Environment Protection Engineering

Vol. 48 2022 No. 1

DOI: 10.37190/epe220108

MÁRIA VOJTEKOVÁ (ORCID: 0000-0001-9040-0443)[1]
OĽGA BLAŽEKOVÁ (ORCID: 0000-0003-2394-2351)[1]
MICHAL PAVLICKO (ORCID: 0000-0001-7311-9625)[1]

FORECASTING GREENHOUSE GAS EMISSIONS OF THE SLOVAK REPUBLIC BASED ON GREY MODELS

Reducing greenhouse gas (GHG) emissions has become a necessity and not an option to sustain the environment in both human and natural systems. The Slovak Republic (SR), like the European Union (EU), aims to become greenhouse gas neutral by 2050. To reach this ambitious target, emissions will need to fall by 55% compared to those in the base year 1990. Therefore, forecasting GHG emission amounts is important. The grey model is one of the widespread mathematical forecasting methods. There exist studies that have used some types of grey models to predict GHG but not in the case of the Slovak Republic. We have optimized the length of the input sequence in the rolling mechanism to enhance the forecast accuracy of a new grey model combining the Bernoulli equation with the rolling mechanism. Standard grey model, nonlinear grey Bernoulli model, and grey model with rolling mechanism were used to prove the validity of our optimization and to compare prediction performance among grey models. The novel model was also used for a long-term forecast of GHG emissions in the SR for the years from 2020 to 2040 and compared with officially reported projections. Calculated values showed that the SR is on a good way to reach set targets towards climate change mitigation.

1. INTRODUCTION

The prediction of greenhouse gas (GHG) emissions is very important due to their harmful effects on climate and global warming. The increasing global concentration of GHGs (especially CO_2, CH_4, and N_2O) is the main cause of climate change, and this increase is a result of an imbalance between GHG emissions from human sources and

[1]University of Žilina, Faculty of Operation and Economics of Transport and Communications, Department of Quantitative Methods and Economic Informatics, Univerzitná 1, 01026 Žilina, Slovakia, corresponding author M. Pavlicko, email address: michal.pavlicko@fpedas.uniza.sk

their absorption by the biosphere and oceans. Since the accession to the OECD in 2000, and the European Union (EU) in 2004, the Slovak Republic (SR) managed to stabilize or reduce GHGs emissions. Key targets set by the EU were: a reduction of 20% in 2020 and at least 40% in 2030 (compared to the 1990 level). Mid-term Progress Report in 2018 [1] described some of the main policy developments as well as the actions taken to implement the review's recommendations. The SR reduced GHG emissions by approximately 18% between 2008 and 2015, and by 44.6% compared to the 1990 baseline. GHG emissions per capita in the SR have long been below the EU average. In 2018, it was 8 tonnes per capita (the EU average was 8.7), which ranks it in 16th place in the EU (Fig. 1).

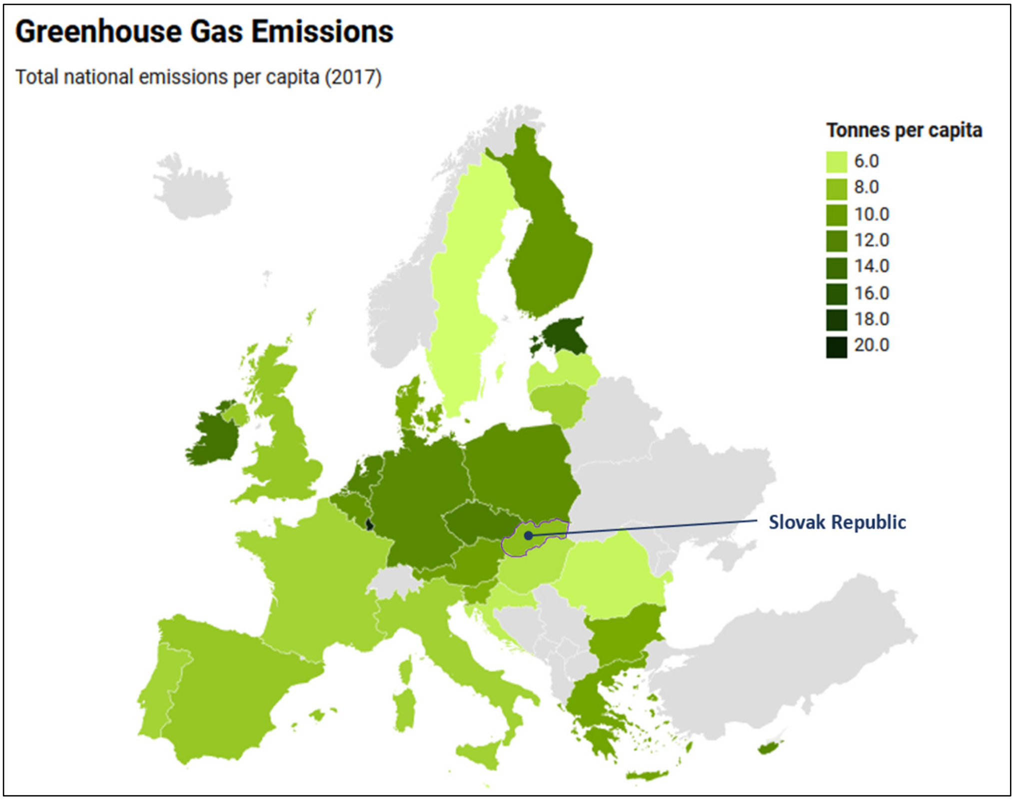

Fig. 1. GHG emissions per capita in EU countries [2]

The problem of GHG emissions is very broad and can be approached from different perspectives in terms of options for reducing emissions, methodologies for determining the volume or predicting future developments. From the number of published articles on this topic, for example, González-Sánchez and Martín-Ortega [3] identified the main determinants that affect GHG emissions growth and assesses their impact and differences among countries in Europe. Comparison of the development of GHG emissions in selected European countries with the targets set by the EU by 2020 and 2030 was analyzed using Markov chains [4]. The relationship between GHG emissions and GDP in Slovakia in the period of 2000–2015 and forecast their rapport in 2030 was quantitatively assessed by Blazekova et al. [5].

