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Forecasting Carbon Dioxide Emissions, Total Energy Consumption and Economic Growth in Asian Countries Based on Grey Theory

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Abstract— *This paper predicts the total energy consumption, carbon dioxide emissions and gross domestic product in eight Asian countries over the period 2019-2023. According to actual parameters, this article applied Grey models including GM(1,1), DGM(1,1) and DGM(2,1) to forecast the future value of three variables. By evaluating the results of the three forecasting models, the DGM(1,1) model has higher accuracy than others. The results of the study provide useful information for Asian policy makers in balancing economic development and environmental protection.*

Keywords— *Carbon dioxide emissions, total energy consumption, economic growth, forecasting, grey models.*

I. INTRODUCTION

Nowadays, the greenhouse effect and global warming has become a worldwide issue of concern. The International Energy Agency (IEA) point out that high CO_2 emissions are the main cause of the increase in temperature and climate change around the world. Moreover, worldwide energy consumption rose by 2.3% in 2018, almost twice the average rate of growth since 2010. Due to higher energy consumption, global energy-related CO_2 emissions also increased by 1.7%. Higher energy demand was driven by the global economy which expanded by 3.7% in 2018 compared to 2010. With the rapid development of Asian economy, the energy demands of Asian countries are increasing in the past few years. According to the IEA, Asian's energy consumption increased 60% in the past 15 years. Therefore, Asian countries need to promote energy efficiency. Moreover, Asian countries account for 2/3 of global CO_2 emissions, in which the largest CO_2 emissions are from China. In 2018, the large emitting countries are China (28%), India (7%), Japan (3%), Indonesia (2%), South Korea (2%), respectively [1].

Ozturk and Acaravci [2] also showed that CO_2 emissions plays a key role in promoting the greenhouse effect and more than 60% of the impact of greenhouse gas emissions comes from CO_2 emissions. Lee and Chang [3] point out that energy consumption is the main cause of increased CO_2 emissions that are harmful to health and environmental pollution. The other sides, climate change is associated with excessive energy consumption, constraining economic growth, and creates unsustainable growth cycles [4].

Therefore, many studies have been finding solutions to balance economic development and environmental protection. The relationship between CO_2 emissions, energy consumption and gross domestic product (GDP) has been extensively exanimated over the past two decades [5-8]. The investigates and forecasts of energy consumption, economic growth and CO_2 emissions, which has important policy significance for many countries to reduce carbon dioxide emissions. Thus, forecasting of energy consumption, CO_2 emissions and GDP for countries is an essential issue, especially in Asian countries. Recently, there are many researcher have implemented difference forecasting approaches to forecast the energy consumption, GDP as well as environmental problems. Mardani et al. [9] applied an adaptive neuro-fuzzy inference system (ANFIS) model to investigate the relationships among CO_2 emissions, energy consumption, and economic growth in G20 countries. The results point out that increasing energy consumption and economic growth in some countries, CO_2 emissions will continue to rise. Wu et al. [10] implemented a novel multi-variable grey model to forecast economic growth, urban population, energy consumption and CO_2 emissions in Brazil, Russia, India, China, and South Africa. The results showed that these countries should improve their energy efficiency to reduce the CO_2 emissions. Ardakani et al. [11] used the multiple linear regressions (MLR), multivariate adaptive regression splines (MARS), and the artificial neural network (ANN) to predict the annual energy consumption of the Nordic countries including Denmark, Finland, Norway, Iceland and Sweden. Hamzacebi and Karakurt [12] applied Grey prediction model to forecast energy related CO_2 emissions of Turkey. The results showed that CO_2 emissions of Turkey will reach up in 2025 compared with 2010. Sadorsky [13] implemented Panel integration techniques to estimate renewable energy consumption, CO_2 emissions and oil prices in the G7 countries. Ho [14] applied Grey forecasting model to forecast renewable energy consumption, CO_2 emissions and economic growth in Vietnam. The results give information to help policymakers in order to improve economic growth, energy efficiency and CO_2 emissions in Vietnam. Ofosu-Adarkwa et al. [15] applied Grey forecasting method to estimate CO_2 emissions of China's cement industry. The study provided a reference to help policy maker to achieve emissions reduction targets. Guo et al. [16] implemented a pre-processing grey model to analyze industrial energy conservation in China. The results point out that the ecological development path not only encourages economic

