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Forecast of Carbon Dioxide Emissions from Energy Consumption in Industry Sectors in Thailand

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Abstract **– The aim of this research is to forecast CO_2 emissions from consumption of energy in Industry sectors in Thailand. To study, input-output tables based on Thailand for the years 2000 to 2015 are deployed to estimate CO_2 emissions, population growth and GDP growth. Moreover, those are also used to anticipate the energy consumption for fifteen years and thirty years ahead. The ARIMAX Model is applied to two sub-models, and the result indicates that Thailand will have 14.3541 % on average higher in CO_2 emissions in a fifteen-year period (2016–2030), and 31.1536 % in a thirty-year period (2016–2045). This study hopes to be useful in shaping future national policies and more effective planning. The researcher uses a statistical model called the ARIMAX Model, which is a stationary data model, and is a model that eliminates the problems of autocorrelations, heteroskedasticity, and multicollinearity. Thus, the forecasts will be made with minor error.**

Keywords **– CO_2 emissions; GDP growth; energy consumption; income per capita; population growth**

1. INTRODUCTION

Thailand is continuously growing in terms of economic development with support from the government to promote all aspects [1], and to boost foreign investments through various national policies; a reduction policy of interest, a tax levy policy and a financial aid policy, for instance [1]–[3]. The implementation of such policies result in a continuous increase in the Gross Domestic Product (GDP) of Thailand over this time to the present [1], [4].

The growth in the economy also indicates growth in the population as the increment in income per capita. Thus, societies change to create a better place to live, differing from those years back. At the same time, consumption has the potential to increase too, especially in energy consumption. Thus, this high consumption in energy may affect the surroundings and destruct the environment [5]–[7]. Sutthichaimethee et al. [4], [5] have found that, with economic growth, the population has increased their consumption, and the environmental damage is seen to rise. This is to say that both consumption and environmental destruction are increasing, while conservation of the environment is still slow to take action to sustain it for the future [1], [8], [9].

However, there are lots of changes caused by high energy consumption which lead to greenhouse gas emissions as shown as the index of CO_2 [10]–[12]. Thus, when developing policies one must consider changes in CO_2 to equip such policies with methods for improving sustainable development in the perspective of the economy, society and environment [13], [14]. In addition, the prediction in greenhouse gas emissions shall be used in order to create efficiency in making policies, and this study is conducted to create the best forecasting model for national policy planning [15]–[17]. With that, the researcher has reviewed literature from many sources; Jain [18]

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applies the Gray Markov model, Grey-model with rolling mechanism, and singular spectrum analysis (SSA) to predict the consumption of conventional energy in India. Weijun Hu et al. [19] establish a new model with improved GM-ARIMA based on HP Filter in order to forecast the final energy consumption of Guangdong Province in China. Furthermore, Pao et al. [20] have employed the NGBM (nonlinear grey Bernoulli model) to anticipate carbon emissions, energy consumption and real outputs.

From reviewing a number of relevant studies conducted, it has, however, been observed that those studies introduced a forecasting model without taking the issue of Heteroskedasticity, Multicollinearity and Autocorrelation into consideration. These studies also ignored the exogeneous variables. Therefore, the current study determined the necessity to apply a high statistic in constructing a model, thus the new forecasting model is built. This model considers all relevant variables. Modeling and forecasting by ARIMAX Model have then been utilized to solve the research problem, as well as to maximize its application for future studies and use.

2. MODEL AND METHODOLOGY

2.1. ARIMAX Model

There are four parts in the model ARIMAX; Auto Regressive (AR), Moving Average (MA), Exogenous Variable and Integrated (I) [4], [5], [7]. The model comes with the following details.

1. Auto Regressive (AR) has the characteristics as shown below:

$$Y_{\mathrm{t}} = \alpha + \beta_1 \cdot Y_{\mathrm{t}-1} + \beta_2 \cdot Y_{\mathrm{t}-2} + \cdots + \beta_{\mathrm{p}} \cdot Y_{\mathrm{t}-\mathrm{p}} + \varepsilon_{\mathrm{t}}, \tag{1}$$

where

$\beta_1 \ldots \beta_n$ parameters;

α a constant;

ε_t random variable (white noise).

