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Research Article

VARIMAX MODEL TO FORECAST THE EMISSION OF CARBON DIOXIDE FROM ENERGY CONSUMPTION IN RUBBER AND PETROLEUM INDUSTRIES SECTORS IN THAILAND

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ABSTRACT

This study aims to analyze the forecasting of CO_2 emission from the energy consumption in the Rubber, Chemical and Petroleum Industries sectors in Thailand. The scope of research employed the input-output table of Thailand from the year 2000 to 2015. It was used to create the model of CO_2 emission, population, GDP growth and predict ten years and thirty years in advance. The model used was the VARIMAX Model which was divided into two models. The results show that from the first model by using which predicted the duration of ten years (2016–2025) by using VARIMAX Model (2,1,2), On average, Thailand has 17.65% higher quantity of CO_2 emission than the energy consumption sector (in 2025). The second model predicted the duration of 30 years (2016–2045) by using VARIMAX Model (2,1,3) shows that Thailand has average 39.68% higher quantity of CO_2 emission than the energy consumption sector (in 2025). From the analyses, it shows that Thailand has continuously higher quantity of CO_2 emission from the energy consumption. This negatively affects the environmental system and economical system of the country incessantly. This effect can lead to unsustainable development.

Keywords: rubber, chemical and petroleum industries sectors; population; forecasting model; energy consumption; CO_2 emission; GDP growth

INTRODUCTION

Nowadays, this global problem about GHG emissions is most worrying because, as an issue that affects food security within many Countries [Office of the National Economic and Social Development Board (NESDB) 2015], it would have a major effect in the long term [Asian Development Bank (ADB) 2014] because it will impact the global supply chain [Thailand Development Research Institute (TDRI) 2007, Alizadeh, Aminnayeri 2012]. However, relevant authorities have decided to give priority to this problem and find solutions together [NESDB 2015]. The records of the IPCC found that there is a major release of CO_2 and this causes up to 95.11% of GHG emission [ADB 2014].

Development plans of each country stipulated in the previous paragraph need to follow a sustainable Development Model [Leontief 1986], which is said to almost certainly lead to growth and develop of 3 aspects of economic, social and environmental criteria because sustainable development will contribute to any country's steady growth [Mamlook et al. 2009].

Thailand is one of those countries aiming to create sustainable development [ADB 2014], along the lines mentioned in the previous paragraph [NESDB 2015], and that Thailand has developed an economy making a healthy contribution to GDP but struggling to attract revenue income into the country by focusing on producing goods and services then exporting them, generating income flowing into the country [ADB 2014, Pappas 2008]. They try to raise the income distribution in an impartial manner. People in the community have a good education, a stable workforce, are generally healthy, have reduced crime, etc. It can be seen that by following this policy that Thailand is enjoying economic development and society is growing throughout the years. But what is worrying is that this may well be undone because we are no longer ensuring that the Environment is a constant theme in all policy procedures and this is becoming a major concern for the Nation. This failure to give the Environment the role it previously enjoyed is occurring in both the production and consumption fields across all Industries. However, the Rubber, Chemical and Petroleum Industries sectors also have a high energy cost (67%) as shown in the figure 1 [NESDB 2015]. Similarly, there is an adverse effect on the environment [Osorio et al. 2015]. Based on similar reasoning to the above, the government is planning for the nation effectively and sustainably.

Hence, the plan for a sustainable development model for the country as a whole is not working effectively in spite of being actively embraced by strong management teams throughout Thailand [ADB 2014]. The researcher has been emphasizing about such matters and has tried to create supplementary tools to use to ensure this country has a plan in place for the accurate implementation, without any mistakes, of a sound policy which focuses on the important 3 aspects of economic, social and environmental aspects simultaneously [NESDB 2015].

This research has focused on representing 3 aspects of economic policy, namely the GDP growth, good social attitudes amongst the Population and a great Environment. Is CO_2 forecast modeling the best model to bring about the prophecy to analyze all of the quantity, direction, relationship with others issues in a way which is able to influence the size of the change with of elasticity for the error decision to be as low as possible?