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and industrial developments but also significantly reduces energy consumption. Liu et al. [17] applied Grey forecasting model to predict China' Gross domestic product. The results showed that the future development trend of China's GDP is reliable with China's national conditions. Pao et al. [18] used Grey prediction model to forecast CO_2 emissions, energy consumption and economic growth in China. The results showed that China should improve energy efficiency to reduce wastage of energy. Feng et al. [19] implemented grey model GM(1,1) to forecast the energy consumption of China. The results point out that the growth rate of clean energy is higher than coal energy in the period of 2007 to 2012. Hamzacebi and Es [20] employed Grey (1,1) model to predict electricity consumption of Turkey. The values of primary energy resources of Turkey have calculated for the future. Liu et al. [21] forecasted economic sectors and primary energy consumption in Spanish. The results showed that Spanish must improve in energy-efficiency economy to reduce energy consumption. Moonchai and Chutsagulprom [22] proposed a modified grey model to forecast renewable energy consumption, population, gross domestic product, CO_2 emissions and human development index in Thailand from 1990 to 2015. Jia et al. [23] applied Grey Markov chain model to predict coal consumption in in Gansu from 2020 to 2035. The results indicated that the consumption of coal in Gansu will tend to increase in the next 15 years. Cheng et al. [24] improved Grey model GM (1, N) to predict Clean Energy Consumption in China during the period of 2019-2025. The results pointed that China's clean energy consumption will increase in the next few years. Liu & Wu [25] proposed an adjacent non-homogeneous discrete grey model to forecast annual consumption of renewable energy in European countries. Xie et al [26] proposed a novel robust reweighted multivariate grey model to predict the CO_2 emissions in European Union member countries during the period of 2010 to 2016. Luo et al. [27] proposed an improved grey model to forecast the electricity production in Pakistan. The results revealed that Pakistani government needs to improve the installed capacity of electricity production. Hu et al.[28] proposed optimized Grey prediction model to predict the carbon dioxide emissions of twenty countries. Wang et al.[29] implemented Grey model to predict the solar energy consumption in the United States during the periods of 2005 to 2017. Wang [30] predicted the consumption of clean energy in China by using Grey model. The results revealed that China should increase clean energy consumption. Ding et al. [31] proposed a novel grey multivariable model to forecast CO_2 emissions from fuel consumption in China. The results pointed that the growth of CO_2 emissions in China due to the high energy consumption. Lu [32] proposed modified grey forecasting model to predict renewable energy in Taiwan. The results demonstrated good reliability. Dengiz et al.[33] predicted carbon dioxide emissions of seven developed countries by applying Grey forecasting method. The results indicated that seven selected countries have to take action to reduce CO_2 emissions. Liu et al. [34] employed Grey system theory to predict China' s GDP. The results showed that the GDP growth rate of China continue remain steady. Şahin [35] applied optimized fractional nonlinear grey Bernoulli model to predict renewable energy consumption in France, Germany, Italy, Spain, and Turkey. After careful reviewing the previous study, there has no study forecasting the CO_2 emissions, energy consumption and economic growth for Asian countries including China, India, Indonesia, Japan, Malaysia, South Korea, Taiwan and Thailand. Thus, this study employs Grey forecasting models to calculate the future values of CO_2 emissions, energy consumption and economic growth for eights Asian countries in the period of 2019 to 2023.

