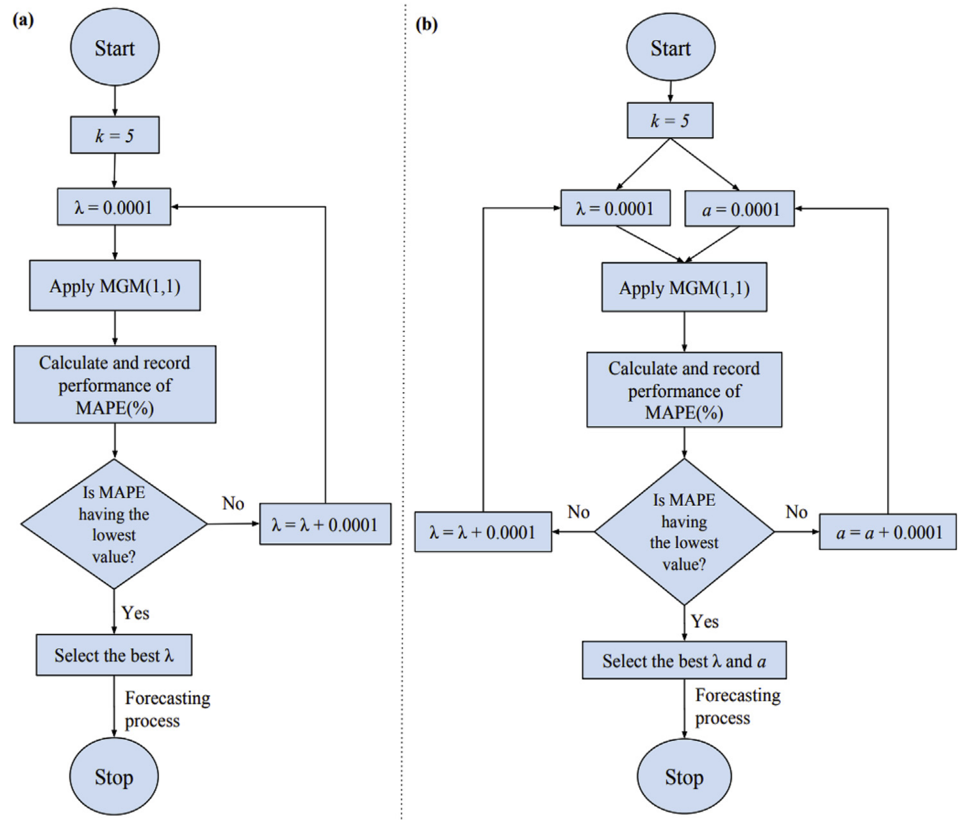

Fig. 2. The flow chart of the (a) OMGM(1,1) and (b) ONMGM(1,1).

model MGM(1,1) and nonlinear metabolic grey model NMGM(1,1) is explained. In traditional MGM(1,1), the horizontal adjustment value λ is equal to 0.5. However, this parameter may be different from the 0.5 according to the characterization of actual data versus time because it affects the accuracy of prediction. In this study, optimal λ is preferred instead of 0.5 therefore this process is called as optimized rolling metabolic grey model OMGM(1,1).

Fig. 2a shows the flow chart of OMGM(1,1). In the OMGM(1,1), the length of subsequence is chosen as $k = 5$. On the other hand, it is known that λ is in the range 0–1. The initial value of λ is 0.0001 and the step size is $\Delta = 0.0001$. The iteration procedure is finished until λ is equal to 0.9999. At this stage, MAPE values between the prediction model and actual data are calculated and compared. Finally, the minimum value of MAPE gives the best λ value for the OMGM(1,1) and the selected λ is used for forecasting process. In the NMGM(1,1), the horizontal adjustment value (λ) and the power coefficient value (α) of the accumulated matrix, which is given in Equation (11), affect the performance of the prediction. In this study, these parameters are optimized by iterative computation and the process is called optimized nonlinear metabolic grey model ONMGM(1,1). Fig. 2b presents the flow chart of the ONMGM(1,1) procedure. Unlike the OMGM(1,1) procedure, also the power coefficient value is optimized in the ONMGM(1,1). By this way, the improved prediction model is aimed to give more accuracy results.

In this study, the iterations for the defining of the best values of parameters λ and α are calculated using nonlinear generalized reduced gradient (GRG) algorithm method (Lasdon et al., 1974) that is solved by Excel Solver. The optimal values of parameters are selected according to having the lowest MAPE value.