Numerous methods have been proposed to forecast and estimate GHG emissions or particularly CO_2 emissions. Related articles appearing in the international journals from 2003 to 2013 were gathered by Abdullah and Pauzi [6]. The artificial neural network (ANN) method was the most popular predicting method with 14.29% from overall of the journal articles, followed by grey models (GM) [6]. Various models of ANN have been published, e.g., [7]. Other prediction methods were based on traditional linear regression, computer-based simulation, or optimal growth model, e.g., [8].

Since our purpose was to predict GHG emissions in SR by the grey theory, we focused on the literature review of the use of different GMs in GHG emissions forecasting. Pao et al. [9] presented an improved GM model called the nonlinear grey Bernoulli model (NGBM) in their research. The model was developed to predict three indicators which were: carbon emissions, energy consumption, and real output in China. They obtained robust results when compared the model with ARIMA and GM models. Lin et al. [10] applied GM to estimate future CO_2 emissions in Taiwan. The considered variables were the CO_2 emissions related to the consumption of energy from coal, petroleum, and natural gas in Taiwan. Lu et al. [11] presented the rolling grey prediction model in their study to capture the development trends of the number of motor vehicles, vehicular energy consumption, and CO_2 emissions in Taiwan to present more recent information on the system behavior and to compare the prediction results with the GM model.

Hu [12] used a grey multivariable Verhulst model to study the relationship between CO_2 emissions, bilateral foreign direct investment, and gross domestic product. Ding et al. [13] estimated Chinese energy-related CO_2 emissions by introducing the grey power indexes into the structure of the traditional GM. Ding et al. [14] quantified future Chinese CO_2 emissions from fuel combustion by an improved grey multivariable model combined with the changing trends of driving variables. Şahin [15] optimized the value of the convex combination coefficient instead of the mean and also optimized the time window to improve the accuracy of grey models in the forecasting of Turkey's GHG emissions. Xu et al. [16] used the adaptive grey model with a buffered rolling method to improve the adaptability in pursuit of data characteristics in forecasting Chinese GHG emissions from energy consumption. Xie et al. [17] attempted to reduce the potential for overfitting in grey models by constraining the coefficients in forecasting the GHG emissions for each of 28 EU member countries.

We did not find GHG emissions forecasting models studies in the national literature. Every two years, the SR as the EU member state reports projections of emissions in years 2020, 2025, 2030, 2035, 2040. The official report: Slovak Republic – *Fourth*

Biennial Report [18] did not specify used predictive methods in detail, so our article aimed to predict the development of GHG emissions in the SR in the next years since available databases contain data only until 2018.

There are many challenges to making accurate GHG emissions forecasts because they help to establish economic policies for governments, to model climate changes, and the assessment of impacts. It is believed that this study will fill the gap in the literature about Slovak GHG emissions forecasts. We selected grey models because they are widely applied in forecasting and do not need a long time series of historical data.

The mentioned grey models have been successfully used for short-term forecasts. To improve their forecast accuracy, a rolling mechanism has been applied in grey models, say RGM(1, 1). We also used the novel grey Bernoulli model with rolling mechanism RNGBM(1, 1) combining the Bernoulli equation. We have optimized the exponent of the Bernoulli equation and the length of the input sequence in the rolling mechanism to forecast GHG emissions in the SR. Such a model was used for a long-term prediction for the years 2020 to 2040. The predicted data were compared with data provided from the official report: Slovak Republic – Fourth Biennial Report 2018 [18].

2. MATERIALS AND METHODS

This section describes four prediction models we used: the conventional grey model GM(1, 1), nonlinear grey Bernoulli model NGBM(1, 1), grey model with rolling mechanism RGM(1, 1), and novel grey Bernoulli model with rolling mechanism RNGBM(1, 1). To evaluate the predictive performance of models, three evaluation metrics were utilized, namely, the absolute percentage error (APE), the mean absolute percentage error (MAPE), and the root mean square error (RMSE).

The grey theory was first proposed by Deng in 1989 [19] and has over 30 years of history. 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 partially known. Grey prediction power comes from its ability to predict the future value with only a limited amount of data. 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 [9]. Generally, the GM(1, 1) model is a basic prediction model, and two important checking conditions are outlined [14]:

- First checking condition: The original input data need to be more than four non-negative points.
- Second checking condition: If the raw data value $x^{(0)}$ and its corresponding accumulated sequence $x^{(1)}$ meet the conditions, as presented in (1) and (2), then the GM can be established.

– Quasi-smooth checking

$$\begin{cases} 0 \le \rho(k) = \dfrac{x^{(0)}(k)}{x^{(1)}(k-1)} < 0.5, \ k = 2, 3, ..., n \\ \dfrac{\rho(k+1)}{\rho(k)} < 1, \ k = 1, 2, ..., n-1 \end{cases} \tag{1}$$

– Quasi-exponential checking

$$1 \le \sigma(k) = \frac{x^{(1)}(k)}{x^{(1)}(k-1)} < 1.5 \tag{2}$$

2.1. GREY MODEL GM(1, 1)

GM(1, 1) is a first-order single variable grey model which is the most frequently used because of its reliability, accuracy, and simplicity. It uses the variation within the system to find the relations between sequential data and then establish the prediction model encompassing a system of first-order differential equations. The complete procedures of the GM include accumulated generating operation, grey difference equation, least square method, and inverse accumulated generating operation (IAGO). The algorithm can be summarized as follows [19]:

- Establish the initial non-negative sequence

$$X^{(0)} = \left\{x^{(0)}(1), x^{(0)}(2), ..., x^{(0)}(n)\right\} X(0)$$

where $x^{(0)}(i)$ represents the raw data concerning time *i*.