2. Moving Average (MA) is using the error term brought from forecasting to find the difference between variables that actually happen (Y Actual) with the dependent variables (Y Forecast) or $\varepsilon_t = Y_{at} - Y_{ft}$ in the past to facilitate in anticipating the variables needed in the future as the equation below: $\varepsilon_t = Y_{at} - Y_{ft}$:

$$Y_{\mathrm{t}} = \delta + \varepsilon_{\mathrm{t}} - \gamma_1 \cdot \varepsilon_{\mathrm{t}-1} - \gamma_2 \cdot \varepsilon_{\mathrm{t}-2} - \cdots - \gamma_{\mathrm{q}} \cdot \varepsilon_{\mathrm{t}-\mathrm{q}}, \tag{2}$$

where Moving Average of Order q or MA(q) by q means last order of error value is applied.

3. Integrated (I) is to find the difference of variables. It is important to look for the difference as the ARIMA is non-stationary.

In order to manipulate the model to become more accurate and good in forecasting the energy consumption in the future, the researcher, thus, decides to use the Autocorrelation Integrated Moving Average model (ARIMAX Model) adapted from the ARIMA model (p, d, q) [7], [8], as follows:

Steps to make the modeling and forecasting are as shown below:

1. Analyze the data for Stationary by testing the Unit Root from the concept of Augment Dickey and Fuller.

Stationary: Stationary Stochastic Process is the series of time data with mean or expected value, variance, constant overtime, and covariance. Time is not the matter here, but distance or lag is.

Y_t is given as the Stochastic Time Series and comes with a form of Stationary, there must be three properties as shown below:

Mean: $$E \cdot Y_{\mathrm{t}} = E \cdot Y_{\mathrm{t+k}} = \mu \,. \tag{3}$$

Variance: $$VAR\ (Y_{\mathrm{t}}) = E \cdot (Y_{\mathrm{t-\mu}})^2 = \sigma^2. \tag{4}$$

Covariance: $$E \cdot \left(Y_{\mathrm{t-\mu}}\right) \cdot \left(Y_{\mathrm{t+k-\mu}}\right) = \gamma_{\mathrm{k}} \,. \tag{5}$$

From the Eq. (3), Eq. (4), and Eq. (5), it can be seen that γ_{k} is covariance between Y_t and Y_{t+k}, which is the distance between two values of Y, and that is not varied based on time. In order to form the model with white noise, the theory of Augmented Dickey-Fuller (ADF) is required. The lagged variables are added to the equation in the higher level to eliminate the autocorrelation, heteroskedasticity, and multicollinearity as it has been shown below:

$$\Delta Y_{\mathrm{t}} = \delta_1 \cdot Y_{\mathrm{t}} + \textstyle\sum_{i=2}^{p} \beta_{\mathrm{i}} \cdot \Delta Y_{\mathrm{t-i+1}} + \varepsilon_{\mathrm{t}}, \tag{6}$$

$$\Delta Y_{\mathrm{t}} = \alpha_1 + \delta \cdot Y_{\mathrm{t-1}} + \textstyle\sum_{i=2}^{p} \beta_{\mathrm{i}} \cdot \Delta Y_{\mathrm{t-i+1}} + \varepsilon_{\mathrm{t}}, \tag{7}$$

$$\Delta Y_{\mathrm{t}} = \alpha_1 + \alpha_2 \cdot T + \delta \cdot Y_{\mathrm{t-1}} + \textstyle\sum_{i=2}^{p} \beta_{\mathrm{i}} \cdot \Delta Y_{\mathrm{t-i+1}} + \varepsilon_{\mathrm{t}}. \tag{8}$$