2.4. The accuracy measurement

The selection of the best λ in the OMGM(1,1) and parameters α and λ in the ONMGM(1,1) can be carried out mean absolute percentage error (MAPE). Also, the accuracy of prediction models which are the MGM(1,1), OMGM(1,1), NMGM(1,1) and ONMGM(1,1) is measured by using MAPE. If the accuracy between the predicted and actual data at t time needs to be measured, absolute percentage error (APE) can be used. The calculation of APE and MAPE is given by the following equation (Xu et al., 2019):

$$APE\ (\%) = \left|\frac{u(i) - \hat{u}(i)}{u(i)}\right| x100 \tag{12}$$

$$MAPE\ (\%) = \sum_{i=1}^{n}\left|\frac{u(i) - \hat{u}(i)}{u(i)}\right| x\frac{100}{n} \tag{13}$$

where, u is the actual data, $\hat{u}$ is the predicted data and n is the observation data. The selection of the best prediction model generally depends on the having the lowest values of MAPE (Shaikh et al., 2017). If the MAPE is less than 10% is considered as highly level; 10–20% is as considered good level; 20–50% is considered as reasonable level, and more than 50% is considered as inaccurate level (Lewis, 1982).

3. Results and discussions

Data for Turkey's greenhouse gas emissions with LULUCF, without LULUCF and from the energy sector in the range 1990–2016 is shown in Fig. 3. According to the results, the annual growth rates are 3.35%, 3.35% and 3.88% for Turkey's GHG emissions

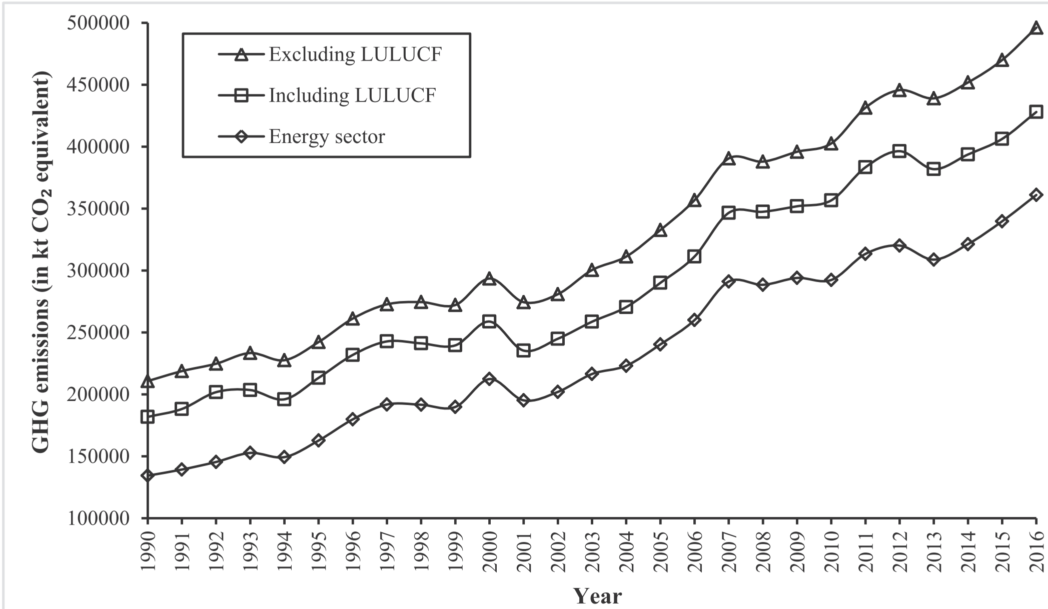

Fig. 3. Turkey's GHG emissions with LULUCF, without LULUCF and from the energy sector between 1990 and 2016 (UNFCCC, 2019).

with LULUCF, without LULUCF and from the energy sector, respectively. Although there has been an increasing trend in the total GHG emissions, the economic crisis in the years 1994, 1999, 2001 and 2008 caused a decreasing in total GHG emissions (MEU, 2018). Additionally, the energy sector has the share of 63.7–74.5% in GHG emissions excluding LULUCF between 1990 and 2016, which corresponds to the largest sector. Therefore, in addition to Turkey's GHG emissions with and without LULUCF, the energy sector was also predicted and forecasted in this study.

3.1. Prediction and forecasting of GHG emissions without LULUCF

Turkey's GHG emissions without LULUCF are predicted using the MGM(1,1), OMGM(1,1), NMGM(1,1) and ONMGM(1,1) from the year 1995–2016. Optimization of two parameters, which are the horizontal adjustment value (λ) and the power coefficient value (α), are

Table 1
Predicted and APE values of the prediction models for Turkey's GHG emissions in kilo tons (kt) CO_2 equivalent without LULUCF.