II. Methodology

This section describes three prediction models including GM(1,1) model, DGM(1,1) model and DGM(2,1) model. All models are explained as follows:

A. The GM (1,1) model

Grey GM (1,1) model is presented by Deng Julong [36], has been widely implemented in many project. GM (1,1) model is constructed as follows:

Assume that the sequence

$$M^{(0)} = \{m^{(0)}(1), m^{(0)}(2), \dots, m^{(0)}(n)\}$$

Is an original data sequence, the sequence:

$$M^{(1)} = \{m^{(1)}(1), m^{(1)}(2), \dots, m^{(1)}(n)\}$$

Is the accumulated generations sequence of $M^{(0)}$, where

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

The sequence

$$Z^{(1)} = \{z^{(1)}(2), z^{(1)}(3), \dots, z^{(1)}(n)\}$$

Is the main sequence of $M^{(1)}$, where

$$Z^{(1)}(k) = \frac{1}{2}\left(m^{(1)}(k) + m^{(1)}(k-1)\right), k = 2, 3, \dots, n \quad (2)$$

The equation

$$x^{(0)}(k) + az^{(0)}(k) = b$$

Is called the basic form of GM (1,1) model.

The equation

$$m^{n(1)}(k+1) = \left(m^{(0)}(1) - \frac{b}{a}\right)e^{-ak} + \frac{b}{a}, k = 1, 2, \dots, n-1)$$

is called the time response equation.

B. The DGM (1,1) model

Assume that

$$M^{0} = \{m^{(0)}(1), m^{(0)}(2), \dots, m^{(0)}(n)\}$$

Is a negative sequence and the 1-AGO sequence of $M^{(0)}$ is

$$M^{(1)} = \{m^{(1)}(1), m^{(1)}(2), \dots, m^{(1)}(n)\}$$

Where

$$m^{(1)}(k) = \sum_{i=1}^{k} m^{(0)}(i), k = 1, 2, \dots, n \quad (3)$$

$$m^{(1)}(k+1) = \beta_1 m^{(1)}(k) + \beta_2 \quad (4)$$

Where B_1 is the partition coefficient and B_2 is the intercept coefficient.

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If $\beta^{\wedge} = (\beta_1, \beta_2)^T$ is a parameter sequence and

$$\gamma = \begin{cases} m^{(1)}(2) \\ m^{(1)}(3) \\ \dots \\ m^{(1)}(n) \end{cases}, \quad \beta = \begin{cases} m^{(1)}(1) \\ m^{(1)}(2) \\ \dots \\ m^{(1)}(n-1) \end{cases}$$

Then the least square estimate sequence of the parameters of grey differential Eq (3) satisfied

$$\beta^{\wedge} = (\beta^T\beta)^{-1}\beta^T\gamma$$

Assume $\beta^{\wedge} = (\beta_1, \beta_2)^T = (\beta^T\beta)^{-1}\beta^T\gamma$, let $m^{(1)}(1) = m^{(0)}(1)$, then the recurerence formula of DGM model is

$$m^{\wedge(1)}(k+1) = \beta_1{}^k m^{(0)}(1) + \frac{1-\beta_1{}^k}{1-\beta_1}\beta_2, k = 1, 2, \dots, n-1 \quad (5)$$

So, the response sequence of DGM model is

$$m^{\wedge(0)}(k+1) = m^{\wedge(1)}(k+1) - x^{\wedge(1)}(k) = \beta_1{}^{k-1}\left((\beta_1 - 1)m^{(0)}(1) + \beta_2\right), \quad k = 1, 2, \dots, n-1 \quad (6)$$

In a word, the prediction equation of DGM (1,1) model is

$$m^{(0)}(k) = \begin{cases} m^{(0)}(1) \\ \beta_1{}^{k-2}\left((\beta_1 - 1)m^{(0)}(1) + \beta_2\right), k = 2, 3, \dots, n \end{cases} \quad (7)$$