From the above equations, the value of p is set to be the lagged value of first difference of the variable by testing the Unit Root with the Augmented Dickey Fuller method as shown in the following:

$$Y_{\mathrm{t}} = \alpha_1 + \alpha_2 \cdot T + \delta \cdot Y_{\mathrm{t-1}} + \textstyle\sum_{i=2}^{p} \beta_{\mathrm{i}} \cdot \Delta Y_{\mathrm{t-i+1}} + \varepsilon_{\mathrm{t}}. \tag{9}$$

With this equation above, three problems are considered and taken into account, especially the autocorrelation in ε_t set to have the property of White Noise, which is the Error Term that has the mean of 0 and it is constant under the following hypotheses:

- H_0: $\delta = 0$, non-stationary;
- H_1: $\delta < 0$, stationary.

If the tau-statistic is greater than a critical value, it shows that the testing variable is stationary.

2. Use that same level stationary data from both dependent variables and independent variables (at level of 1st moment and/or 2nd moment only) to analyze the long-term relationship or find co-integration whether variables in the model are relevant to each other in the long term and at the same level, this must show that vector error-correction model (ECM) exists in order to create the best model.

The theory of co-integration and error correction model are the following:

It is the application of the Eagle and Granger method, and it has brought a theoretical conclusion as two sets of time series may be related in motion Steady State. This is called 'Co-integration,' and it happens even if each time series data is non-stationary. With the use of traditional analytical methods, such as Ordinary Least Squares and Two-Stage Least Squares, the time series data is analyzed statistically or economically with most important consideration being that Time Series

Data must be stationary. And most of the time, many researches and study have shown that the time series data of macroeconomic variables in other countries including Thailand is non-Stationary rather than stationary in respect of "level" information. Thus, it is necessary to ensure that the time series data is stationary before doing an analysis.

However, for many time series data to be analyzed and even if each data set is non-stationary, the evaluation of studied variables on co-integration in conducted as follows:

- checking the Integrated Sequence of Y and X variables by Unit Root Test; if the testing variable is found to be stationary at the same Level, a Co-integration analysis is needed in the next step;
- computing a Co-integrating Parameter by a technique of Ordinary Least Squares (OLS);
- evaluating a stationary of error term. The u_t is the Linear Combination of Y_t and X_t. The test with DF method is used when the case of the noise is White Noise. If the interference problem is Autocorrelation, the method has to be ADF. However, if the assumption requires u_t with Non-Stationary, which is Unit Root, this means that Y_t and X_t are no in long-term equilibrium relationships.

2.2. Error-Correction Mechanisms (ECM)

The Error Correction Mechanism is a model that will show an adaptation process that is more consistent with reality. And it also analyzes the adaptation that occurs in the short term and long-term adaptation. Long-term adjustment can be calculated from the coefficients of the variables in the long-run equation Co-integration Regression. The adaptation in the short term can be calculated from the coefficients of the variables in the ECM equation. The separation of short-term and long-term adjustment is very useful in economic analysis.

In the estimation process, the common problem found in projections is that the use of time series data is found to be non-stationary. This has resulted in wrong analysis of the facts, and statistical values are not reliable. Estimating by using the ECM model will not cause distorted correlation problems, and it will also not change the nature of the data. From this point of view, the ECM model is used to test short-term demand for empirical studies. If the absolute value of the coefficient or Augmented Dickey Fuller (ADF) is less than the Critical Value of MacKinnon, then the discrepancy will not have a longitudinal equilibrium.

However, for the adjustment in the short term, it is important to consider the effect of the variance of the longitudinal variations (U_{t-1}) on the coefficients of the error. This will show the size of the imbalance between the values of X and Y that occurs at the recent time. This can be said in another sense that 'Coefficient Value' of the tolerances in the ECM equation represents the short-term dynamic of the adjustment towards long-term adjustment, if the coefficient (γ) is large, it shows that the adjustment towards an equilibrium is better than a small scale of coefficient (γ).

