

Optimized CO₂ Emission Forecasting for Thailand's Electricity Sector Using a Multivariate Gray Model [†]

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Abstract

This paper proposes an advanced forecasting model for predicting carbon dioxide (CO₂) emissions in Thailand's electricity generation sector. The model integrates a multivariate gray model with the fminsearch optimization algorithm in MATLAB (R2025a) to address the critical challenge of accurate emission forecasting, a key driver of climate change. Historical data on CO₂ emissions, gross domestic product (GDP), peak electricity demand, and electricity user numbers are utilized to enhance predictive accuracy. Comparative analysis demonstrates that the optimized model significantly outperforms the conventional multivariate gray model, achieving mean absolute percentage error (MAPE) values of 7.74% for the training set and 1.75% for the testing set. The results highlight the effectiveness of the proposed approach as a robust tool for policymakers and stakeholders in Thailand's energy sector, offering actionable insights to support informed decision-making in managing and reducing CO₂ emissions.

Keywords: CO₂ emissions; gray models; fminsearch optimization; forecasting; electricity sector; Thailand; energy policy



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1. Introduction

The amount of carbon dioxide (CO₂) generated during electricity production significantly impacts the environment and human health. In the context of global climate change, reducing CO₂ emissions is a global priority. Thailand's electricity sector is a significant contributor to the country's overall emissions, primarily due to the heavy reliance on fossil fuels, such as coal and natural gas. As a result, there is an urgent need to adopt sustainable and efficient strategies to forecast and mitigate emissions, thereby supporting environmental sustainability [1].

Various predictive models have been employed for CO₂ forecasting. Techniques such as artificial neural networks (ANNs) have demonstrated high accuracy through error feedback mechanisms [2]. Time series methods like ARIMA have proven effective for smaller datasets [3], while multivariate models such as GM (1,n) offer advantages in scenarios with uncertain or incomplete data [4]. However, most existing models face challenges in balancing complexity and precision, especially when applied to specific sectors like electricity generation. Moreover, the integration of optimization methods, such

as the *fminsearch* algorithm, has yet to be fully explored to enhance the predictive accuracy of multivariate models in this domain [5].

This research bridges the aforementioned gap by developing an advanced CO₂ emission forecasting model tailored for Thailand's electricity sector. By integrating a multivariate gray model with the *fminsearch* optimization function in MATLAB, this study achieves significant improvements in prediction accuracy. This approach not only enhances parameter tuning but also provides actionable insights for policymakers to design effective carbon reduction strategies, thereby addressing the dual objectives of environmental and economic sustainability.

2. Materials

2.1. Gray Forecasting Method

The gray system theory, developed by Julong Deng, has been widely applied across various fields, including agriculture, economics, medicine, and history. The gray model (GM) integrates both complete and incomplete data into the forecasting process [6]. Compared to other forecasting methods, the GM is particularly well-suited for systems characterized by uncertainty, limited information, and small datasets [7–9].

2.1.1. Univariate Gray Technique

The univariate gray technique, known as GM(1,1), is named such because the first “1” denotes the order of the differential equation, while the second “1” represents the number of factors used in constructing the forecast model. The actual data sequence is arranged chronologically as follows:

$$x^{(0)}(k) = \{x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(k), \dots, x^{(0)}(n)\} \quad (1)$$

where $x^{(0)}(k) \geq 0$, $k = 1, 2, \dots, n$, and k is the data required to create the forecasting model.

2.1.2. Multivariate Gray

The multivariate gray technique, or GM(1,n) technique, where the first number represents the order of the differential equation and the subsequent number (n) refers to the number of factors used to create the forecasting model, which depends on time, can be expressed as follows:

$$\hat{x}^{(1)}(k+1) = x^{(1)}(1)e^{-b_1(k)} + \frac{\sum_{j=2}^N b_j x_j^{(1)}(k-1)}{b_1} \left(1 - e^{-b_1(k)}\right) \quad (2)$$

where $\hat{x}^{(0)}(k+1)$ is the value from the forecasting model $\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(1)$, which can be defined by $x^{(1)}(1) = x^{(0)}(1)$.

2.2. The Fminsearch Function in MATLAB

The *fminsearch* function is a built-in function in MATLAB. It is designed to find the minimum of an unconstrained multivariate function without relying on derivatives. The input is provided as a matrix or vector, which serves as the starting point for the function [10]. The function then performs iterative minimization on the specified objective function provided in the argument. The appropriateness of the forecast is then evaluated considering the relationship of the average absolute error percentage value with the Lewis

criteria. The relationship of the average absolute error percentage with the Lewis criterion by the appropriateness assessment criteria is shown in Table 1.

$$\text{MAPE}(\%) = \frac{\sum \left| \frac{x^{(0)} - \hat{x}^{(0)}}{x^{(0)}} \right|}{n} \times 100\% \quad (3)$$

where $x^{(0)}$ is a real value, $\hat{x}^{(0)}$ is the forecasted value, and n is total number of data.