- Generate the first-order accumulated generating operation (AGO) sequence $X^{(1)}$ based on the initial sequence $X^{(0)}$ (the aim is to reduce the randomness of raw data to a monotonically increasing series)

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

where the element $x^{(1)}(k)$ is derived as the following formula

$$x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i) \tag{4}$$

- Compute the mean value of the first-order AGO sequence members

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

- Define the first-order differential equation for the sequence $X^{(1)}$ as

$$\frac{d\hat{X}^{(1)}}{dt} + a\hat{X}^{(1)} = b \tag{6}$$

where a and b express the estimated parameters of the forecasting model, a is the development coefficient and b is the grey controlled variable.

Applying the least-squares estimation one can derive the estimated first-order AGO sequence in form of an exponential function

$$\hat{x}^{(1)}(k+1) = \left(x^{(0)}(1) - \frac{b}{a} \right) \mathrm{e}^{-ak} + \frac{b}{a} \tag{7}$$

Parameters a and b can be conducted by the following equations

$$\begin{bmatrix} a \\ b \end{bmatrix} = \left(B^T B\right)^{-1} B^T Y_N \tag{8}$$

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix} \tag{9}$$

$$Y_N = \left(x^{(0)}(2), x^{(0)}(3), \ldots, x^{(0)}(n) \right)^T \tag{10}$$

From the listed sequence one can easily obtain the estimated members $\hat{x}^{(0)}(k+1)$ to the initial sequence by the inverse accumulated generating operation (IAGO)

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) \tag{11}$$

2.2. NONLINEAR GREY BERNOULLI MODEL

Many models have been proposed to increase the accuracy of GM(1, 1). The nonlinear grey Bernoulli model NGBM(1, 1) combined GM(1, 1) with the Bernoulli differential equation. The advantage of NGBM(1, 1) 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 [20].

The Bernoulli differential equation for the sequence $X^{(1)}$ is defined:

$$\frac{d\hat{X}^{(1)}}{dt} = a\hat{X}^{(1)} = b\left(\hat{X}^{(1)}\right)^i, \ i \in R \tag{12}$$

If the exponent i was set to 0, the model would be equal to the definition GM(1, 1). Therefore, the optimal value of the exponent i should be found by its iteration with aspect to the minimal mean absolute percentage error (MAPE) of the forecasting model

$$\hat{x}^{(1)}(k+1) = \left(\left(\left(x^{(0)}(1)\right)^{1-i} - \frac{b}{a}\right)\mathrm{e}^{-a(1-i)k} + \frac{b}{a}\right)^{1/(1-i)}, \quad i \neq 1 \tag{13}$$

Parameters a and b can be calculated following equation (8) with vector Y_N (eq. (10)) but with different matrix B:

$$B = \begin{bmatrix} -z^{(1)}(2) & \left(z^{(1)}(2)\right)^i \\ -z^{(1)}(3) & \left(z^{(1)}(3)\right)^i \\ \vdots & \vdots \\ -z^{(1)}(n) & \left(z^{(1)}(n)\right)^i \end{bmatrix} \tag{14}$$

By performing IAGO, the predicted values $\hat{x}^{(0)}(k+1)$ can be calculated following Eq. (11).

2.3. ROLLING MECHANISM

The prediction error of GM(1, 1) increases with the number of prediction steps. The rolling mechanism is an effective method to improve the performance of GM that updates the input data by discarding old data for each loop in grey prediction. The purpose is that, in each rolling step, the data utilized for the next forecast is the most recent data calculated from the assembled model [21].

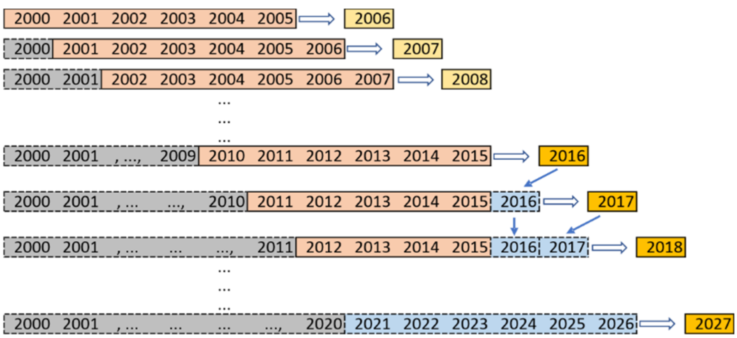

Fig. 2. The principle of the rolling mechanism

For example, if we take the period from 2010 to 2015 as an input time series, then we calculate the first model from values $x^{(0)}(2010)$, $x^{(0)}(2011)$, ..., $x^{(0)}(2015)$. In the happy hoardersecond rolling step we use values $x^{(0)}(2011)$, $x^{(0)}(2012)$, ..., $x^{(0)}(2016)$ and so on. To give a clear picture we provide the computational process flowchart in Fig. 2.

2.4. NONLINEAR GREY BERNOULLI MODEL WITH ROLLING MECHANISM

The novel nonlinear grey Bernoulli model with a rolling mechanism proceeds like RGM(1, 1) described in the previous subchapter, but the exponent, given by the Bernoulli equation is calculated for each input time series (roll) and differs among individual rolls. We have constructed the RNGBM(1, 1) and combined optimization of the exponent index *i* in the Bernoulli differential equation with the optimal length of the input sequence in the rolling mechanism. We have calculated optimal exponent *i* in the Bernoulli formula for stepwise different lengths of input time series *k* in the roll. The optimization was assessed by the MAPE value.