For this research, Co-integrated Relationships are obtained with the Full Information Maximum Likelihood (FIML) Approach as introduced by [21]. This is because the model can be used with two variables or more, and the number of Co-Integrating Vectors can be tested without the specification of variables as to which is an exogenous variable and endogenous variable.

As of Johansen and Juselius's approach, it is the method of testing in the form of Multivariate Co-integration based on the model called Vector Autoregressive (VAR) Model.

$$\Delta X_{\mathrm{t}} = \mu + \sum \Gamma_{\mathrm{i}} \cdot \Delta X_{\mathrm{t}}, \Delta X_{\mathrm{t-1}} - \Pi \cdot X_{\mathrm{t-k}} + u_{\mathrm{t}}. \tag{10}$$

From the approach of Johansen and Juselius, the test must be conducted to find Co-integrating Vectors of variables X_t in the VAR Model. It is necessary to find the most suitable Lag to verify the VAR Model. This is most often done by considering the Likelihood Ratio Test of Sims [22] or the approach of Minimum Final Prediction Error Test Akaike, and that comes with the following steps:

- set the equation that is needed for testing based on Vector Autoregressive Model (VAR), for example;

$$\Delta X_{\mathrm{t}} = \sum \Pi_{\mathrm{i}} \cdot \Delta X_{\mathrm{t}-i} + \Pi X_{\mathrm{t-k}} + u_{\mathrm{t}}; \tag{11}$$

- test the equation to find the suitable number of Lag for this equation;
- cointegrate vectors between variables in the model and get the rank of metric π, which is equal to Rows or Columns that are independent of π;
- apply two different statistical tests to get the number of Co-Integrating Vectors (r) for the model, such as Trace Test and Maximum Eigenvalue Test. Here, the accuracy can be checked by these two tests.

3. Estimate the model to create the Best Model. That is, the independent variable must show true influence on dependent variables. The impacts are considered from the value of tau-statistics which must have significance of difference at the level of 5 %, 10 %, and 15 %.

4. Put forth the newly-built Best Model to test on these three types of problem. The first type is Autocorrelation.

4.1. Test the Autocorrelation by using Lagrangian Multiplier Test – LM test.

LM Test is used when the equation has lagged variables of dependent variables appeared to be independent variables. Here, Durbin-Watson cannot be used to test. Besides, the LM can be used to test in case Error Terms have autocorrelation problems at a high level. The following is the testing methods.

$$Y_{\mathrm{t}} = \alpha_0 \cdot X_{\mathrm{t}} + \beta_1 \cdot U_{\mathrm{t-1}} + \beta_2 \cdot U_{\mathrm{t-2}} + \cdots + \beta_{\mathrm{n}} \cdot U_{\mathrm{t-n}}. \tag{12}$$

If χ^2p and $F_{\mathrm{m,n-k}}$ – Test Statistic is more that the value Critical χ^2 and value of F Critical is at the chosen level of significance, the major hypothesis is not confirmed. That is at least one b has the value difference from 0. This means that there is an Autocorrelation problem.

4.2. Test Heteroskedasticity by implementing ARCH Test.

ARCH Testing is the method to test Heteroskedasticity in time series. When the residual is obtained, the lagged variables of the residual is calculated with the Residual by taking the value of F and nR^2, which has Chi-Square distribution. If the critical value of χ^2p from the table of chosen significance level has lower value than the χ^2p statistical test, the hypothesis is rejected, because it seems to have Heteroskedasticity.

4.3. Test Multicorrelinearity by using a correlation test and responses from the value of Correlogram compared to chi-square value.

5. Evaluate the forecasting accuracy to determine the out of sample forecast capability. For this research, the model that has a mean absolute percentage error (MAPE) value less than 30 % is selected in order to find the result with the least error [7], [23], [24].

3. Results and Discussion

The results of the forecasting model of the CO_2 emission, Population growth, and Real GDP classified by each category of the production. This research can be summarized as follows:

Unit Root Test: with the Augmented Dickey-Fuller test is shown in Table 1.