Year	Actual	MGM(1,1) (λ = 0.5)		OMGM(1,1) (λ = 0.9999)		NMGM(1,1) (λ = 0.5; α = 1.0095)		ONMGM(1,1) (λ = 0.9999; α = 1.002)	
		Predicted	APE (%)	Predicted	APE (%)	Predicted	APE (%)	Predicted	APE (%)
1900	210715								
1991	218748								
1992	224700								
1993	233352								
1994	227554								
1995	242195	234895	3.01	233026	3.79	232487	4.01	232501	4.00
1996	261165	243912	6.61	241307	7.60	240617	7.87	240590	7.88
1997	272647	267090	2.04	260787	4.35	259696	4.75	259204	4.93
1998	274496	291643	6.25	280672	2.25	279672	1.89	278170	1.34
1999	272121	290435	6.73	283657	4.24	282585	3.85	281983	3.62
2000	293494	278804	5.01	276978	5.63	276423	5.82	276458	5.80
2001	274403	293766	7.06	290361	5.82	289424	5.47	289415	5.47
2002	280820	283877	1.09	282977	0.77	282420	0.57	282644	0.65
2003	300349	281947	6.13	281787	6.18	281461	6.29	281666	6.22
2004	311222	294261	5.45	293053	5.84	292359	6.06	292617	5.98
2005	332654	325701	2.09	317205	4.64	315702	5.10	315081	5.28
2006	356823	350102	1.88	338649	5.09	337284	5.48	335952	5.85
2007	390458	376109	3.68	362549	7.15	361190	7.50	359421	7.95
2008	387913	418543	7.90	398292	2.68	397179	2.39	393881	1.54
2009	395867	418663	5.76	405347	2.39	403532	1.94	402147	1.59
2010	402564	411848	2.31	405208	0.66	403561	0.25	403416	0.21
2011	431407	405441	6.02	403066	6.57	402306	6.75	402382	6.73
2012	445631	440233	1.21	431755	3.11	429747	3.56	429503	3.62
2013	438982	465402	6.02	453892	3.40	451671	2.89	450967	2.73
2014	451809	460850	2.00	453766	0.43	451807	0.01	451808	0.01
2015	469930	455750	3.02	452839	3.64	451855	3.85	451988	3.82
2016	496067	473656	4.52	468838	5.49	467311	5.80	467456	5.77
MAPE			**4.35**		**4.17**		**4.18**		**4.14**

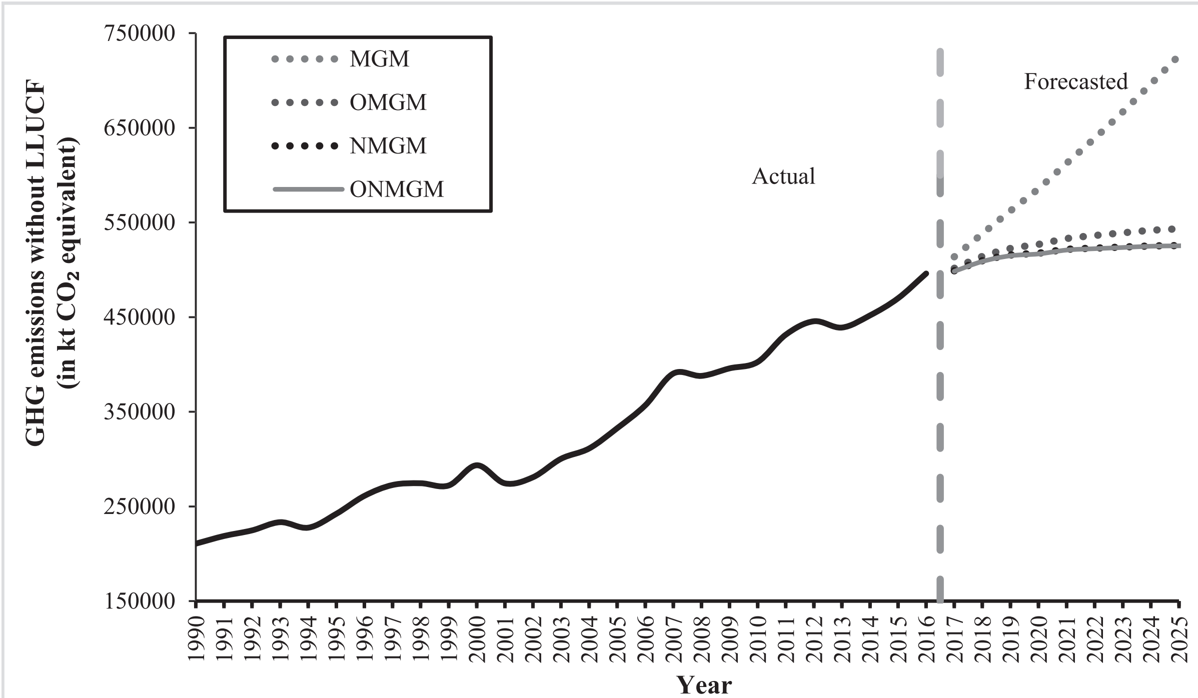

Fig. 4. Comparison of forecasted values of Turkey's GHG emissions without LULUCF from 2017 to 2025 using the MGM(1,1), OMGM(1,1), NMGM(1,1) and ONMGM(1,1).