C. *The DGM (2,1)*

Assume an original series to be $M^{(0)}$

$$M^{(0)} = \{m^{(0)}(1), m^{(0)}(2), \dots, m^{(0)}(n)\}$$

A new sequence $X^{(1)}$ is generated by the accumulated generating operation (AGO)

$$M^{(1)} = \{m^{(1)}(1), m^{(1)}(2), \dots, m^{(1)}(n)\}$$

Where

$$m^{(1)}(k) = \sum_{j=1}^{k} m^{(0)}(j), (k = 1, 2, \dots, n) \quad (8)$$

Setting up a second-order difference equation

$$\frac{d^2x^{(1)}}{dt^2} + a\frac{dx^{(1)}}{dt} = u \quad (9)$$

Where

$$a^{\wedge} = [a, u]^T = (\beta^T\beta)^{-1}\beta^T\gamma$$

$$\gamma = \begin{bmatrix} \left(m^{(0)}(2) - m^{(0)}(1)\right) \\ \left(m^{(0)}(3) - m^{(0)}(2)\right) \\ \dots \\ \left(m^{(0)}(n) - m^{(0)}(n-1)\right) \end{bmatrix} \quad (10)$$

$$\beta = \begin{bmatrix} -m^{(0)}(2) & 1 \\ -m^{(0)}(3) & 1 \\ \dots \\ -m^{(0)}(2) & 1 \end{bmatrix} \quad (11)$$

According to (1), we have

$$m^{(1)}(k+1) = \left(\frac{u}{a^2} - \frac{x^{(0)}(1)}{a}\right)e^{-ak} + \frac{u}{a}(k+1) + \left(m^{(0)}(1) - \frac{u}{a}\right)\left(\frac{1+a}{a}\right) \quad (12)$$

The prediction value of original sequence can be obtained by applying inverse AGO to $x^{\wedge(1)}$. Namely

$$m^{\wedge(0)}(k+1) = m^{\wedge(1)}(k+1) - m^{\wedge(1)}(k), (k = 0, 1, 2, \dots, n)$$

III. Empirical Study

A. *Data*

This study uses annual data of eight Asian countries on carbon dioxide emissions (million tons), energy consumption (million tons) and GDP covering the period from 2014 to 2018. The data on total energy consumption (million tons of oil equivalent) involves coal, gas, oil, electricity, heat, and biomass. The CO_2 emissions are collecting from fuel combustion (coal, oil and gas). These two variables are collected from Enerdata Yearbook [37]. GDP (current US $) at purchase's prices is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources. The data on GDP are obtained from the World bank [38]

B. *Predict and Analysis:*

This research applies the GM(1,1), DGM(1,1) and DGM(2,1) models to forecast the trend of carbon dioxide emissions, energy consumption and GDP in Asian countries in the periods of 2019 to 2023. The results of the three models are analyzed. According to result of the average relative error of predicted value, the paper select the model with the highest accuracy to predict the trend in carbon dioxide emissions, energy consumption and GDP in Asian countries from 2019 to 2023. For evaluating the sample forecast capability, the forecasting accuracy is tested by calculating the mean absolute percentage error (MAPE) [39]. It is expressed as follow:

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\frac{|D_i - F_i|}{D_i}$$

Where D_i and F_i are the predicting and actual values, respectively, and n is the total number of forecast. The MAPE result as the evaluation the accuracy of the predict, 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 weak forecast. To approve the effectiveness of the proposed grey predicting models. In this section, the authors construct the GM(1,1) model, DGM(1,1) model and DGM(2,1) model with the same dada sequence. Then, the study compares the simulative variables and the relative simulative errors of the three models. The study takes the real case of CO_2 emissions in China as an example.