TABLE 1 .UNIT ROOT TEST AT LEVEL

Variables	Lag	ADF Test	MacKinnon Critical Value			Status
			1 %	5 %	10 %	
ln (CO_2)	1	–2.05	–4.12	–3.27	–3.05	I(0)
ln (Population)	1	–2.13	–4.12	–3.27	–3.05	I(0)
ln (GDP)	1	–3.01	–4.12	–3.27	–3.05	I(0)

Table 1: the ADF Test Statistic at level of all variables indicates a variable unit root component or non-stationary. For instance, the calculated value from ADF is all lower than the critical value from the table at the significance level of 1 %, 5 % and 10 %. Thus, it requires the first difference to characterize the variables as Stationary. This research has shown that all stationary variables at the first differencing contain Carbon Dioxide (CO_2), population growth (Population growth), and Real GDP (GDP). The value from the test in accordance with "Tau-test" is greater than the all "Tau-critical" at the first difference, results can be seen in Table 2.

TABLE 2 .UNIT ROOT TEST AT THE FIRST DIFFERENCE

Variables	Lag	ADF Test	MacKinnon Critical Value			Status
			1 %	5 %	10 %	
ln (CO_2)	1	–4.39	–4.22	–3.36	–3.25	I(1)
ln (Population)	1	–4.84	–4.22	–3.36	–3.25	I(1)
ln (GDP)	1	–5.46	–4.22	–3.36	–3.25	I(1)

3.1. *Result of the Co-integration Test*

The result in Table 2 shows that all variables are Stationary at the first difference to test Co integration by using the method of "Jansen Juselius" shown in Table 3.

TABLE 3 .CO-INTEGRATION TEST BY JOHANSEN JUSELIUS

Variables	Hypothesized No. of CE(S)	Trace Statistic Test	MacKinnon Critical Value		Max-Eigen Statistic Test	MacKinnon Critical Value		Status
			1 %	5 %		1 %	5 %	
Δ ln (CO_2)	None**	275.65	19.75	15.41	201.34	15.68	14.07	I(1)
Δ ln (Population)	At Most 1**	74.71	5.75	3.16	74.71	5.75	3.16	I(1)
Δ ln (GDP)								

In terms of the result, the "Co-integration test" shows that the model is Co-integrated, because the Trace Test is 275.64, which is higher than the critical value at significance level of 1 % and 5 %, while the Maximum Eigen value test gives 201.34, which is higher than the critical value significance level of 1 % and 5 %.

3.2. The Result of ARIMAX Model

3.2.1. ARIMAX Model 1 (2,1,1)

$$\Delta\ln(CO_2)_t = -0.44 + 3.79\Delta\ln(CO_2)^{**}_{t-1} + 3.34\Delta\ln(CO_2)^{**}_{t-2} + 5.03\Delta\ln(\text{Population})^{**}_{t-1} + 6.43\Delta\ln(GDP)^{**}_{t-1} + 3..45MA^{**}_1 + 3.91ECM^{**},$$

$$\Delta\ln(\text{Population})_t = -0.39 + 5.35\Delta\ln(\text{Population})^{**}_{t-1} + 2.97\Delta\ln(\text{Population})^{**}_{t-2} + 6.91\Delta\ln(CO_2)^{**}_{t-1} + 4.63\Delta\ln(GDP)^{**}_{t-1} + 2.5MA^{*}_1 + 4.01ECM^{**},$$

$$\Delta\ln(GDP)_t = -0.21 + 3.44\Delta\ln(GDP)^{**}_{t-1} + 2.56\Delta\ln(GDP)^{**}_{t-2} + 4.32\Delta\ln(\text{Population})^{**}_{t-1} + 2.99\Delta\ln(CO_2)^{**}_{t-1} + 3.11MA^{**}_1 + 2.98ECM^{*},$$

where

**	significance α = 0.01;
*	significance α = 0.05;
R^2	0.97;
Adj. R^2	0.95;
Durbin-Watson stat	2.20;
F-statistic	277.05 probability is 0.00;
ARCH-test	33.41 probability is 0.1;
LM-test	1.65 probability is 0.10 and response test χ^2 > critical is significance.