Table 1. Assessment of MAPE with respect to the Lewis Criteria.

MAPE	Accuracy Judgment
$\leq 10\%$	Very high accuracy
11% to 20%	Good accuracy
21% to 50%	Fair accuracy
$\geq 51\%$	no precision

3. Methods

This section outlines the procedures and methods employed in utilizing the `fminsearch` technique in MATLAB. The steps are illustrated in Figure 1.

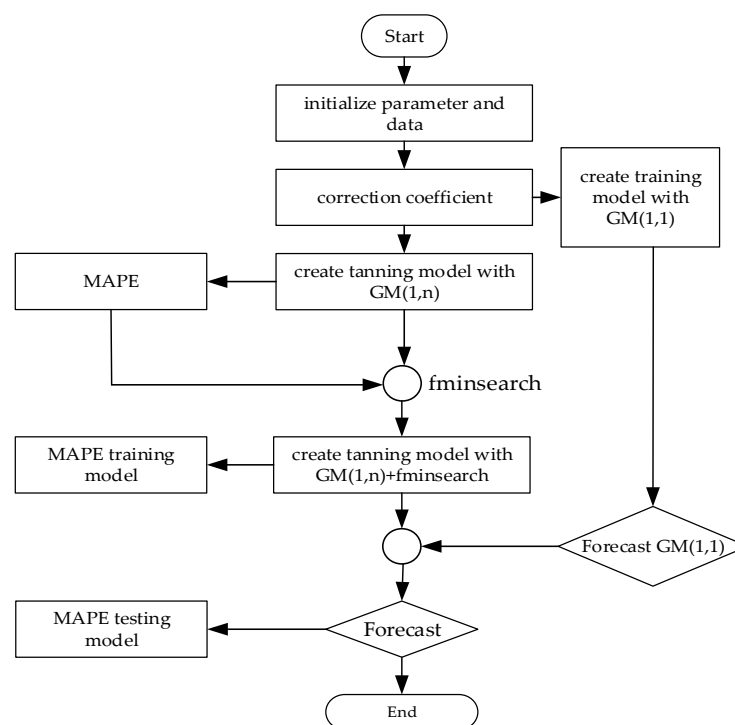


Figure 1. Flowchart of designing the algorithm with `fminsearch`.

Figure 1 presents a flowchart for designing an optimization-based forecasting algorithm using `fminsearch` in MATLAB, commonly applied in predictive analysis. The algorithm begins with the initialization of parameters and data relevant to the system or process being modeled, establishing baseline inputs for accurate forecasting. Following initialization, a correction coefficient is applied to adjust initial conditions or account for potential discrepancies in data, enhancing model accuracy. The process then diverges to create two distinct predictive models, $GM(1,1)$, a single-variable gray model, and $GM(1,n)$, a multivariable extension, both of which are tailored for systems exhibiting uncertain or

limited data, a typical scenario in electrical engineering applications like load forecasting or fault prediction. To validate these models, the mean absolute percentage error (MAPE) training model was used to evaluate each model's accuracy in capturing the underlying trends and variations in the data.

3.1. Gathering Information

Historical statistical data were collected on carbon dioxide emissions from Thailand's electricity production sector, GDP, maximum electricity demand, and the number of electricity users [10–13]. The dataset for training the model covers the period from 2007 to 2020, while the testing dataset spans from 2021 to 2022, as shown in Table 2.

Table 2. Data on the amount of carbon dioxide produced by the electricity production sector and other factors.

k	Year	A1	A2	A3	A4
1	2007	83,893.15	7579.5	22,586.1	2,701,634
2	2008	84,534.17	7710.3	22,568.2	2,793,337
3	2009	83,063.50	7657.1	22,044.9	2,922,936
4	2010	90,883.44	8232.4	24,009.9	3,035,144
5	2011	87,001.67	8301.6	23,900.21	3,115,695
6	2012	95,087.81	8902.8	26,121.1	3,194,167
7	2013	96,355.07	9142.1	26,598.14	3,295,382
8	2014	99,053.77	9232.1	26,942.1	3,395,367
9	2015	97,539.13	9521.4	27,345.8	3,522,038
10	2016	98,403.94	9848.5	29,618.8	3,632,722
11	2017	94,675.96	10,259.9	28,578.4	3,703,312
12	2018	93,917.56	10,693.2	28,338.1	3,805,840
13	2019	94,527.97	10,923.3	30,853.2	3,915,613
14	2020	90,983.99	10,246.5	28,636.7	4,052,963
15	2021	90,868.62			
16	2022	87,919.84			

A1 is the amount of carbon dioxide produced by the electricity production sector (million tons), A2 is the value of GDP, A3 is the maximum electricity demand value (MW), and A4 is the total number of electricity consumers (persons).