based on having the lowest MAPE value. In the OMGM(1,1), λ is optimized by iterative calculation and it is obtained as 0.9999. Additionally, α is obtained as 1.0095 for the NMGM(1,1). Finally, the optimal parameters λ and α are found as 0.9999 and 1.002, respectively, for the ONMGM(1,1). Also, λ is equal to 0.5 for the MGM(1,1) and NMGM(1,1). The predicted values and absolute percentage error (APE) values for four prediction models are given in Table 1. According to this results, the ONMGM(1,1) has the lowest MAPE value which corresponds to 4.14% and maximum APE value is 7.88%. when the MAPE values are compared, it can be said that the optimization technique gives more accuracy results for both linear and nonlinear metabolic grey models.

After the prediction models are compared with the actual data, Turkey's GHG emissions without LULUCF are forecasted from the year 2017–2025. Fig. 4 presents the characterization of forecasted values of the MGM(1,1), OMGM(1,1), NMGM(1,1) and OMGM(1,1). The results show that increase of GHG emissions without LULUCF from 2017 to 2025 is found as 212.68 Mt for the MGM(1,1). Also, it is obtained that the NMGM(1,1) and ONMGM(1,1) have similar forecasting results. According to the results of the ONMGM(1,1), Turkey's GHG emissions without LULUCF is forecasted as 498.38 Mt in 2017 and 525.36 Mt of CO_2 equivalent in 2025.

3.2. Prediction and forecasting of GHG emissions with LULUCF

Prediction performance of the MGM(1,1), OMGM(1,1), NMGM(1,1) and ONMGM(1,1) for Turkey's GHG emissions with LULUCF from the year 1995–2016 is given in Table 2. The optimal parameter λ is obtained as 0.9999 for both of the OMGM(1,1) and ONMGM(1,1). Additionally, the parameter α is found as 1.0119 and 1.0024 for the NMGM(1,1) and ONMGM(1,1), respectively. The MAPE value is obtained as 5.22%, 4.88%, 4.82% and 4.80% for the MGM(1,1), OMGM(1,1), NMGM(1,1) and ONMGM(1,1), respectively. Thus, the ONMGM(1,1) gives the most accuracy prediction. It is obvious that optimization technique improves the prediction performance when the OMGM(1,1) is compared with the MGM(1,1) and the ONMGM(1,1) is compared with the NMGM(1,1). On the other hand, the NMGM(1,1) has lower MAPE value than the MGM(1,1).

Fig. 5 shows the comparison of forecasted values of the MGM(1,1), OMGM(1,1), NMGM(1,1) and ONMGM(1,1) from the year 2017–2025 for Turkey's GHG emissions with LULUCF. It is obtained that increase of GHG emissions with LULUCF from 2017 to 2025 is found as 165.15 Mt for the MGM(1,1). Additionally, Turkey's GHG emissions with LULUCF is forecasted as 465.6 Mt, 440.6 Mt and 448.7 Mt of CO_2 equivalent in the year 2025 for the OMGM(1,1), NMGM(1,1) and ONMGM(1,1), respectively. Also, it can be seen that the curve of the MGM(1,1) increases at a diminishing rate while the curve of others increases a decreasing rate from 2017 to 2025. This state can be explained that the curve of the actual data from 2013 to 2016 increases at a diminishing rate. Turkey submitted its Intended Nationally Determined Contribution (INDC) on 30 September 2015. According to this report, Turkey's GHG emissions with LULUCF will increase from 673 Mt of CO_2 equivalent in 2020 to 934 Mt of CO_2 equivalent in 2025 by a Business-As-Usual (BAU) scenario and from 673 Mt of CO_2 equivalent in 2020 to 790 Mt of CO_2 equivalent in 2025 by a Mitigation scenario (INDC, 2019). Therefore, results of this study estimate lower values of Turkey's GHG emissions with LULUCF than the values of Turkey's INDC.

3.3. Prediction and forecasting of GHG emissions from the energy sector

The predicted and APE values of Turkey's GHG emissions from the energy sector using the MGM(1,1), OMGM(1,1), NMGM(1,1) and ONMGM(1,1) from the year 1995–2016 are given in Table 3. The optimal horizontal adjustment value (λ) is obtained as 0.9999 for both of the OMGM(1,1) and ONMGM(1,1) and the optimal power

Table 2
Predicted and APE values of the prediction models for Turkey's GHG emissions in kilo tons (kt) CO_2 equivalent with LULUCF.

