Forecasting CO_2 emissions from industrial processes: a Grey model-based approach

VAN THANH PHAN*, ANH TUAN LE
Faculty of Digital Economy and E-Commerce
Vietnam-Korea University of Information and Communication Technology, University of Danang
470 Tran Dai Nghia, Ngu Hanh Son Ward, Da Nang City
VIETNAM

Corresponding Author

Abstract: - This study forecasts CO2 emissions from industrial processes in Vietnam to support climate change mitigation and sustainable development. Accurate forecasting provides valuable insights for policymakers and businesses in designing emission reduction strategies and achieving the Net Zero target by 2050. Three Grey forecasting models, namely the Gompertz Grey Model (GGM), Auto-Regressive Grey Model (ARGM (1,1)), and Nonlinear Grey Model (NGM (1,1,k,c)), were evaluated using World Bank data from 2000–2023. Forecasting performance was assessed using Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE). The results indicate that all models achieved acceptable accuracy (MAPE < 10%), with GGM outperforming the others (MAPE = 5.51%, RMSE = 2.1363). Therefore, GGM was selected to forecast CO2 emissions for 2025–2030, projecting a continued upward trend and highlighting the need for cleaner technologies and effective emission reduction policies.

Key-Words: - CO2 emissions, Grey forecasting model, Net Zero, Gompertz Grey Model, Viet Nam, Auto-Regressive Grey Model, Nonlinear Grey Model

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1 Introduction

Amid climate disruption becoming an increasingly pressing challenge to sustainable development, greenhouse gas (GHG) emissions, especially carbon dioxide (CO_2), are drawing worldwide attention. The constant increase of industrial processes due to the accelerated industrialization and urbanization has resulted in a rise in the amount of CO_2 in the atmosphere, producing the greenhouse effect, and resulting in global warming. Against this trend, nations and firms around the globe are turning to green economic policy, with the latter being known as "Net Zero," a goal of reaching net zero carbon by the mid-21st century. Countries have established commitments to the Paris Agreement in 2015, and emission-reducing measures are being implemented by way of technological innovations, renewable, and efficient production processes for industry, for example. At COP29 in 2024, all the member countries - the US, UK and European Union -- committed to become Net Zero by 2050, China by 2060 and India by 2070 [1]. The EDGAR (Emissions Database for Global Atmospheric Research) report stated that the emission of greenhouse gases in 2024, based on combustion and industrial processes, continued to rise, indicating the strong growth of global industrial processes. Emissions over the past three decades have increased by 93% vs. 1990 and 43% vs. 2005; in essence, high emission concentrations continued unabated over the past three decades. In the shorter time period between 2023 and 2024, approximately 1% higher emissions were observed [2]. To construct a realistic Net Zero road map requires an accurate forecast of CO_2 emissions from the industrial processes. It can also be used by policy makers and industry for the identification of trends in the impacts and for the analysis of effects, and prevention thereof. The purpose of this study is to lay at the scientific and pragmatic ground upon which to analyze emission trends, to develop realistic estimation models, and to empower decision-makers with the necessary tools for industrial emission reduction planning. The research integrates data from the World Bank with advanced forecasting methods to contribute to the world strategy for transition within a low-carbon economy and to fulfill the future Net Zero targets.

Grey system theory is a method for studying uncertain systems, especially in cases with limited data and incomplete information, proposed by Prof. Deng in 1982 [3]. This approach focuses on maximizing the use of available information to describe and forecast system behavior, rather than requiring large datasets like probability and statistics or handling vagueness like fuzzy mathematics. Uncertain systems are typically characterized by incomplete information, data deviations, and the difficulty of constructing perfectly accurate models; therefore, grey system theory emphasizes approximate but effective models. Over time, it has developed into a comprehensive framework that includes tools such as grey forecasting models, grey relational analysis, and decision-making models. As a result, it has been widely applied in fields such as energy [4], finance and economics [5], semiconductor technology [6], tourism [7], and logistics [8].