3.2. Filtering Information and Correlation Coefficients

The process of screening independent variables by finding the correlation coefficient was performed in order to evaluate the consistency of the relationships between the three sets of independent variables and the amount of carbon dioxide produced by the electricity production sector. The results are shown in Table 3.

Table 3. The correlation coefficients of carbon dioxide produced by the electricity production sector.

Independent Variable	A1	A2	A3
r	0.70	0.80	0.64

Table 3 summarizes the correlation coefficients between the three sets of independent variables and the amount of carbon dioxide produced by the electricity production sector. When analyzed based on the value r , it can be concluded that all three sets of independent variables show positive results and have a value greater than 0.5. Therefore, in this article, we chose to use the amount of carbon dioxide produced by the electricity production sector (million tons), the value of GDP, the maximum electricity demand value (MW), and the total number of electricity consumers (persons) for creating models to predict the results.

3.3. Creating a Set Training Model

A forecasting model was developed using the GM(1,1) technique to predict GDP, maximum electricity demand, and the total number of electricity consumers for the years 2021 and 2022. The forecasted GDP values are 11,305.20 and 11,637.69, respectively. The predicted maximum electricity demand values are 31,370.95 and 32,140.48, and the forecasted total number of electricity consumers is 4,177,223.95 and 4,303,156.77, respectively.

3.4. Creating a Set Training Model with the GM(1,n) Technique

A model was developed using the GM(1,n) technique to estimate carbon dioxide emissions from the electricity production sector, with one dependent variable and three independent variables. The GM(1,n) model, where $n = 4$, yielded the following parameter values: [2.1235, 27.0509, 0.0005, -56.4652]. The simulation results are presented in Figure 2.

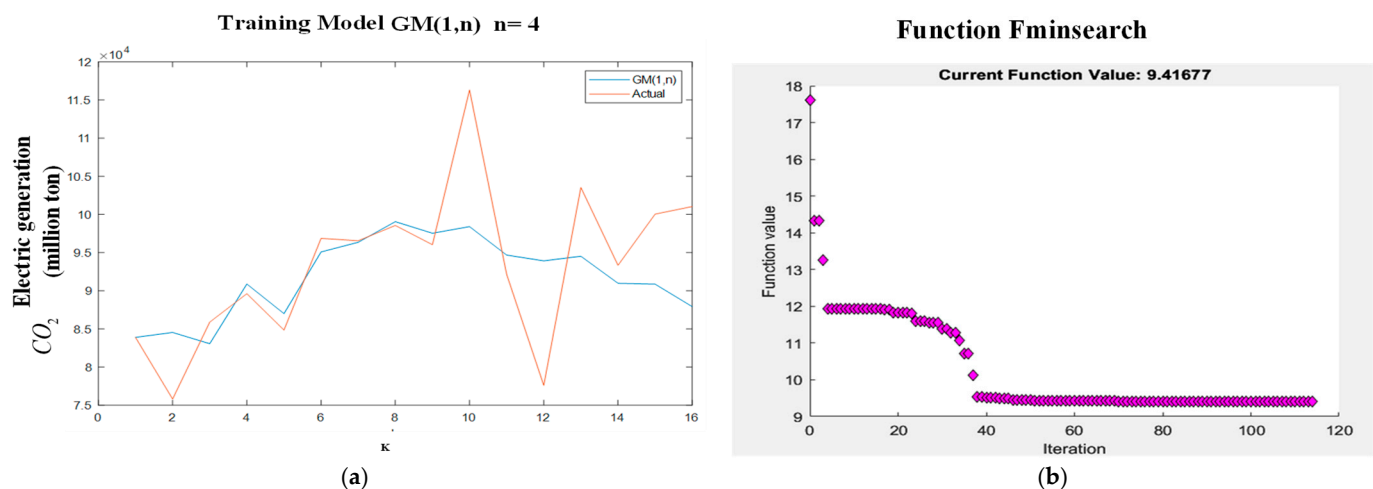


Figure 2. Training model created using the GM(1,n) technique.