MODEL AND METHODOLOGY

VARIMAX Model

VARIMAX Model is a model that the researcher has created to bring three concepts and knowledge, namely, ARIMA Model mixed with VAR Model and Exogenous Variable used in the model. This is a model that can be used for both good and short-term forecasting. This research can be summarized as following:

Vector Autoregressive -Moving Average Model (VARMA Model or VAR Model) describes the evolution of a set of k variables (called endogenous variables) over the sample period (t = 1, ..., T) as a linear function of only their past values. The variables are collected in a k × 1 vector y_t, which has as the ith element, $y_{i,t}$, the observation at time "t" of the ith variable. A p-th order VAR, denoted VAR(p), is

$$y_t = \alpha + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \\ + \ldots + \beta_p y_{t-p} + \varepsilon_t \quad (1)$$

where: the l-periods back observation

y_{t-l} is called the l-th lag of y,

c is a k×1 vector of constants (intercepts),

A_i is a time-invariant k×k matrix and

e_t is a k×1 vector of error terms satisfying

1. $E(e_t) = 0$, every error term has mean zero
2. $E(e_t e_t') = \Omega$, the contemporaneous covariance matrix of error terms is Ω
3. $E(e_t e_{t-k}') = 0$, for any non-zero k there is no correlation across time

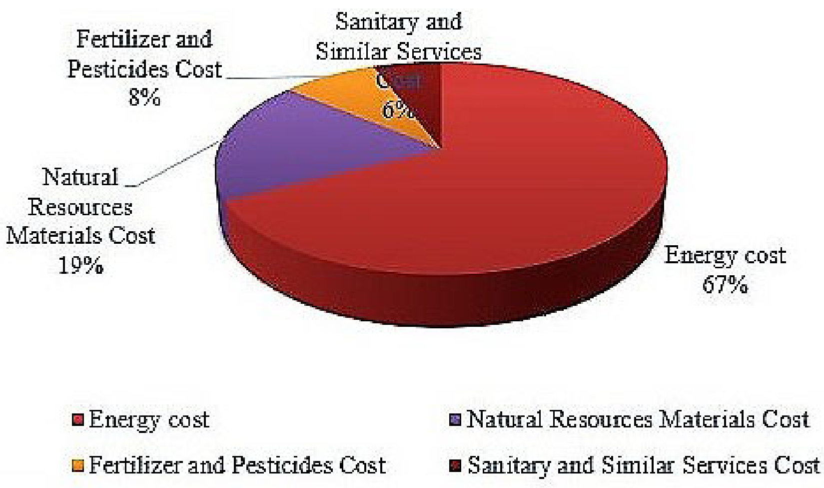

Figure 1. The proportion of environmental cost

Standard VAR and Structural VAR

Consider the example of First – Order Vector Autoregressive, the second variable is the y_t and x_t

$$y_{t,1} = \alpha_1 + \beta_{11} y_{t-1,1} + \beta_{12} y_{t-1,2} + x_{t,1} \qquad (2)$$

$$y_{t,2} = \alpha_2 + \beta_{21} y_{t-1,1} + \beta_{22} y_{t-1,2} + x_{t,2} \qquad (3)$$

In a VAR(2) model, the lag 2 values for all variables are added to the right sides of the equations. In the case of three x-variables (or time series) there would be six predictors on the right side of each equation, three lag 1 terms and three lag 2 terms.

In general, for a VAR(p) model, the first p lags of each variable in the system would be used as regression predictors for each variable.

VAR models are a specific case of more general VARMA models.VARMA models for multivariate time series include the VAR structure along with moving average terms for each variable. More generally yet, these are special cases of ARIMAX models that allow for the addition of other predictors that are outside the multivariate set of principal interest.

Equation (2) and (3) called Structural VAR or The Primitive System, which is similar to the Structural Equations in the continuity equation (Simultaneous – Equation System) under the Structural VAR, Place before that, each variable is determined by the lagged variable of itself and the other variables have been determined by the other variables in the current period (Contemporaneous Value of Endogenous Variables) as well as annoy value that called "Shocks" or "Innovations". The individual annoyances show or represent changes result of the each within the variables. The details as follows;

VAR analysis is using the Impulse Response Functions, details below;

$$B X_t = \Gamma_0 + \Gamma_1 X_{t-1} + \varepsilon_t \qquad (4)$$

From equation (4) would be written in terms of the variables associated with the residual

Impulse Response Function is the primary key for the VAR Model to analyze the simulation Shock results to the Endogenous variables. In forecasting and methodology used to consider the changes of Shock or Innovation as a Response to how the variable research that conducted education in the volume and direction.Which has the following steps:

Step 1 Use the variable that is stationary in relate to the same form as ARIMA Model.