From the ARIMAX Model 1 (2,1,1) its analysis indicates that this studying model is free from Heteroskedasticity and Autocorrelation. In addition, the ECM parameters are 3.91, 4.01, and 2.98, meaning that, when residual values are taken from long term equation co-integration to be another independent variable, the coefficients are 3.91, 4.01, and 2.98 respectively.

3.2.2. ARIMAX Model 2 (2,1,2)

$$\Delta\ln(CO_2)_t = -0.22 + 3.65\Delta\ln(CO_2)^{**}_{t-1} + 2.78\Delta\ln(CO_2)^{**}_{t-2} + 3.75\Delta(\text{Population})^{**}_{t-1} + 2.98\Delta\ln(GDP)^{**}_{t-1} + 2.03MA^{*}_1 + 2.55MA^{*}_2 + 4.01ECM^{**},$$

$$\Delta\ln(\text{Population})_t = -0.53 + 4.11\Delta\ln(\text{Population})^{**}_{t-1} + 3.79\Delta\ln(\text{Population})^{*}_{t-2} + +6.04\Delta\ln(CO_2)^{**}_{t-1} + 2.59\Delta\ln(GDP)^{**}_{t-1} + 2.09MA^{*}_1 + 2.57MA^{*}_2 + 3.14ECM^{**},$$

$$\Delta\ln(GDP)_t = -0.06 + 2.81\Delta\ln(GDP)^{**}_{t-1} + 2.71\Delta\ln(GDP)^{**}_{t-2} + 5.71\Delta\ln(\text{Population})^{**}_{t-1} + 3.89\Delta\ln(CO_2)^{**}_{t-1} + 2.15MA^{**}_1 + 1.88MA^{*}_2 + 2.72ECM^{*},$$

where

Durbin-Watson stat 2.25;

F-statistic	310.15 probability is 0.00;
ARCH-test	27.81 probability is 0.1;
LM-test	1.67 probability is 0.15 and response test χ^2 > critical is significance.

From the ARIMAX Model 1 (2,1,2), the Auto Regressive (AR), Integrated (I) and Moving Average (MA) values show the results of this analysis are not problematic to be Autocorrelation. Also, it is found that the ECM parameters are 4.01, 3.14, and 2.72. This basically means that when taking Residual values from long term equation Co-integration to be another independent variable, the coefficients are of 4.01, 3.14, and 2.72, and they are significant. This shows that independent variables can explain the variance as detailed above or the deviation from the long-run equilibrium is increased by 40.1 %, 31.4 %, and 27.2 %, respectively. The adjustment was statistically significant.

3.3. The Results of Forecasting Model

In the forecasting, the ARIMAX Model 1 (2,1,1) is applied for 15 years (2016–2030) forecasting, and the ARIMAX Model 2 (2,1,2) is deployed for 30 years (2016–2045) forecasting. The forecasted results are shown in Fig. 1 and Fig. 2.

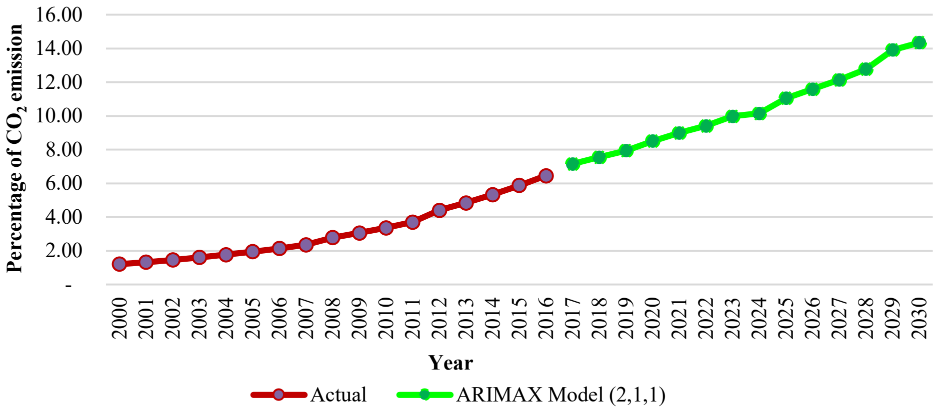

Fig. 2. Forecasting from ARIMAX Model 1 (2,1,1).