For GM(1,1), according to the original data sequence:

$$X^{(0)} = \{x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(5)\}$$

= (9082, 9061, 9003, 9179, 9467)

We can obtain the accumulating generated sequence

$X^{(1)} = \{x^{(1)}(1), x^{(1)}(2), \dots, x^{(1)}(5)\}$ = (9082, 18143, 27146, 36325, 45792)

And the neighbors mean generated sequence

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$$Z^{(1)} = \{z^{(1)}(2), z^{(1)}(3), \dots, z^{(1)}(5)\}$$
$$= (13612.5, 22644.5, 31735.5, 41058.5)$$

We get the parameters
α=-0.01530; b= 8760.2719
For DGM(1,1), we can get the parameters
β_1= 101539; β_2=8828.65992
For DGM (2,1), we can get the parameters
α=-0.75259; b= -6810.65602

To compare the forecast accuracy of the above three predicting model, the mean absolute percentage error is implemented. It can be seen from Table 1. Table 1 points out that the simulative values and the simulative errors of DGM(1,1) model are the best, follow is GM(1,1) and DGM(2,1). Thus, this study choose DGM(1,1) model to forecast the trend in CO_2 emissions, energy consumption and GDP in eight Asian countries.

Table 1: Predicted values and MAPE of CO_2 emissions, total energy consumption and GDP in China (2014-2023).

	CO2 emissions (MtCO2)				Total energy consumption (Mtoe)				GDP (current US$)			
		GM(1,1)	DGM(1,1)	DGM(2,1)		GM(1,1)	DGM(1,1)	DGM(2,1)		GM(1,1)	DGM(1,1)	DGM(2,1)
Year	Actual	Model value	Model value	Model value	Actual	Model value	Model value	Model value	Actual	Model value	Model value	Model value
2014	9,082	9,082	9,082	9,082	2,965	2,965	2,965	2,965	10,439	10,439	10,439	10,439
2015	9,061	8,968	8,968	9,098	2,994	2,954	2,954	2,964	11,016	10,659	10,669	10,506
2016	9,003	9,106	9,106	9,152	2,965	3,013	3,013	2,961	11,138	11,488	11,496	10,687
2017	9,179	9,246	9,246	9,267	3,051	3,073	3,073	2,956	12,143	12,381	12,387	10,969
2018	9,467	9,389	9,389	9,512	3,164	3,134	3,134	2,946	13,608	13,344	13,347	11,406
2019		9,533	9,532	10,030		3,197	3,196	2,927		14,382	14,382	12,086
2020		9,680	9,679	11,131		3,261	3,260	2,890		15,501	15,497	13,142
2021		9,829	9,827	13,467		3,326	3,325	2,819		16,706	16,698	14,784
2022		9,980	9,978	18,425		3,392	3,391	2,683		18,006	17,992	17,334
2023		10,134	10,132	28,948		3,460	3,459	2,422		19,406	19,387	21,297
MAPE		0.93%	0.23%	0.86%		1.15%	0.29%	2.93%		2.57%	0.64%	9.77%

The predicted results of these three variables during 2014 to 2023 are described. The CO_2 emissions in the periods of 2019 to 2023 in the selected countries are presented in figure 1.

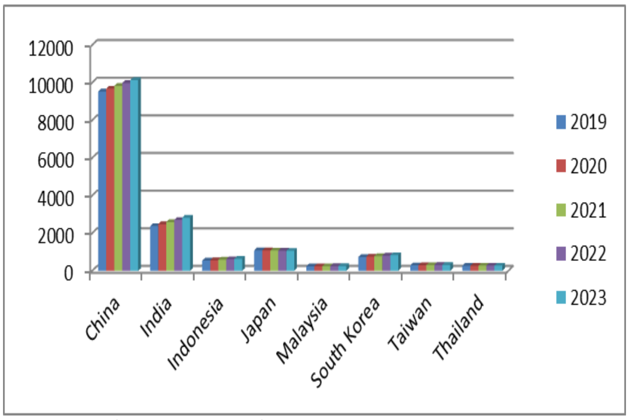

Figure 1: The forecasted data of CO_2 emissions in the eight Asian countries.

Figure1 findings that carbon emissions in the China, India, Indonesia, Malaysia, South Korea, Taiwan and Thailand will gradually increase in the period of 2019- 2023 compare with the period of 2014- 2018. However, Japan's CO_2 emissions tend to decrease during 2019-2023. Based on the results of DGM(1,1) model, the average CO_2 emissions of China, India, Indonesia, Japan, Malaysia, South Korea, Taiwan and Thailand are 9829, 2593, 587.14, 1074.53, 344.34, 799.01, 302.24, 270.96 million tons respectively in the period of 2019-2023.