In the research paper of [9], the authors proposed 14 carbon emission factors across four major groups (population, economy, transportation, and technology) and used the Random Forest feature ranking algorithm to evaluate the importance of these factors in three regions of China (Western, Central, and Eastern regions) as well as the entire country. Additionally, the authors introduced a hybrid ARIMA + LSTM carbon emission forecasting model based on backward error combination to address both linear and nonlinear relationships in emission data. The results indicate that the ARIMA + LSTM model achieves higher accuracy in predicting CO_2 emission trends in China, as reflected by performance indicators such as RMSE, MAE, and MAPE. Reference of [10] used Multiple Linear Regression (MLR) and Multivariate Polynomial Regression (MPR) to forecast Iran's CO_2 emissions under two assumed scenarios: "business-as-usual" and the Sixth Development Plan (SDP). By applying regression analysis, the study estimated annual CO_2 emissions based on factors including population, CO_2 intensity, GDP per capital, the share of electricity generated from fossil fuels, and per capital energy use. The coefficient of determination (R^2) for both models exceeded 0.99; however, the total residual sum of squares (RSS) of the MPR model was significantly lower. In [11], the authors explored a causal relationship between determinants of CO_2 emissions in Indonesia, which include population, GDP, energy consumption, and forest area. Long-term and short-term relationships were characterized using the Vector Error Correction Model (VECM) in the study through the Granger causality test. A MAPE of 2.637836% was obtained from the forecasted model using the data period time 1990-2019. Reference of [12] applied multiple forecasting techniques including nonlinear time-series neural networks, Gaussian Process Regression, and the Holt method to predict CO_2 emissions in Bahrain. The results showed that the neural network model achieved the lowest root mean square error (RMSE) of 0.206, compared to RMSE values of 1.0171 and 1.4096 from the other two models. In [13], It developed a combined forecasting model based on quadratic exponential smoothing, multiple linear regression, and Gaussian Process Regression, integrated using the Generalized Induced Ordered Weighted Averaging (GIOWA) operator. Using China's CO_2 emission data from 1980 to 2020, the combined model achieved an average accuracy exceeding 99.5%. The reference of [14], the authors reviewed the consequences of policy changes to CO_2 emissions with respect to three estimation algorithms: ANN, SVR, and ARIMAX. The datasets included factors such as population, GDP, and vehicle-kilometers traveled covering the period 1993-2022. It was found that the ANN model had the best predictions, which had the lowest mean absolute percentage error (MAPE) of 6.395. In [15], the author developed a deep learning model to predict CO_2 emissions in Vietnam by analyzing the factors influencing emission growth. A data transformation method is applied to enhance prediction accuracy. The model achieves high performance, with an RMSE of 0.025 and R^2 of 0.97, outperforming traditional methods such as KNN, SVR, and Naive Bayes.

However, no existing research has applied grey forecasting models yet to predict CO_2 emissions from industrial processes in Vietnam. Therefore, this study proposes three forecasting models - GGM, ARGM (1,1), and NGM (1,1,k,c) - with the following objectives: (1) To examine whether Grey Forecasting Models are suitable for predicting CO_2 emissions from industrial processes. (2) To provide a basis for policymakers and especially industrial enterprises to propose effective measures for reducing CO_2 emissions from industrial processes.

2 Research Methodology

2.1 Grey Gompertz Model (GGM)

GGM is developed based on Gompertz'law. The Gompertz function was first introduced by Benjamin Gompertz [16]. The GGM is highly compatible with the GM (1,1) model. The GGM can be developed using GM (1,1).