- Step 2 Find Lag Intervals for Endogenous selected models that provide AIC or SC at the lowest, comparison model by AIC or SC value. It must be a model with the same parameters and same Functional form, only the amount of Lag could be different.
- Step 3 The test for each pair of variables Impulses Response to examine relation of variables that how affect to each other in any negative or positive ways including how long the impact continued.
- Step 4 Select the model is the best model to create forecast model and monitoring forecast accuracy by using RMSE, MAPE, and MAE, and then, determine the actual value again.
- Step 5 Check for the accuracy of forecasting for the purpose of evaluating the out of sample forecast capability, the forecasting accuracy is examined by calculating three different evaluation statistics: the root mean square error (RMSE), the mean absolute (MAE), and the mean absolute percentage error (MAPE) These are expressed as follows:

$$\text{RMSE} = \sqrt{\sum_{i=1}^{n} (F_i - A_i)^2 / n} \qquad (5)$$

$$\text{MAE} = \sum_{i=1}^{n} \left| F_i - A_i \right| / n \qquad (6)$$

$$\text{MAPE} = \sum_{i=1}^{n} \left| \left(F_i - A_i \right) // A_i \right| / n \times 100 \qquad (7)$$

where: *Fi* and *Ai* are the forecasting and actual value, respectively, and n is the total number of predictions. For this research, the model that has MAPE value less than 30% is selected in order to find the result with the least error.

RESULTS AND DISCUSSION

The results of the forecasting model the CO_2 emission, population, GDP growth are classified by each category of the production. This research can be summarized as following:

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

The ADF Test Statistic at level of all variables has a variable unit root component or Non Stationary i.e. the value calculated from the ADF, all lower than the critical value (Table 1). From the table at the significance level of 1%, 5% and 10%, so that it must be to qualify as Stationary by the difference moment. This research found that all variables Stationary at the first differencing included Carbon Dioxide (CO_2), population (Population), and GDP growth (GDP). The value of the test based on the "Tau-test" is greater than the all "Tau-critical" at the first difference, results in Table 2.

Result of the Co-integration test

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

As the results, "Co-integration test" showed that model is a Co-integration because of the Trace Test is 175.77, which is higher than the critical value at significance level of 1% and 5%, the Maximum Eigen value test at 159.04, which is higher than the critical value significance level of 1% and 5% (Table 3).

The result of VARIMAX Model

VARIMAX Model 1 (2,1,3)

$$\Delta\ln(CO_2)_t = -0.015 + 2.98\Delta\ln(CO_2)*_{t-1} + 3.21\Delta\ln(CO_2)**_{t-2} + 4.12\Delta\ln Population**_{t-1} + 2.33\Delta\ln(GDP)**_{t-1} + 1.75MA*_1 + 2.01MA*_2 + 1.15MA*_3 + 3.46ECM**$$

$$\Delta\ln(Population)_t = -0.125 + 3.12\Delta\ln(Population)**_{t-1} + 3.49\Delta\ln(Population)**_{t-2} + 2.96\Delta\ln(CO_2)**_{t-1} + 4.65\Delta\ln(GDP)**_{t-1} + 1.05MA*_1 + 1.75MA*_2 + 1.51MA*_3 + 2.96ECM**$$

$$\Delta\ln(GDP)_t = -0.33 + 3.69\Delta\ln(GDP)**_{t-1} + 2.75\Delta\ln(GDP)**_{t-2} + 3.13\Delta\ln Population**_{t-1} + 3.98\Delta\ln(CO_2)**_{t-1} + 2.89MA**_1 + 2.69MA**_2 + 1.97MA*_3 + 3.45ECM**$$

where ** is significance $\alpha = 0.01$,
* is significance $\alpha = 0.05$,

Table 1. Unit Root test at level

Variables	Lag	ADF Test	MacKinnon Critical Value			Status
			1%	5%	10%	
ln(CO_2)	1	-2.01	-4.35	-3.11	-3.05	I(0)
ln(*Population*)	1	-2.97	-4.35	-3.11	-3.05	I(0)
ln(*GDP*)	1	-2.73	-4.35	-3.11	-3.05	I(0)

Table 2. Unit Root test at the first difference

Variables	Lag	ADF Test	MacKinnon Critical Value			Status
			1%	5%	10%	
ln(CO_2)	1	-5.14	-4.35	-3.11	-3.05	I(1)
ln(*Population*)	1	-5.79	-4.35	-3.11	-3.05	I(1)
ln(*GDP*)	1	-4.11	-4.35	-3.11	-3.05	I(1)

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%	
Δln(CO_2) Δln(*Population*) Δln(*GDP*)	None**	175.77	20.55	15.11	159.04	13.78	14.00	I(1)
	At Most 1**	70.05	7.25	4.55	70.05	7.25	4.55	I(1)

R-squared is 0.88,
Adjusted R-squared is 0.85,
Durbin-Watson stat is 2.25,
F-statistic is 125.15 (Probability is 0.00),
ARCH-test is 30.61 (Probability is 0.10),
LM-test is 1.45 (Probability is 0.11) and
response test ($\chi^2 > critical$) is significance.

The results of forecasting model

VARIMAX Model, is the best model that was used to predict 2 models. First, 10 years forecast (2016–2025) and the second, 30 years forecast (2016–2045) the forecast results shown in Figure 2 and Figure 3.