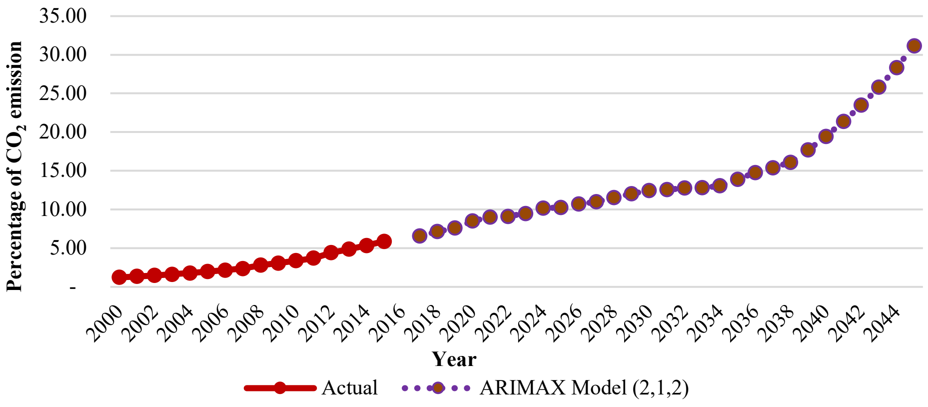

Fig. 3. Forecasting from ARIMAX Model 2 (2,1,2).

From Fig. 1, the x-axis shows the years 2000 to 2030, and the Y axis is the percentage of CO_2 emissions. For Fig. 2, the x-axis shows the years 2000 to 2044, and the Y axis is the percentage of CO_2 emissions.

The forecasted results have found that in model 1 (2016–2030) CO_2 emissions volume increased steadily and on average rising up to 14.35 % in 2030 and in t model 2 (2016–2045) CO_2 emissions volume increased steadily as well and on average rising to 31.15 % in 2045. However, the model 1 and model 2 were tested for the effectiveness of the model compared to the actual value, and it has found that both models are highly effective with the low deviation, which later can be used in decision making with MAPE equivalent to 1.01 and 1.58, respectively, (less than 3 %) and test results showed that correlogram, the modeling value, can be used as the best model for predicting and forecasting the lowest tolerances value.

4. Conclusions

The study with the application of the ARIMAX Model in the prediction has found that model 1 with the scale of 15 years forecasted in between 2016 to 2030, the rate of CO_2 emissions continuously increases. Whereas the model 2 with the scale of 30 years forecasted in between 2016 to 2045, it indicates that the rate of CO_2 emissions greatly increases as well. From this study, a conclusion can be drawn that Thailand's economy is continuously growing along with the increment in Thai population growth, and that affects the environmental aspect resulting an increase of CO_2 emissions.

Based on Thailand's past assumptions, it is found that using simple models, such as regression, the analysis results fail to provide the actual data towards the change and impact on the environment. This is to say that the model is highly Spurious, which results in an error in forecasting. When it comes to defining the country's policies, it can be very misleading because autocorrelation, heteroskedasticity, and multicollinearity are not eliminated. The above failure is basically caused by inaccurate forecasts. Therefore, the ARIMAX Model from this research is designed and manages to eliminate the above elements. The accuracy and preciseness of the data have been clearly reflected in the data, which has resulted in the correct application of national policies and sustainable development.

Hence, the Thai government must take action to ensure that the economy, societies and environment are developed and preserved. Otherwise, massive destruction may take place, and sustainable development may disappear.

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