Year	Actual	MGM(1,1) (λ = 0.5)		OMGM(1,1) (λ = 0.9999)		NMGM(1,1) (λ = 0.5; α = 1.0119)		ONMGM(1,1) (λ = 0.9999; α = 1.0024)	
		Predicted	APE (%)	Predicted	APE (%)	Predicted	APE (%)	Predicted	APE (%)
1900	181792								
1991	188174								
1992	201744								
1993	203474								
1994	195988								
1995	213288	203581	4.55	202356	5.13	201497	5.53	201894	5.34
1996	231818	210605	9.15	209218	9.75	208289	10.15	208704	9.97
1997	242733	238606	1.70	231727	4.53	228902	5.70	229657	5.39
1998	241155	263160	9.12	251313	4.21	247834	2.77	248130	2.89
1999	239541	256382	7.03	250557	4.60	248091	3.57	248783	3.86
2000	258754	244200	5.62	243108	6.05	242399	6.32	242712	6.20
2001	235313	257576	9.46	255013	8.37	253482	7.72	254117	7.99
2002	244857	244105	0.31	244280	0.24	243952	0.37	244223	0.26
2003	258627	242763	6.13	243379	5.90	243372	5.90	243491	5.85
2004	270422	251756	6.90	251590	6.96	250989	7.19	251392	7.04
2005	290001	283496	2.24	275596	4.97	272207	6.14	273202	5.79
2006	311276	304933	2.04	294697	5.33	291039	6.50	291772	6.27
2007	346547	329987	4.78	317114	8.49	312903	9.71	313538	9.53
2008	347421	372649	7.26	352616	1.50	347421	0.01	347422	0.01
2009	351861	378203	7.49	363560	3.32	358555	1.90	359432	2.15
2010	356607	370432	3.88	363134	1.83	359503	0.81	360777	1.17
2011	383315	359366	6.25	357521	6.73	356383	7.03	356870	6.90
2012	396328	389125	1.82	382292	3.54	378654	4.46	380034	4.11
2013	381824	413909	8.40	403531	5.69	398755	4.43	400298	4.84
2014	393657	401696	2.04	396913	0.83	393868	0.05	395199	0.39
2015	406261	392926	3.28	392151	3.47	391504	3.63	391833	3.55
2016	427989	405178	5.33	403028	5.83	401469	6.20	402207	6.02
MAPE			**5.22**		**4.88**		**4.82**		**4.80**

coefficient value (α) is found as 1.0143 and 1.0043 for the NMGM(1,1) and ONMGM(1,1), respectively. Also, the parameter λ is equal to 0.5 for the MGM(1,1) and NMGM(1,1). It is obtained that the ONMGM(1,1) gives the best result with having the lowest MAPE value, which is 5.19%. In addition, it is seen that application of optimization technique in the OMGM(1,1) and ONMGM(1,1) results lower MAPE value than the MGM(1,1) and NMGM(1,1). Additionally, nonlinearity thought in metabolic grey model gives lower MAPE value than linear metabolic grey model.

The comparison of the MGM(1,1), OMGM(1,1), NMGM(1,1) and ONMGM(1,1) for Turkey's greenhouse gas emissions from the year 2017–2025 is shown in Fig. 6. Results show that the curve of the MGM(1,1) increases at a diminishing rate while the curve of others increases at a decreasing rate. The increase of GHG emissions from 2017 to 2025 is obtained as 206.3 Mt for MGM(1,1). This increase is almost equal to the increase in actual data from 1993 to 2016. In this study, approved the ONMGM(1,1) forecasted Turkey's GHG emissions from the energy sector as 375.2 Mt in CO_2 equivalent for the year 2025. Aydın (2015), Hamzacebi and Karakurt (2015) and Ayvaz et al. (2017) forecasted Turkey's energy-related CO_2 emissions for the year 2025 as 335.41 Mt, 496.4 Mt and in the range of 517.2–523.8 Mt, respectively. Thus, it can be said that the present study contributes to the literature.

Consequently, the ONMGM(1,1) has the lowest MAPE value among the other prediction models. The MAPE value of the ONMGM(1,1) is obtained as 4.14%, 4.80% and 5.19% for Turkey's greenhouse gas emissions with LULUCF, without LULUCF and from the energy sector, respectively. It is obvious that the prediction accuracy rate of the ONMGM(1,1) is above 88% (see in Fig. 7). Additionally, Turkey's greenhouse gas emissions with LULUCF, without LULUCF and from the energy sector are forecasted as 448.7 Mt, 525.4 Mt and 375.2 Mt in CO_2 equivalent for the year 2025 which also correspond to the annual growth rates are 0.56%, 0.66% and 0.49% from 2017 to 2025, respectively.