The results forecasts found that the VARIMAX Model (2,1,2) (2016–2025) CO_2 emissions volume increased steadily and average rising up to 17.65% in 2025, the VARIMAX Model (2,1,3) (2016–2045) CO_2 emissions volume increased steadily as well and average rising to 39.68% in 2045. However, VARIMAX Model tested the effectiveness of the model, compared with the actual value found that both models are highly effective with the low deviation can be used to decision making that was shown in MAPE equal to 1.01 and 1.16, respectively, (less than 3%) and the test results showed that Correlogram, the modeling value, can be used as the best model for predicting and forecasting the lowest tolerances value.

From review of literature of many of sources such as Jain (2010) apply Gray-Markov model, Grey-model with rolling mechanism, and singular spectrum analysis (SSA) to forecast the consumption of conventional energy in India, Hsiai-Tien Pao et al. (2012) employ the NGBM (nonlinear grey Bernoulli model) to predict carbon emission, energy consumption and real outputs, and Weijun Xu et al. (2015) establish a new model with improved GM-ARIMA based on HP Filter to forecast the final energy consumption of Guangdong Province in China, etc. This study research related to any previous research, found that no particular forecasting model could accurately ensure the lowest tolerances, whilst keeping closest to the Actual data. One reason is clearly, lack of

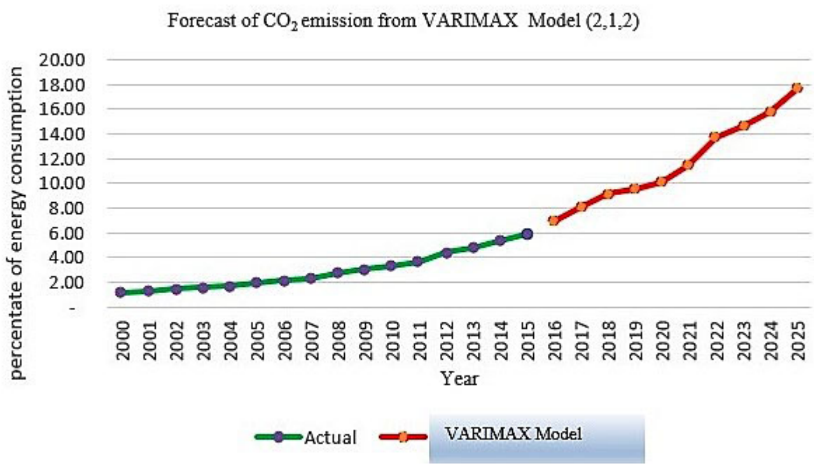

Figure 2. Forecasting from VARIMAX Model (2,1,2)

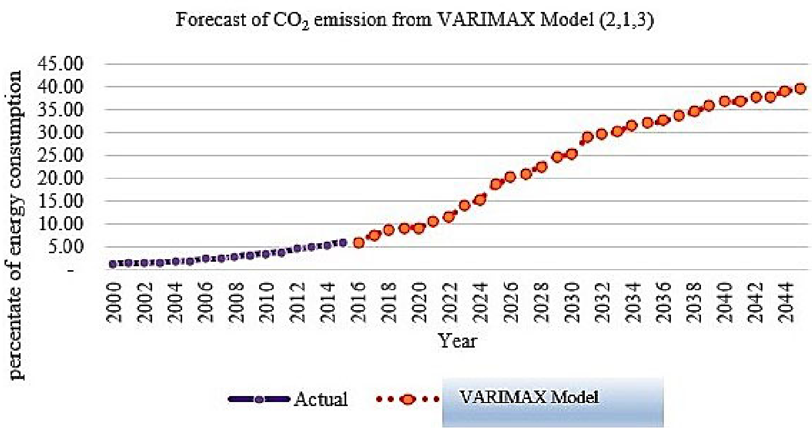

Figure 3. Forecasting from VARIMAX Model (2,1,3)

related variables to analyze simultaneously or using statistical models that thoughtless to be the BLUE. The researcher was farsighted enough to be aware of the problem and has created the Forecasting model which considers all relevant variables into the model. Forecasting using the VARIMAX Model has been used to bring research results and achieve maximum benefit for the nation as a guide for further studies in the future.

CONCLUSION

The forecast result by mixing the VARIMAX Model found that 1) model 1 – forecast in 10 years (2016–2025), the rate of CO_2 increased 17.65%, and 2) model 2 (2016–2045) – increased 39.68%. So if this nations contribution towards the CO_2 rising steadily, in this way will never cause any sustainable development. Eventually, it is the trouble to food security which will affect the economic and community decline, as well. In consequence, the important instruments to environmental management are forecasting the CO_2, Population, and green GDP, to be applying for the maximum benefit to that country and continue to set the sustainable development occurring for those countries.

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