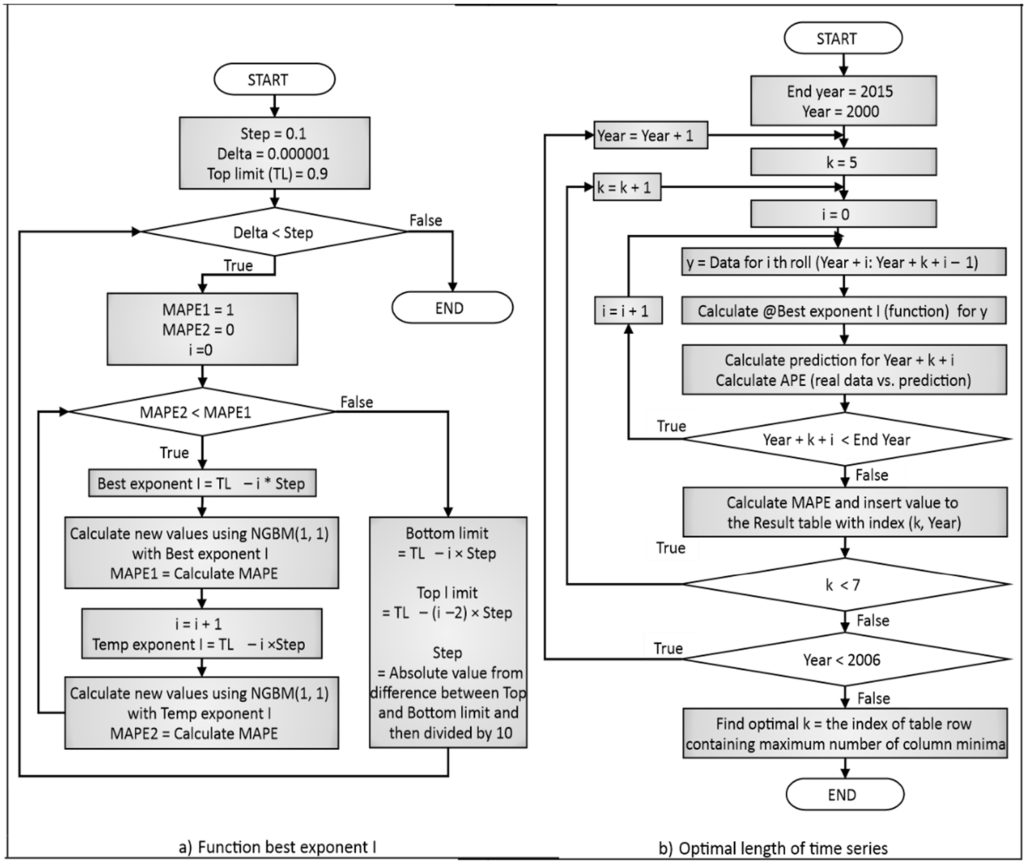

Fig. 3. The flowchart of the optimization in the RNGBM(1, 1)

To find out the optimal exponent for the Bernoulli formula, we have used the function named best exponent I with algorithm (a) depicted on the left side of Fig. 3 and for the optimal length of the input sequence, the algorithm (b) depicted on right hand side of the figure.

2.5. DATA

We collected annual data on GHG emissions in the SR from 2000 to 2018 [22]. Projections of GHG emissions and trends for the years 2025, 2030, 2035, 2040 were taken from [18]. The amount of GHG emissions is issued in thousand tons (the official SI unit for such a weight is Gigagram [Gg]) of CO_2 equivalent excluding LULUCF (land use, land use change, and forestry).

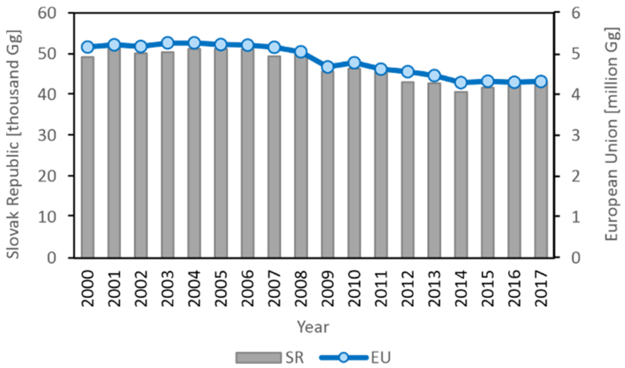

Fig. 4. The GHG emissions in SR from the year 2000 to 2017

Figure 4 shows the history of the total GHG emissions from the start of the century to the year 2017. The bars represent emissions of the Slovak Republic in thousand Gg (Mt). The line represents the total emissions of the European Union in million Gg (Gt). As we can see from the chart, the amount of GHG emissions produced in the Slovak Republic represents approximately one-hundredth of the total European emissions. Moreover, the trend is very similar and thus a similar trend can be assumed into the future. Data from 2000 to 2015 served as a training sample and were used to estimate the parameters and verify the fit performance. The remaining data from 2016 to 2018 were applied to test the forecasting precision.

2.6. THE ACCURACY MEASUREMENT

The main performance metrics that is used in this paper and also in the optimization process is the absolute percentage error (APE) of predicted value (eq. (15)), and in the case of a prediction sample, it is the mean absolute percentage error (MAPE, eq. (16)). This measure provides a clear view of the prediction performance giving the predicted value into the relationship with the actual data. Nevertheless, the results also contain the root mean square error (RMSE, eq. (17)) to provide the nominal value of prediction error

$$\mathrm{APE} = \left|\frac{x_i - \hat{x}_i}{x_i}\right| \times 100\% \tag{15}$$

$$\mathrm{MAPE} = \left(\frac{1}{n}\sum_{i=1}^{n}\mathrm{APE}\right) \times 100\% \tag{16}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(x_i - \hat{x}_i\right)^2} \tag{17}$$

where $\hat{x}_i$ and x_i are the *i*th predicted and adequate actual valuea, *n* is the total number of predictions. The values of these above three indices are lower, the predictive performance is more accurate. Lewis [23] interprets the MAPE results as a 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.