According to Turkish INDC, Turkey aims to reduce its GHG emissions from the BAU scenario level up to 15.4% by 2025 and 20.9% by 2030 (INDC, 2019). And results of this study show that the energy sector has the largest share of Turkey's greenhouse gas emissions from 2017 to 2025. Therefore, new strategies for reducing GHG emissions in energy sector should be developed. Especially the installed capacity of renewable power plants, such as hydro, wind, geothermal and solar, which have lower greenhouse gas emissions than fossil fuels (Ozcan, 2016), should be increased in the share of Turkey's electricity generation. According to Turkey's 11th Development Plan, Turkey plans to increase the share of total renewable energy from 32.5% in 2018 to 38.8% in 2023 and to decrease the share of natural gas in total electricity generation from 29.85% in 2018 to 20.7% in 2023 (PSB, 2019). By increasing of renewable energy sources, Turkey can meet its INDC targets by 2030 (Ari and Yikmaz, 2019). On the other hand, capacity factor of energy sources in electricity generation has an important issue for more efficient use of energy. Turkey's mean of capacity factor of electricity generation decreased from 49.5% in 2011 to 39.9% in 2016 (Şahin, 2019). Therefore, increasing the capacity factor of the power plants should be encouraged by the state with emphasis on research and development in power plants.

4. Conclusions

In this study, metabolic grey model MGM(1,1), optimized metabolic grey model OMGM(1,1), nonlinear metabolic grey model NMGM(1,1) and optimized nonlinear metabolic grey model ONMGM(1,1) are applied for prediction and forecasting of Turkey's greenhouse gas emissions with the Land Use, Land Use Change and

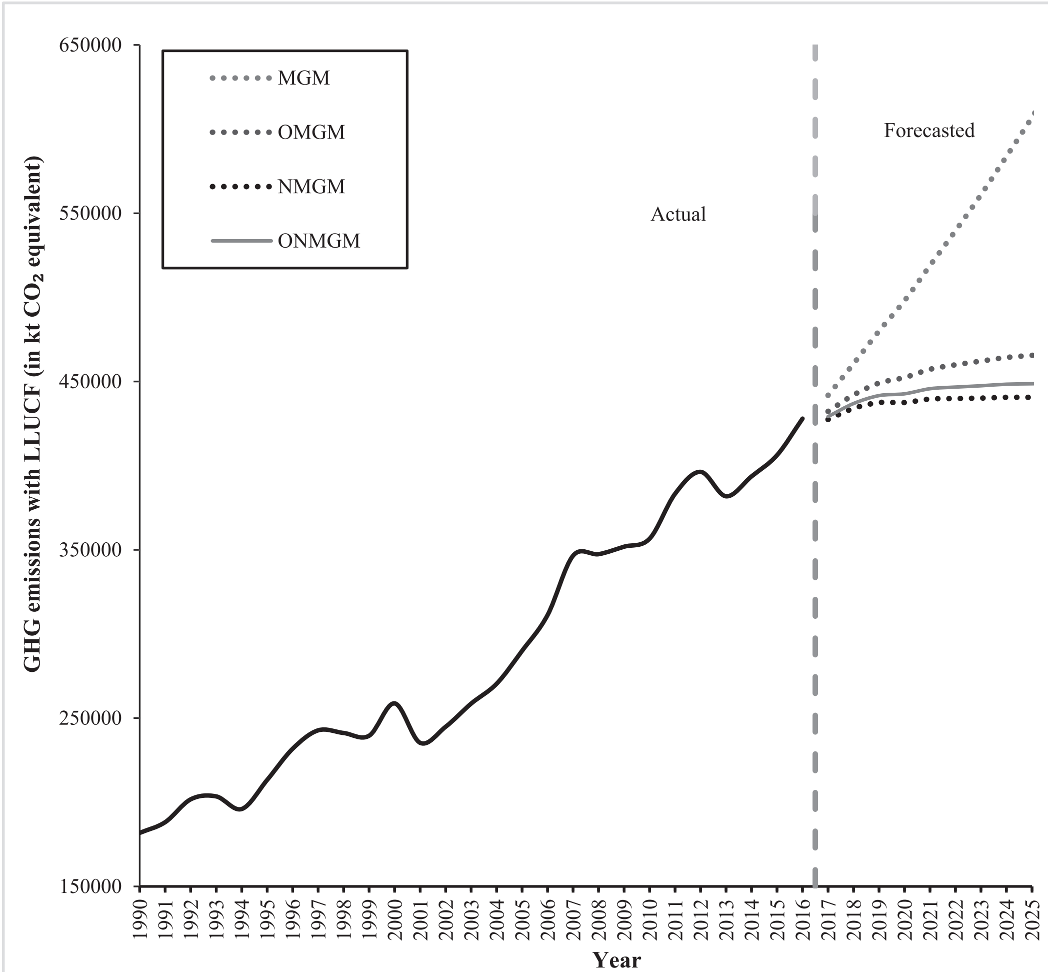

Fig. 5. Comparison of forecasted values of Turkey's GHG emissions with LULUCF from 2017 to 2025 using the MGM(1,1), OMGM(1,1), NMGM(1,1) and ONMGM(1,1).