The steps of the GGM are present as follows:

Step 1: Identify a raw data set $X^{(0)}$ consisting of at least four data points

$$X^{(0)}=\left(x^{(0)}(1), x^{(0)}(2),..., x^{(0)}(n)\right), n\geq 4 \ \& \ X^{(0)}(k)\geq 0,\ k=1,2,\ ...,\ n. \quad (1)$$

Step 2: Apply a logarithm operation to the data set $X^{(0)}$ to obtain the data set $y^{(0)}$

$$y^{(0)} = \left(y^{(0)}(1), y^{(0)}(2), \ldots, y^{(0)}(n)\right) (2)$$

Here:

$$y^{(0)}(i) = \ln\left(x^{(0)}(i)\right),\ i = 1,2,\ldots,n$$

Step 3: Apply the AGO to the data set $y^{(0)}(i)$ to obtain the data set $X^{(1)}$

$$X^{(1)} = (x^{(1)}(1),\ x^{(1)}(2), \ldots x^{(1)}(n)) (3)$$

Here

$$x^{(1)}(k) = \sum_{i=1}^{k} y^{(0)}(i),\ k = 1,2,\ldots,n$$

Step 4: Utilize the data set $X^{(1)}$ to derive the data set $Z^{(1)}$

$$Z^{(1)} = \left(z^{(1)}(1),\ z^{(1)}(2), \ldots,\ z^{(1)}(n)\right) (4)$$

Here

$$z^{(1)}(k) = \frac{1}{2}\left(x^{(1)}(k) + x^{(1)}(k\text{-}1)\right)$$

$$z^{(1)}(k) = x^{(1)}(k)$$

Step 5: Create the y_n và matrix B,

$$y_n = \begin{bmatrix} y^{(0)}(2) \\ y^{(0)}(3) \\ \vdots \\ y^{(0)}(n) \end{bmatrix},\quad B = \begin{bmatrix} -z^{(1)}(2) & 2 & -0.5 & 1 \\ -z^{(1)}(3) & 3 & -0.5 & 1 \\ \vdots & \vdots & \vdots & \vdots \\ -z^{(1)}(n) & n & -0.5 & 1 \end{bmatrix} \quad (5)$$

Step 6: Determine the values of a, b and c

$$[a,b,c]^T = \left(B^T B\right)^{-1} B^T y_n (6)$$

Step 7: Obtain the prediction values

$$\hat{x}^{(0)}(k+1) = \exp\left(\frac{b}{a} + \left(y^{(0)}(1) - \frac{b}{a} + \frac{b\text{-}ac}{a^2}\right)(1\text{-}e^{a})\, e^{-ak}\right),$$

$$k = 1,2,\ldots,n\text{-}1 (7)$$

$$\hat{x}^{(0)}(1) = x^{(0)}(1)$$

2.2 Auto-regressive Grey Model (ARGM (1,1))

Assume X = (x (1), x (2), x (3), ..., x(n)), where X stands for a data sequence. The equation

$x(k) = \propto x(k\text{-}1) + \beta$, k = 2,3,…,n (9)

is called the auto-regressive GM (1,1) model (ARGM (1,1)) [17]. Use the ordinary least squares method to estimate the parameters as follows

$$\begin{bmatrix} \hat{a} \\ \hat{b} \end{bmatrix} = (B^T B)^{-1} B^T Y \quad (10)$$

Where

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

Theorem 1. Assume that $\hat{a}$, $\hat{b}$ are the same as (1). Set $\hat{x}(1) = x(1)$; The recursive function is given

$$\hat{x}(k) = \propto^{k\text{-}1}\left[x(1) - \frac{\hat{\beta}}{1\text{-}\hat{\alpha}}\right] + \frac{\hat{\beta}}{1\text{-}\hat{\alpha}}$$

with k = 1,2,.., n-1 (11)

2.3 Nonlinear Grey Model (NGM (1,1,k,c))

The above theoretical analyses and case study suggest that the NGM model has its own flaw [18]; that is, its simulate sequence cannot express an arbitrary non-homogeneous index sequence. Compare it with other similar grey forecasting models.

The whitenization differential equation of the grey model proposed by Yu and Wei is

$$(dx^{(1)}/dp) + ax^{(1)} = b + c(p-1). \quad (12)$$

The whitenization differential equation of the grey model proposed by Zhang and Gu is

$$(dx^{(1)}/dt) + ax^{(1)} = bt + c. \quad (13)$$

The above models both have three parameters, and the parameters of solutions of their whitenization differential equations are all independent of each other. Thus, these models are both applicable for simulation and prediction of approximate non-homogeneous index sequences, which are relatively effective models. According to similar models, a parameter must be added to the NGM (1,1,k,c) model.