3. RESULTS

3.1. INICIAL CONDITIONS

In this section, we used the four models mentioned above: GM(1, 1), NGBM(1, 1), RGM(1, 1), and RNGBM(1, 1) to predict GHG emissions in the SR. Before assembling the models, we verified the suitability of the data used for the model fitting. The first checking condition is satisfied, so we can test the quasi-smooth and quasi-exponential conditions based on (1) and (2). Table 1 illustrates that the data also meet the second checking condition.

Table 1

Quasi-smooth and quasi-exponential checking

k	$\rho(k)$	$\frac{\rho(k+1)}{\rho(k)}$	$\sigma(k)$	k	$\rho(k)$	$\frac{\rho(k+1)}{\rho(k)}$	$\sigma(k)$	k	$\rho(k)$	$\frac{\rho(k+1)}{\rho(k)}$	$\sigma(k)$
2	0.4977	0.6705	1.4977	7	0.1390	0.8872	1.1391	12	0.0729	0.9248	1.0729
3	0.3337	0.7625	1.3337	8	0.1234	0.8136	1.1233	13	0.0674	0.8911	1.0674
4	0.2544	0.7970	1.2545	9	0.1004	0.9236	1.1004	14	0.0600	0.9676	1.0600
5	0.2028	0.8296	1.2028	10	0.0927	0.9011	1.0927	15	0.0581	–	1.0581
6	0.1683	0.8266	1.1683	11	0.0835	0.8720	1.0835	–	–	–	–

3.2. OPTIMAL LENGTH OF INPUT TIME SERIES IN THE ROLL

The optimization of the input time series length in the roll (hereinafter referred to as the roll length) was conducted regarding two aspects. We want to find out if the optimal roll length varies with the different starting points of the calculation. Therefore, except for the different roll lengths we considered different starting points. Thus, we calculated the MAPE of the predicted values for each whole cycle starting from the year 2000.

For example, in the case of the whole cycle starting in 2000 with the roll length equal to 5, we predicted the first value for the year 2005 based on data from 2000 to 2004 and the optimal exponent of the Bernoulli equation. We compared the predicted value with the actual value for the adequate year via the APE metric. We followed with the second roll with data from 2001 to 2005 to predict the value for the year 2006, and so on up to the predicted value for 2015. Then the corresponding MAPE value was calculated.

The starting year was incremented by one year and the process was repeated until the last starting year 2006. This was set because we wanted to calculate MAPE from at least three values, and if the starting year were greater than 2006, less than three predicted values could be calculated for the roll length equal to 7.

Figure 5 shows a comparison of the MAPE values for the cycles starting in the year 2000 up to the starting year 2006 with the roll lengths of 5, 6, and 7. As can be seen in the figure, the optimal value for the roll length equals 6.

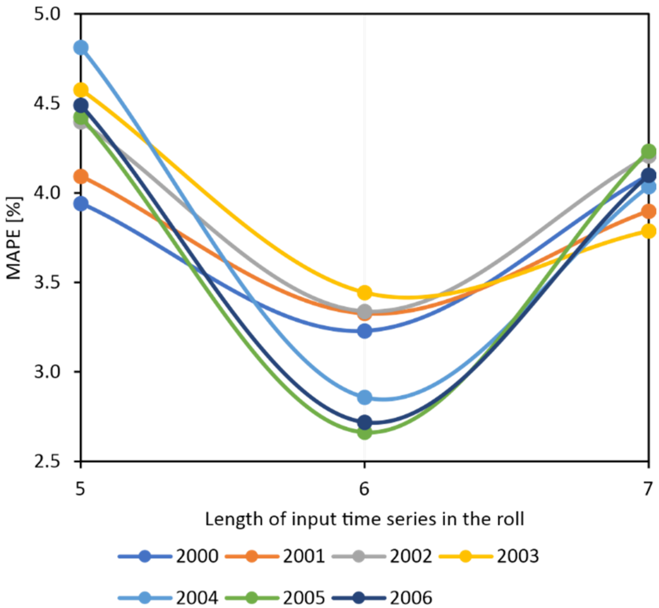

Fig. 5. Optimization of the roll length

3.3. COMPARISION OF GREY MODELS

Table 2 includes predicted values of GHG emissions in SR during the test period 2000–2015 by above mentioned four grey models. In RNGBM(1, 1) model, the value of the exponent i was optimized for each predicted year. The value of the roll length calculated throughout the optimization, which is equal to 6, was used in both the RGM(1, 1) and RNGBM(1, 1) models.

Table 2

Forecasting by grey models and comparison with actual data in the periods 2000–20015 and 2016–2018

Year	Actual	GM(1, 1)		NBGM(1, 1)		RGM(1, 1)		RNGBM(1, 1)	
		Predicted	APE [%]	Predicted	APE [%]	Predicted	APE [%]	Predicted	APE [%]
Training sample									
2000	49 274	–	–	–	–	–	–	–	–
2001	51 553	53 154	3.11	49 678	3.64	–	–	–	–
2002	50 184	52 272	4.16	51 237	2.10	–	–	–	–
2003	50 396	51 404	2.00	51 657	2.50	–	–	–	–
2004	51 250	50 551	1.36	51 496	0.48	–	–	–	–
2005	51 241	49 712	2.98	50 988	0.49	–	–	–	–
2006	51 134	48 887	4.39	50 257	1.71	51 058	0.15	52 332	2.34
2007	49 376	48 075	2.63	49 376	0.00	51 667	4.64	50 972	3.23
2008	49 896	47 277	5.25	48 392	3.01	50 042	0.29	48 598	2.60
2009	45 605	46 492	1.94	47 337	3.80	49 223	7.93	48 778	6.96
2010	46 351	45 721	1.36	46 236	0.25	45 849	1.08	44 575	3.83
2011	45 639	44 962	1.48	45 103	1.17	44 596	2.28	44 526	2.44
2012	43 120	44 215	2.54	43 953	1.93	44 138	2.36	43 721	1.40
2013	42 784	43 482	1.63	42 795	0.03	42 184	1.40	41 514	2.97
2014	40 695	42 760	5.08	41 636	2.31	42 120	3.50	40 508	0.46
2015	41 741	42 050	0.74	40 483	3.02	39 629	5.06	39 214	6.05
MAPE [%]	–	–	2.71	–	1.76	–	2.87	–	3.23
Testing sample									
2016	42 214	41 352	2.04	39 339	6.81	39 776	5.78	41 100	2.64
2017	43 343	40 666	6.18	38 208	11.85	39 353	9.20	40 740	6.00
2018	43 264	39 991	7.57	37 093	14.26	38 585	10.82	40 485	6.42
MAPE [%]	–	–	5.26	–	10.97	–	8.60	–	5.02