Forestry (LULUCF), without LULUCF and from the energy sector.

In the OMGM(1,1), the horizontal adjustment value (λ) is optimized and this parameter is obtained as 0.9999 for all case. In ONMGM(1,1), both of the horizontal adjustment value and the power coefficient value (α) are optimized. Especially, the parameter α is found above 1 for this study and also Wang et al. (2018a) showed that this parameter can be up to 2.

The results show that the optimization technique increases the prediction accuracy. When the MAPE values are compared in all cases, the OMGM(1,1) and ONMGM(1,1) has better performance than the MGM(1,1) and NMGM(1,1), respectively. On the other hand, addition of the nonlinearity parameter α in the NMGM(1,1) causes lower MAPE value than linear MGM(1,1). This result is also consistent with the other studies about prediction of China's energy demand (Wang et al., 2018b) and prediction of the United States shale oil production (Wang et al., 2018a).

On the other hand, Turkey's GHG emissions are forecasted from 2017 to 2025. The curve of the MGM(1,1) increases at a diminishing rate while the curve of others increases at a decreasing rate in all cases. This handicap may be attributed to the curve of the actual data from 2013 to 2016 increases at a diminishing rate in all cases for this study. However, using optimization technique or adding nonlinearity parameter (α) in the MGM(1,1) changes the characterization of forecasting.

Additionally, Turkey's GHG emissions from the energy sector are estimated as 375.2–585.2 Mt in 2025, which contributes to the largest share of Turkey's GHG emissions. Turkey should produce policies for more efficient use of energy and increasing of the capacity of renewable energy sources in especially electricity generation.

The limitations of this study: (1) The forecasting results of Turkey's GHG emissions with LULUCF and without LULUCF could not be compared with the other studies due to the scarcity of studies on this issue in literature. (2) The prediction models were applied for nine years' period (up to the year 2025), but not be applied for long-term period. (3) The prediction models were not used for the prediction of human population growth and gross domestic product (GDP) therefore; a relationship with the results of this study could not be investigated.

For further studies, the parameter λ and α of nonlinear metabolic grey model may be correlated with including the development coefficient (a), driving coefficient (b), time, annual growth rate, GDP or other variables. In addition, the other techniques such as ARIMA, Artificial Neural Network (ANN) or Autoregressive Distributed Lag (ARDL) may be combined with the NMGM for improving prediction accuracy and obtaining more reliable forecasting results.

Table 3
Predicted and APE values of the prediction models for Turkey's GHG emissions in kilo tons (kt) CO_2 equivalent from the energy sector.

Year	Actual	MGM(1,1) ($\lambda = 0.5$)		OMGM(1,1) ($\lambda = 0.9999$)		NMGM(1,1) ($\lambda = 0.5$; $\alpha = 1.0143$)		ONMGM(1,1) ($\lambda = 0.9999$; $\alpha = 1.0043$)	
		Predicted	APE (%)	Predicted	APE (%)	Predicted	APE (%)	Predicted	APE (%)
1900	134328								
1991	139277								
1992	145378								
1993	152694								
1994	149313								
1995	162696	156129	4.04	154009	5.34	152445	6.30	152839	6.06
1996	179802	165141	8.15	162219	9.78	160186	10.91	160651	10.65
1997	191783	186808	2.59	180024	6.13	176325	8.06	176775	7.83
1998	191595	209918	9.56	198367	3.53	193433	0.96	193397	0.94
1999	189795	206940	9.03	200396	5.59	196717	3.65	197218	3.91
2000	212330	195695	7.83	194130	8.57	192809	9.19	193203	9.01
2001	195153	212146	8.71	208593	6.89	205866	5.49	206586	5.86
2002	201935	205523	1.78	203965	1.00	202223	0.14	202872	0.46
2003	216413	204583	5.47	203833	5.81	202698	6.34	203189	6.11
2004	223094	211408	5.24	210624	5.59	209506	6.09	209972	5.88
2005	240329	234838	2.28	228350	4.98	224100	6.75	225002	6.38
2006	259959	252625	2.82	244185	6.07	239345	7.93	240074	7.65
2007	291050	274614	5.65	263841	9.35	258097	11.32	258758	11.09
2008	288444	314940	9.19	296443	2.77	288445	0.01	288471	0.01
2009	293982	315782	7.42	303456	3.22	296646	0.91	297543	1.21
2010	292324	308608	5.57	302750	3.57	298370	2.07	299498	2.45
2011	313375	293799	6.25	293329	6.40	292878	6.54	293031	6.49
2012	320114	315951	1.30	311706	2.63	308168	3.73	309225	3.40
2013	308771	330737	7.11	324682	5.15	320065	3.66	321306	4.06
2014	321255	322616	0.42	319708	0.48	316910	1.35	317863	1.06
2015	339722	318976	6.11	318404	6.28	317748	6.47	317999	6.39
2016	360978	341018	5.53	336980	6.65	333395	7.64	334531	7.33
MAPE			**5.55**		**5.26**		**5.25**		**5.19**