Definition 2. The equation

$$x^{(0)}(k) + az^{(1)}(k) = kb + c (14)$$

is called a grey differential equation of the NGM (1,1,k,c) model (abbreviated as NGM (1,1,k,c)), which is the defining type of the NGM (1,1,k,c) model. The parameter a in the NGM (1,1,k,c) model is called the development coefficient, and $kb + c$ is the grey action quantity, just like b in the GM (1,1) model.

The parameters of the NGM (1,1,k,c) model calculated by the least squares method can be written as

$$[a\ b\ c]^T = (B^T B)^{-1} B^T Y \quad (15)$$

Where

$$B = \begin{bmatrix} -z^{(1)}(2) & 2 & 1 \\ -z^{(1)}(3) & 3 & 1 \\ \vdots & \vdots & \vdots \\ -z^{(1)}(n) & n & 1 \end{bmatrix}\ Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix}$$

The first-order differential equation

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = bt + c (16)$$

is called a whitenization differential equation of the NGM (1,1,k,c) model.

The equation

$$\hat{x}^{(1)}(k) = \left(x^{(1)}(1) - \frac{b}{a} + \frac{b}{a^2} + \frac{c}{a}\right) e^{-ak} + \frac{b}{a}k - \frac{b}{a^2} + \frac{c}{a} (17)$$

is called a time response equation of the NGM (1,1,k,c) model. The restored values are

$$\hat{x}^{(0)}(k) = \left(x^{(1)}(1) - \frac{b}{a} + \frac{b}{a^2} + \frac{c}{a}\right)(1\text{-}e^{a})\, e^{-ak} + \frac{b}{a} (18)$$

2.4 Evaluation of Forecasting Model Accuracy

To evaluate the accuracy of the forecasting models, this study employs the Mean Absolute Percentage Error (MAPE). It is calculated using the following formula:

$$\text{MAPE}=\frac{1}{n}\sum_{k=2}^{n}\left|\frac{x^{(0)}(k)-\hat{x}^{(0)}(k)}{x^{(0)}(k)}\right| x\,100\% \qquad (19)$$

With: $x^{(0)}(k)$: Actual value at time k

$\hat{x}^{(0)}(k)$: Forecasted value at time k

The MAPE evaluation scale was illustrated in the reference [19] is divided into four levels, as shown in Table 1.

Table 1. MAPE Evaluation Levels

MAPE	≤1%	1%-5%	5%-10%	>10%
Evaluation	Excellent	Good	Acceptable	Inaccurate

Source: Reference [19]

Meanwhile, RMSE (Root Mean Square Error) as an indicator has been used to evaluate forecasting performance:

$$RMSE=\sqrt{\frac{\sum_{i=1}^{n}(A_t-F_t)^2}{n}} \qquad (20)$$

A_t : Actual value at time k

F_t: Forecasted value at time k

n: The number of observations in the research datasets

3 Result and Discussion

Data on CO_2 emissions from industrial processes for the period 2000–2023 were collected from the World Bank website. All the data is visualized in Figure 1 (Unit: million tons). The data clearly indicate that CO_2 emissions from industrial activities in Vietnam are developing to a noticeably increasing pattern in the long term, having a clear trajectory increasing from 10.57 million tons in 2000 to 39.32 million tons in 2023 – which is almost fourfold higher. Emissions surged rapidly and consistently from 2000 until 2010, especially after 2007. But from 2011 to 2014, growth slowed and varied somewhat, and continued at between 29 and 31 million tons. From 2015 to 2019, emissions rose once more, reaching 43.57 million tons in 2019. Importantly, this was very much less from 2020 to 2021, of 32.12 million tons, then recovered in 2022 and 2023.