According to obtained results, the lowest MAPE value for the training period 2000–2015 (1.76) was achieved by the NGBM(1, 1) model. GM(1, 1) and RGM(1, 1) had similar values of MAPE, and the new RNBGM(1, 1) model corresponded to

3.23. The MAPE values for a test period usually tend to be worse. For our test period from 2016 to 2018, the new RMBGN(1, 1) model had the best MAPE value of 5.02 which means according to Lewis [23] a highly accurate forecast. The model GM(1, 1) and RGM(1, 1) reported a highly accurate forecast too (5.26 and 8.60). The worst score (10.97) on the testing data sample was achieved by the NGBM(1, 1) model that showed the best performance on the training data. This could usually mean a so-called overfitting problem. We believe, that in this case it is partially caused by the ambiguous nature of data trend where the sudden spike in the training data was usually followed by a steady decrease in contrast to the testing data sample with continuous growth.

Figure 6 is used as a complementary way to show how the models mentioned above perform and compare with actual data. The impression is slightly distorted (differences seem to be bigger) as the starting value of the vertical axis is 37,000 Gg and not the zero value to better distinguish the differences among individual models.

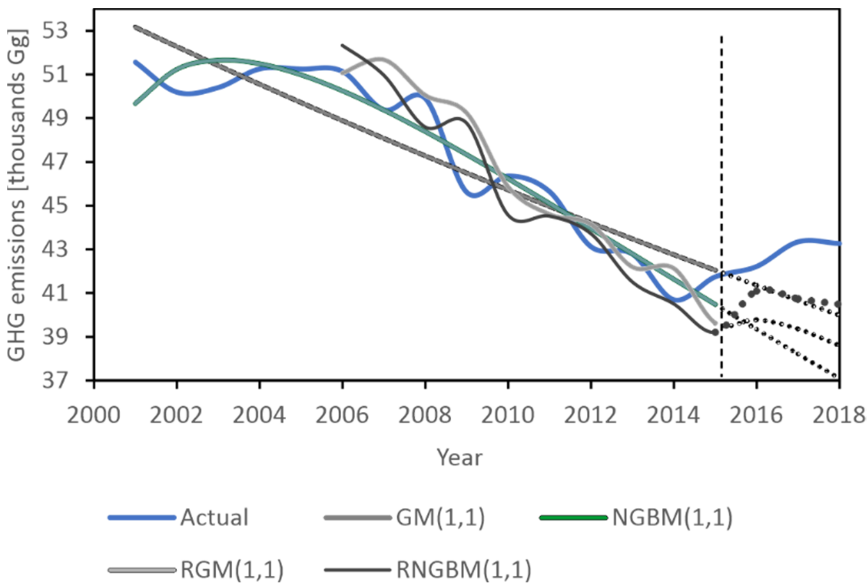

Fig. 6. Graphical comparison of calculated values by selected grey models and actual data

All models without the rolling mechanism, i.e., GM(1, 1) and NGBM(1, 1), did not react to the sudden increase in 2015 that continues until 2018, and they remain in a decreasing trend. Because NGBM(1, 1) match the training data more precisely, the prediction error is higher than standard GM(1, 1). Thus, different training data may change this discrepancy. On the other hand, the models with the rolling mechanism, i.e., RGM(1, 1) and RNGBM(1, 1) reacted to the mentioned increase in 2015.

Table 3 shows the comparison of selected prediction performance metrics on the testing sample data. Besides the average percentual error represented by MAPE, the table also contains RMSE to provide the nominal value of the prediction error.

Table 3

Prediction performance metrics comparison on the testing sample

Model	MAPE [%]	RMSE [Gg]
GM(1, 1)	5.26	2491.56
NGBM(1, 1)	10.97	4923.18
RGM(1, 1)	8.60	3819.02
RNGBM(1, 1)	5.02	2290.19

3.4. GHG EMISSIONS FORECASTING IN THE YEARS 2025, 2030, 2035, AND 2040

The *Monitoring Mechanism Regulation of EU ((EC) No 525/2013)* requires member states to report national projections of anthropogenic GHG emissions. Every two years, each EU member state shall report GHG projections *with existing measures* scenario for the years 2020, 2025, 2030, 2035, and 2040 [24]. The SR reported four biennial reports, the last one in December 2019. The report took into account the base-year 2016 to forecast GHG emissions the mentioned above years and projections were prepared within the following scenarios [18]:

- With Measures Scenario (WEM) which follows the logic of the EC Reference 2016 Scenario. It includes the policies and measures adopted and implemented at the EU and national levels until the end of 2016 and the measures needed to achieve the renewables and energy efficiency targets in the year 2020.
- With Additional Measures Scenario (WAM) which includes ways of achieving various combinations of efficiency, renewables, and emission reduction targets in 2040. For the design of the WAM scenario, a policy package *Clean Energy for All European*, launched by the European Commission in November 2016, was considered.