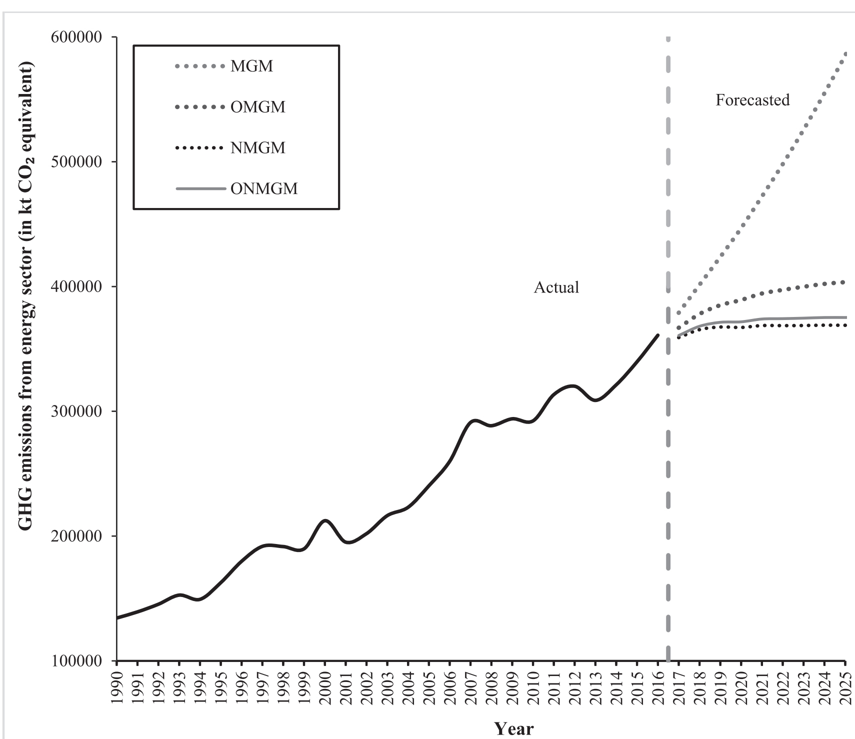

Fig. 6. Comparison of forecasted values of Turkey's GHG emissions from the energy sector from 2017 to 2025 using the MGM(1,1), OMGM(1,1), NMGM(1,1) and ONMGM(1,1).

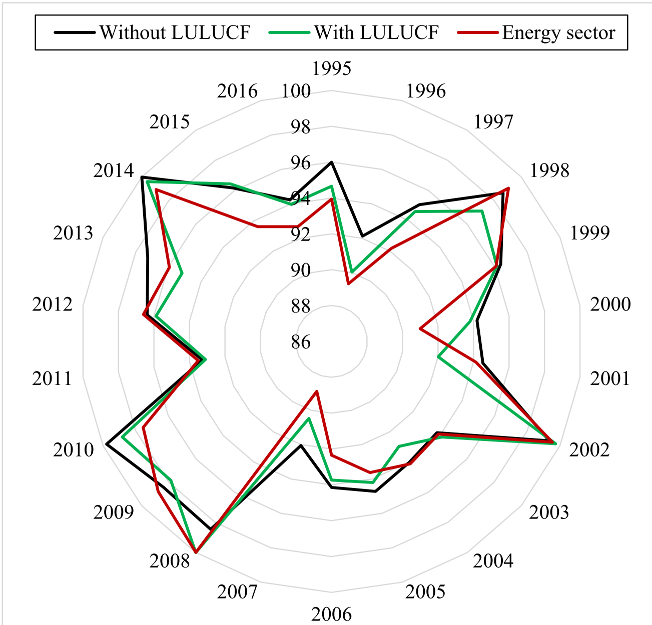

Fig. 7. The prediction accuracy of the ONMGM(1,1) for Turkey's GHG emissions with LULUCF, without LULUCF and from the energy sector.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2019.118079.

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