Figure 2a presents a comparison between the actual data and the results obtained using the GM(1,n) technique. The training model yields a MAPE of 5.15%, while the testing model results in a MAPE of 12.51%, giving a combined MAPE of 17.66%. This combined value is considered in determining the optimal parameters during model creation. The training model was developed using both the GM(1,n) and *fminsearch* techniques. Figure 2b shows that the *fminsearch* function begins optimization with an initial MAPE of 9.42% and successfully identifies new parameter values that minimize the MAPE.

3.5. Creating a Set Training Model with the GM(1,n) and Fminsearch Techniques

Using the *fminsearch* function, we developed a model integrated with the GM(1,n) technique by optimizing new parameter values based on the initial parameters and the MAPE obtained from the original GM(1,n) training model. This process produced the parameters $[b_1, b_2, b_3, b_4] = [2.1235, 27.0509, 0.0005, -56.4652]$, with a corresponding MAPE of 17.66%.

Figure 3 compares the empirical data with the results of the *fminsearch*-optimized GM(1,n) model. The MAPE is 7.74% for the training set and 1.75% for the testing set, resulting in a combined MAPE of 9.42%.

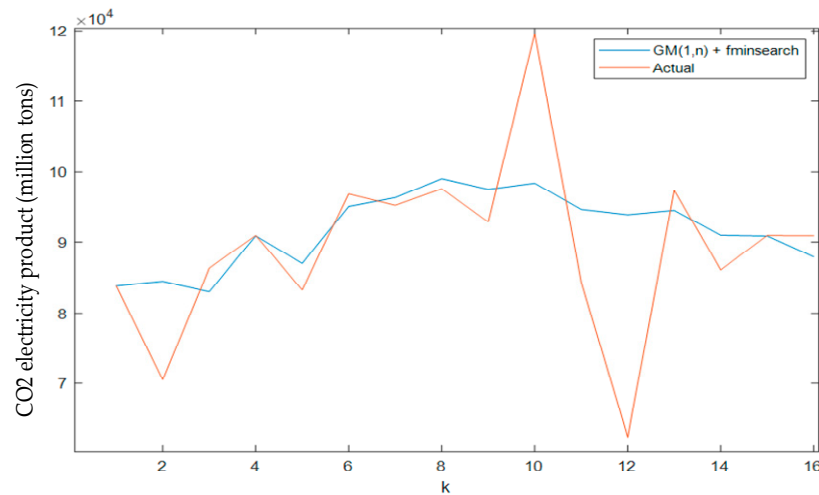


Figure 3. Training model created using GM(1,n) and fminsearch.

4. Results

This section provides the forecast results regarding the amount of carbon dioxide produced by Thailand's electricity production sector generated using gray models and fminsearch optimization.

Table 4 Summary of carbon dioxide emission forecast results from the power generation sector (million tons).

Table 4. Forecast results regarding the amount of carbon dioxide produced by the electricity production sector.

k	Year	Actual	GM(1,n)	GM(1,n) + Fminsearch
1	2007	83,893.15	83,893.15	83,893.15
2	2008	84,534.17	75,806.15	84,534.16
3	2009	83,063.50	85,889.76	83,063.50
4	2010	90,883.44	89,615.43	89,590.37
5	2011	87,001.67	84,843.91	83,576.50
6	2012	95,087.81	96,864.47	98,939.33
7	2013	96,355.07	96,554.06	97,276.24
8	2014	99,053.77	98,559.44	99,789.98
9	2015	97,539.13	96,039.58	94,478.06
10	2016	98,403.94	116,323.78	123,256.28
11	2017	94,675.96	92,148.87	84,818.32
12	2018	93,917.56	77,591.62	60,705.77
13	2019	94,527.97	103,538.99	98,482.06
14	2020	90,983.99	93,334.06	86,460.07
15	2021	90,868.62	100,044.14	91,158.83
16	2022	87,919.84	101,036.96	90,908.13
MAPE_Training Model			5.15%	7.74%
MAPE_Testing Model			12.51%	1.75%
MAPE			17.66%	9.42%

5. Conclusions

This paper introduces an optimized CO₂ emission forecasting model tailored for Thailand's electricity generation sector, employing a multivariate gray model with the fminsearch optimization function. This model demonstrated significant improvements in predictive accuracy, with a mean absolute percentage error (MAPE) of 7.74% for the training set and 1.75% for the testing set. These results indicate a marked enhancement over conventional multivariate gray models, which often struggle with parameter tuning

and may exhibit lower precision due to a lack of optimization. Compared to traditional statistical models like ARIMA and linear regression, which are limited in capturing nonlinear relationships in emission data, the integration of *fminsearch* optimization enables more accurate trend forecasting by adjusting parameters to minimize prediction errors. Future work directions include the integration of real-time data streams and the application of the model to other sectors beyond electricity generation.

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