We were interested in the methodology used for the official projection of GHG emissions in SR, but the mathematical methods used in this document are described only in general. The total amount of GHG emissions are calculated as a sum of emissions by sectors and by gases. Various procedures and software modules for particular sectors were used in the projections of GHG emissions [18]:

- energy and industry – Compact Primes for Slovakia,
- transport –TREMOVE and COPERT IV models and expert estimation,
- solvents – expert approach,
- agriculture – expert approach,
- LULUCF – expert approach,
- waste – expert approach.

In Table 4, the comparison of forecasted amounts of GHG emissions in SR is given: the officially reported values by scenarios WEM, WAM, and data calculated by grey model RNGBM(1, 1).

Table 4

Forecasting of GHG emissions in SR by official report [18] and RNGBM(1, 1) results [Gg]

Year	WEM		WAM		RNGBM(1, 1)	
	Predicted	Decrease [%]	Predicted	Decrease [%]	Predicted	Decrease [%]
2020	42 354.8	42.38	41 202.6	43.95	39 825.9	45.82
2025	42 046.3	42.80	38 761.1	47.27	38 182.5	48.06
2030	41 399.0	43.68	34 019.1	53.72	36 584.1	50.23
2035	39 525.7	46.23	31 684.7	56.90	35 046.3	52.32
2040	38 521.2	47.60	28 750.8	60.89	33 574.9	54.32

The power of grey models is in predicting the near future, as the base is the estimated first-order AGO sequence in form of an exponential function, so the differences may be greater in more distant values. RNGBM(1, 1) model shows a more significant reduction in emissions compared to the officially reported scenarios in the years 2020 and 2025. In the years 2030, 2035, and 2040 our predicted values lie between officially reported projections.

4. DISCUSSION AND CONCLUSIONS

In the literature, several articles deal with the prediction of GHG emissions in various countries. Some of them work only with a time series of emissions data, others make forecasts based on relationships with GDP, energy consumption, transport development, and other impacts. In our paper, we used only the time series of data of GHG emissions. The reason was that to forecast the future emissions values depending on various impacts, it is necessary to predict the development of those factors, and this introduces additional uncertainty in the prediction.

We applied grey modeling, as the method is one of the most widely used predictive methods in this area. The four models: GM(1, 1), NGBM(1, 1), RGM(1, 1), and the newly RNGBM(1, 1) model with the optimal length of the input time series were used to predict GHG emissions in the SR. Firstly, we verified that the original data met the two checking conditions for applying grey prediction. Then, the training data from 2000 to 2015 were used for parameters estimation and verification of performance fit of selected models; and the data from 2016 to 2018 were applied to check the forecasts' validity.

The MAPE values for the training period were between 1.76% and 3.23%, which presents highly accurate forecasts. The MAPE values for a test period usually tend to be worse. For our test period from 2016 to 2018, the new RNGBM(1, 1) model had the best MAPE value of 5.02 which means a highly accurate forecast. The model GM(1, 1) and RGM(1, 1) reported a highly accurate forecast too (5.26 and 8.60). The worst one, but with a relatively good forecasted value, was the NGBM(1, 1) model with the MAPE of around 11%. The ambiguous nature of data trend was declared by various APE values: from 0.03% to 14.26%. The RNGBM(1, 1) model with the optimal roll length was applied to estimate the future values of GHG emissions in the years 2020, 2025, 2030, 2035, 2040, and compare to the officially reported forecasts in WEM and WAM scenarios. RNGBM(1, 1) model showed a more significant reduction in emissions compared to the officially reported scenarios: the decline (1990 baseline) of 45.82% in the year 2020 and 48.06% in 2025. The projections for years 2030, 2035, and 2040, namely 50.23%, 52.32%, and 54.32% lay between two officially reported projections. It seems that SR tends to reach the target to be GHG neutral by 2050, which means, emissions would need to fall by 55%.

The forecasting of GHG emissions has several difficulties. There are differences in published data (e.g., GHG emissions total excluding LULUCF, Slovak Republic, the year 2017, the value is 43482.84 thousand tons in Eurostat database, 43316.44 thousand tons in data of European Environment Agency and 43342.78 thousand tons). There are problems in changing the methodology of summation of various emissions sources. The special issue [25] was compiled to enhance understanding of the uncertainty in estimating GHG emissions and to provide guidance on dealing with the challenges resulting from those uncertainties.

The total national emissions of GHGs in the inventory year 2018 were estimated to be 43263.65 Gg of CO_2 eq. excluding the LULUCF sector. Compared to the year 2017 the aggregated emissions of GHGs decreased in the year 2018 in all sectors (except agriculture and waste with a slight inter-annual increase) [22]. It can be considered that the overall trend of the GHG emissions in Slovakia is stable with a slight increase in the years 2015-2017. However, during the whole period 1991–2018, the total GHG emissions in SR did not exceed the level of 1990, and the decrease in the year 2018 compared to the base year 1990 is 41.14% that is better than the EU target by 2030. Reduction of emissions in SR in past years was a conjunction of different impacts starting from impressive industrial and technological restructuring connected with the fuel-switching of fossil fuels from coal and oil to the natural gas, economic restructuring towards the less intensive energy production, and also by temporary changes in production intensity. The latest available GHG emission projections proposed emissions stabilization as evidence of the successful implementation of the policies and measures, and their effect on the improvement in energy intensity and industrial production efficiency [18].

ACKNOWLEDGMENT

This contribution was prepared based on the grant VEGA No. 1/0518/19.

REFERENCES

[1] OECD, *Working Party on Environmental Performance, Environmental Performance Reviews, Mid-term progress report: Slovak Republic*, available online: https://www.minzp.sk/files/omv/mid-term-review-environmental-performance-slovakia-2017.pdf (accessed on 22 June 2020).

[2] *GHG Emissions by EU Country* [Interactive Map], available online: https://www.greenmatch. co.uk/blog/2019/10/greenhouse-gas-emissions-by-country (accessed on 9 June 2021).