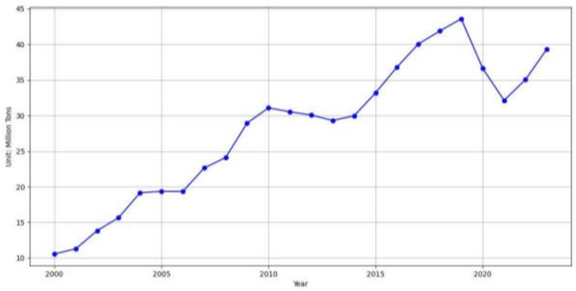

Fig. 1: CO2 Emissions from Industrial processes
Source: World Bank

3.1 Tool and Functions

To calculate and simulate the Grey Forecasting Models GGM, ARGM (1,1), and NGM (1,1,k,c), this study uses Microsoft Excel, a widely used software from Microsoft Excel provides a variety of built-in functions that facilitate computations.

To compute the parameter values for these models, the study employs basic arithmetic operations along with two particularly useful functions: MMULT (matrix1, matrix2), for matrix multiplication; MINVERSE (matrix), for calculating the inverse of a matrix. These two operations are fundamental for calculating the parameters within the models. After performing these computations in Microsoft Excel, the forecasting results of the models are presented as follows:

3.2 Forecasting Results of the GGM Model

By combining the datasets collected from 2000 to 2023 with the algorithm of the GGM forecasting model described above, the study determined the parameter values as a = 0.1329, b = 0.49606, and c = 2.17795, and constructed the GGM behavioral model to forecast CO_2 emissions from industrial processes as follows:

$$\hat{x}^{(0)}(k+1)=\exp\big(3.73246+(10.32)\,\big(1-e^{0.1329}\big)e^{-0.1329k}\big),$$

k=1,2,...,n-1

The performance results of GGM model are shown in detail in Table 2.

3.3 Forecasting Results of the ARGM (1,1) model

By combining the datasets collected from 2000 to 2023 with the algorithm of the ARGM (1,1) forecasting model described above, the study determined the parameter values as $\hat{\alpha}$= 0.91389, $\hat{\beta}$ =362720 and constructed the ARGM (1,1) behavioral model to forecast CO_2 emissions from industrial processes as follows:

$$\hat{x}(k) = 0.91389^{k-1}\,[\,10.5697-42.12416\,] + 42.12416$$

The RMSE and MAPE indexes results of ARGM (1,1) model are shown in detail in Table 2.

3.4 Forecasting Results of the NGM (1,1,k,c) model

By combining the datasets collected from 2000 to 2023 with the algorithm of the NGM (1,1,k,c) forecasting model described above, the study determined the parameter values as a= 0.08059, b = 3.65257, and c = 4.557, and constructed the NGM (1,1,k,c) behavioral model to forecast CO_2 emissions from industrial processes as follows:

$$\hat{x}^{(1)}(k)=584.204e^{-0.08059k}+ 45.3237976k- 505.864589$$

The performance of ARGM (1,1) model are presented in Table 2.

Table 2. Performance of the Forecasting Models

Model	NGM(1,1,k,c)	ARGM (1,1)	GGM
RMSE	2.2866	2.9227	2,1363
MAPE	8.08%	9.23%	5.51%
Evaluation	Acceptable	Acceptable	Acceptable

Source: Created by the authors

Figure 2 presents the analysis results of the forecasting models.

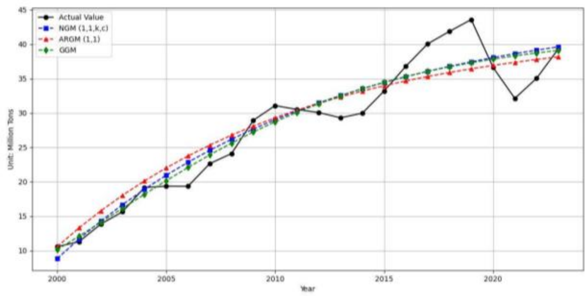

Fig. 2: Analysis results of the Forecasting Models
Source: Created by the authors