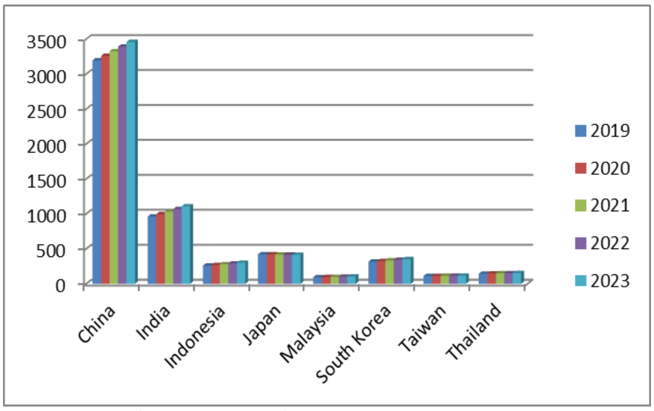

Figure 2: The forecasted data of total energy consumption in the eight Asian countries.

The total energy consumption value from 2014 to 2018 in eight Asian countries are used to predict the value from 2019 to 2023 by DGM(1,1). The results are showed in Figure 2. The annual average growth rates will be at 2% (China), 3% (India), 3% (Indonesia), 2%(South Korea), 1% (Taiwan), 2% (Thailand). Except for Japan with 1% decrease in 2023 compared with 2014. This means that along with the rapid development of economy in India, Indonesia, China, South Korea and Thailand, the need for energy is growing continuously.

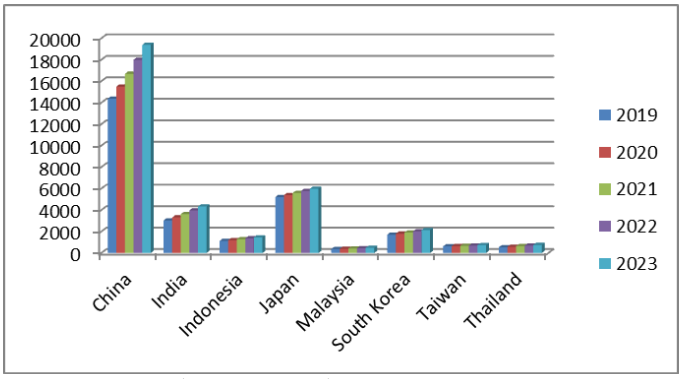

Figure 3: The forecasted data of GDP in the eight Asian countries.

Using the establish DGM(1,1) forecast model to predict GDP of eight Asian countries from 2019 to 2023. The model results show that GDP about US$19,387 for China, US$4,339 for India, US$1,458 for Indonesia, US$ 5,983 for Japan, US$476 for Malaysia, US$ 2,132 for South Korea, US$732 for Taiwan and US$749 for Thailand in 2023.

IV. CONCLUSION

The main aim of the study is to forecast CO_2 emissions, energy consumption and GDP for eight Asian countries based on Grey prediction models. Using recent 5 year historical data, three Grey forecasting models are applied to predict future

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results. The application of these models confirms that the DGM(1,1) model appear to perform better than GM(1,1) and DGM(2,1) model. Meanwhile, the DGM(1,1) model achieves the best results. It can be concluded that DGM(1,1) is suitable for making predicts about the CO_2 emissions, total energy consumption and GDP for eight Asian countries. The results indicate that the CO_2 emissions and total energy consumption of China, India, Indonesia, South Korea, Thailand and Taiwan will not decrease in a long period of time when income increase. However, in the case of Japan, where income was found to have a positive over the time when CO_2 emissions and total energy consumption decrease. The government of China, India, Indonesia, South Korea, Thailand and Taiwan can follow conservative energy and carbon emissions reduction policy without affecting economic growth.

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