[3] GONZÁLEZ-SÁNCHEZ M., MARTÍN-ORTEGA J.L., *Greenhouse gas emissions growth in Europe. A comparative analysis of determinants*, Sust., 2020, 12, 1012. DOI: 10.3390/su12031012.

[4] VOJTEKOVA M., BLAZEKOVA O., *Greenhouse gas emissions as a global problem of nowadays*, Proc. International Scientific Conference on Globalization and its Socio-Economic Consequences, Zilina, Slovakia, 4–5 October 2017, 2888–2894.

[5] BLAZEKOVA O., VOJTEKOVA M., *About one model of greenhouse gas emissions forecasting*, Proc. International Scientific Conference on Knowledge for Market Use 2017: People in Economics – Decisions, Behavior and Normative Models, Olomouc, Czech Republic, 7–8 September 2017, 68–74.

[6] ABDULLAH L., PAUZI H.M., *Methods in forecasting carbon dioxide emissions. A decade review*, J. Tekn., 2015, 75 (1), 67–82. DOI: 10.11113/jt.v75.2603.

[7] RADOJEVIĆ D., POCAJT V., POPOVIĆ I., PERIĆ-GRUJIĆ A., RISTIĆ M., *Forecasting of greenhouse gas emissions in Serbia using artificial neural networks*, En. Sources A: Rec. Util. Environ. Eff., 2013, 35 (8), 733–740. DOI: 10.1080/15567036.2010.514597.

[8] RODRIGUES J.A.P., NETO L.B., COELHO P.H.G., *Estimating greenhouse gas emissions using computational intelligence*, Proc. International Conference on Enterprise Information Systems, Milan, Italy, 6–10 May 2009, 248–250.

[9] PAO H.-T., FU H.-C., TSENG C.-L., *Forecasting of CO_2 emissions, energy consumption and economic growth in China using an improved grey model*, Energy, 2012, 40 (1), 400–409. DOI: 10.1016/j. energy.2012.01.037.

[10] LIN C.-S., LIOU F.-M., HUANG C.-P., *Grey forecasting model for CO_2 emissions. A Taiwan study*, Appl. En., 2011, 88 (11), 3816–3820. DOI: 10.1016/j.apenergy.2011.05.013.

[11] LU I., LEWIS C., LIN S.J., *The forecast of motor vehicle, energy demand and CO_2 emission from Taiwan's road transportation sector*, En. Pol., 2009, 37 (8), 2952–2961. DOI: 10.1016/j.enpol.2009.03.039.

[12] HU Y.-C., JIANG H., JIANG P., KONG P., *An improved grey multivariable verhulst model for predicting CO_2 emissions in China*, [In:] F.F.-H. Nah, K. Siau (Eds.), *HCI in Business, Government and Organizations*, Information Systems and Analytics Lecture Notes in Computer Science, Springer, 2019, 354–366.

[13] DING S., XU N., YE J., ZHOU W., ZHANG X., *Estimating Chinese energy-related CO_2 emissions by employing a novel discrete grey prediction model*, J. Clean. Prod., 2020, 259, 120793. DOI: 10.1016 /j.jclepro.2020.120793.

[14] DING S., DANG Y.-G., LI X.-M., WANG J.-J., ZHAO K., *Forecasting Chinese CO_2 emissions from fuel combustion using a novel grey multivariable model*, J. Clean Prod., 2017, 162, 1527–1538. DOI: 10.1016 /j.jclepro.2017.06.167.

[15] ŞAHIN U., *Forecasting of Turkey's greenhouse gas emissions using linear and nonlinear rolling metabolic grey model based on optimization*, J. Clean. Prod., 2019, 239, 118079. DOI: 10.1016 /j.jclepro. 2019.118079.

[16] XU N., DING S., GONG Y., BAI J., *Forecasting Chinese greenhouse gas emissions from energy consumption using a novel grey rolling model*, Energy, 2019, 175, 218–227. DOI: 10.1016/j.energy.2019.03.056.

[17] XIE M., YAN S., WU L., LIU L., BAI Y., LIU L., TONG Y., *A novel robust reweighted multivariate grey model for forecasting the greenhouse gas emissions*, J. Clean. Prod., 2021, 292, 126001. DOI: 10.1016/ j.jclepro.2021.126001.

[18] *Fourth Biennial Report of the Slovak Republic (4BR SVK)*, available online: https://ghg-inventory.shmu.sk/documents.php (accessed on 12 June 2020).
[19] DENG J.L., *Introduction of grey system theory*, J. Grey Syst., 1989, 1, 1–24.
[20] LU J., XIE W., ZHOU H., ZHANG A., *An optimized nonlinear grey Bernoulli model and its applications*, Neurocomp., 2016, 177, 206–214. DOI: 10.1016/j.neucom.2015.11.032.
[21] LIU L., WANG Q., LIU M., LI L., *An Intelligence Optimized Rolling Grey Forecasting Model Fitting to Small Economic Dataset*, Abstr. Appl. Anal., 2014, 1–10. DOI: h10.1155/2014/641514.
[22] *Slovak Republic – Annual Report 2020*, available online: https://ghg-inventory.shmu. sk/ documents. php (accessed on 12 June 2020).
[23] LEWIS C.D., *Industrial and business forecasting methods: a practical guide to exponential smoothing and curve fitting*, Butterworth Scientific, London 1982.
[24] *Member States' greenhouse gas (GHG) emission projections*, available online: https://www.eea.europa.eu/data-and-maps/data/greenhouse-gas-emission-projections-for-6 (accessed on 2 June 2020).
[25] JONAS M., BUN R., NAHORSKI Z., MARLAND G., GUSTI M., DANYLO O., *Quantifying greenhouse gas emissions*, Mitig. Adapt. Strateg. Glob. Chang., 2019, 24, 839–852. DOI: 10.1007/s11027-019-09867-4.