It can be seen the results in the Table 2 and Figure 2, all three models achieve a MAPE < 10%, which means they achieve a satisfactory forecast accuracy. Nonetheless, there are significant discrepancies between those performances. For GGM, we find that it is the best model, where the lowest RMSE = 2.1363 and MAPE = 5.51%, indicating that the model has good ability to capture and predict the trend in the raw data. The NGM (1,1,k,c) model is the second model with an MAPE = 8.08% and an RMSE = 2.2866, exhibiting steady performance but not as accurate as that of GGM. By comparison, the ARGM (1,1) model performed in the least satisfactory way (highest RMSE = 2.9227, MAPE= 9.23%, showing less appropriateness for this datasets). In conclusion, we find the best fitting model for this datasets is called GGM, followed by NGM (1,1,k,c), and the last is ARGM.

3.5 Forecasting CO_2 emissions from industrial processes

According to an evaluation of the prediction performance of the models mentioned above, our study strongly recommend uses the GGM model to forecast the CO_2 emission from industrial activities between 2025 and 2030. The forecasting results are presented in Table 3.

Table 3. CO_2 emission prediction

Year	**CO_2 emission from industrial processes (Unit: million tons)**
2025	39.414
2026	39.701
2027	39.954
2028	40.177
2029	40.374
2030	40.546

Source: Created by the authors

A projected table shows that the CO_2 emissions from the industrial processes of Vietnam are expected to rise slightly and steadily between 2025 and 2030. More specifically, emissions are expected to increase from 39.414 million tons in 2025 to 40.546 million tons in 2030. The yearly increase is around 0.36 million tons (an average increase of nearly 0.36 million tons), indicating a steady upward trajectory. Even with not much in the way of rapid growth, management and mitigation are still needed to control the emissions and support sustainable industrial trends at a manageable range. The increasing trend indicates that the industrial process is increasing, but not much change in the direction of cleaner energy sources. In view of Vietnam's ambition to attain net-zero GHG emissions by 2050 at COP26, this trend suggests considerable push by the industry to reduce emissions following 2030. For industrial infrastructure to transition to net-zero emissions in just two decades after the introduction of CO_2 emission control tools in this country, beyond more than 40 million tons of CO_2 in 2030, for example. This indicates that the current time frame is critical to lay the basis for a sustainability-based green transition for CO_2 removal, establishing that the Net Zero goal remains attainable and lasting.

4 Conclusion

Based on the outcome of the simulation, the research team presents several observations and avenues for research: All three Grey Forecasting models contribute to the best predicted CO_2 emission. Nevertheless, in the time period 2000-2023, the authors suggest using the GGM model for forecasting with data, resulting in an accuracy of more than 92%, which is significantly higher than the ARGM (1,1) and NGM (1,1,k,c) models. These outcomes help governments and businesses, especially in industry, create their policy to lower CO_2 emissions from industrial activities.

In the next steps, the team wants to implement more Grey forecasting models or compare existing models with other time series forecasting approaches, like, for example, AR- or similar time series regression, which might produce a more reliable forecast on CO_2 emissions from manufacturing activities.

References:

[1] VnExpress. (2024). Mục tiêu “Net Zero” của Việt Nam và các nước. VnExpress. https://vnexpress.net/net-zero-la-gi-4796466.html. Accessed Date: March, 30th, 2025

[2] Crippa, M., Guizzardi, D., Pagani, F., Banja, M., Muntean, M., et al. (2025). GHG emissions of all world countries – 2025 report (JRC143227). Publications Office of the European Union. doi.org/10.2760/9816914

[3] Deng, J. L. (2002). Grey system theory. Huazhong University of Science and Technology Press, Wuhan, 300-309.

[4] Li, K., & Zhang, T. (2021). A novel grey forecasting model and its application in forecasting the energy consumption in Shanghai. Energy Systems, 12(2), 357-372. doi: 10.1007/s12667-019-00344-0

[5] Li, B., Liu, F., Lin, J., & Wang, Z. (2020, October). Financial time series forecasting model based on EMD and Rolling Grey Model. In 2020 IEEE workshop on signal processing systems (SiPS), IEEE, Portugal, 265-270.

[6] Lin, L. C., & Wu, S. Y. (2013). Analyzing Taiwan IC Assembly Industry by Grey-Markov Forecasting Model. Mathematical Problems in Engineering, 2013(1), 658630, doi.org/10.1155/2013/658630

[7] Li, B., & Gao, J. (2022). Regional tourism economic forecasting model based on GM grey forecasting method. Mathematical Problems in Engineering, 2022(1), 3477246. doi.org/10.1155/2022/3477246

[8] Ren, X., Tan, J., Qiao, Q., Wu, L., Ren, L., & Meng, L. (2022). Demand forecast and influential factors of cold chain logistics based on a grey model. Mathematical Bioscience and Engineering, vol. 19 (8), 7669-7686.

[9] Wen, T., Liu, Y., Bai, Y. H., & Liu, H. (2023). Modeling and forecasting CO2 emissions in China and its regions using a novel ARIMA-LSTM model. Heliyon, vol. 9 (11), e21241. doi.org/10.1016/j.heliyon.2023.e21241

[10] Hosseini, S. M., Saifoddin, A., Shirmohammadi, R., & Aslani, A. (2019). Forecasting of CO2 emissions in Iran based on time series and regression analysis. Energy Reports, 5, 619-631. https://doi.org/10.1016/j.egyr.2019.05.004

[11] Farida, Y., Siswanto, N., & Vanany, I. (2023). Forecasting CO2 Emission in Indonesia From the Economic and Environment Impact Using Vector Error Correction Model. Proceedings of the 2023 5th International Conference on Management Science and Industrial Engineering, Thailand. 42-49. doi.org/10.1145/3603955.3603963

[12] Qader, M.R., Khan, S., Kamal, M., Usman, M., & Haseeb, M. (2021). Forecasting carbon emissions due to electricity power generation in Bahrain. Environmental Science and Pollution Research International, 29, 17346 - 17357. doi.org/10.1007/s11356-021-16960-2.

[13] Wang, H., Wei, Z., Fang, T., Xie, Q., Li, R., & Fang, D. (2024). Carbon emissions prediction based on the GIOWA combination forecasting model: A case study of China. Journal of Cleaner Production, vol.445. doi: 10.1016/j.jclepro.2024.141340

[14] Janhuaton, T., Ratanavaraha, V., & Jomnonkwao, S. (2024). Forecasting Thailand’s Transportation CO2 Emissions: A Comparison among Artificial Intelligent Models. Forecasting. vol 6 (2), 462-484, doi.org/10.3390/forecast6020026

[15] Nguyen, H.T. (2025). Predicting carbon dioxide emissions in Vietnam based on factor groups: economic, social, investment, and industry using a deep learning model. Carbon Management, vol.16 (1), doi.org/10.1080/17583004.2025.2566289

[16] Ertilav, M.M., & Kılıç, M.B. (2024). Forecasting the Population of Türkiye Using Grey Models. Alphanumeric Journal, vol.12 (3), 227-248.

[17] Wu, L., Liu, S., Chen, H., & Zhang, N. (2015). Using a novel grey system model to forecast natural gas consumption in China.

Mathematical Problems in Engineering, 2015(1), 686501, doi.org/10.1155/2015/686501.

[18] Chen, P. Y., & Yu, H. M. (2014). Foundation settlement prediction based on a novel NGM model. Mathematical Problems in Engineering, 2014 (1), 242809. doi.org/10.1155/2014/242809

[19] Chia-Nan, W., & Van-Thanh, P. (2014). An improvement the accuracy of grey forecasting model for cargo throughput in international commercial ports of Kaohsiung. WSEAS Transactions on Business and Economics, 11, 322-327.

Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

Van Thanh Phan was primarily responsible for the research idea, literature review, methodology, interpretation of results, and revised of the manuscript. Anh Tuan Le contributed to the literature review, data collection, and data processing. All authors read, provided feedback, and agreed upon the final manuscript.

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Conflicts of Interest

The authors have no conflicts of interest to declare.