The Future Environmental Impact in the Food Industry Sector of Thailand and China as a Result of Economic and Social Growth based on Sustainable Development Policy

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Abstract

The objective of this study is to forecast the effects of economic growth along with population growth on Greenhouse gas emission in Food Industry sector of Thailand and China due to Economic and Social growth under Sustainable Development policy for the year 2018 to 2045. The study has found that Thailand's economic growth rate steadily rises to 23.45 percent in 2045 and the population has an increase by 7.24 percent. In the meanwhile, the greenhouse gas from the consumption in the food industry sectors would have been increased by 39.2 percent. To China's economic growth rate, there is also a continuous rise by 45.9 percent while its population grows by 5.32 percent. At the same time, its greenhouse gas from the consumption in the food industry sector has increased by 12.75 percent. However, based on the research investigated in the food industry sector from 2018 to 2045, the environmental impact of Thailand has continuously increased and its impact is much higher than in China. The main reason is that China has a strict policy and seriously implements the carrying capacity policy. In addition to this, China has succeeded at promoting the consumption of clean technology. Therefore, as far as Thailand’s sustainable development is concerned, Thailand shall take a serious action to implement the rigorous policy of carrying capacity.

Keywords: sustainable development, population growth, GDP growth, income per capita, greenhouse gas, carrying capacity, clean technology, plan and policy, sustainability

ผลกระทบต่อสิ่งแวดล้อมในอนาคตในภาคอุตสาหกรรมอาหาร สำหรับประเทศไทย และประเทศจีน จากการเติบโตทางเศรษฐกิจและสังคมภายใต้นโยบายการพัฒนาที่ยั่งยืน

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บทคัดย่อ

การศึกษาครั้งนี้มีวัตถุประสงค์เพื่อพยากรณ์ผลกระทบของการเติบโตทางเศรษฐกิจและการเติบโตของประชากรต่อการปล่อยก๊าซเรือนกระจกในภาคอุตสาหกรรมอาหารของประเทศไทยและประเทศจีนภายใต้นโยบายการพัฒนาที่ยั่งยืน สำหรับกรณีประเทศไทย พ.ศ. 2561 ถึง พ.ศ. 2588 พบว่า อัตราการเติบโตทางเศรษฐกิจของประเทศไทยเพิ่มขึ้นอย่างต่อเนื่องเป็น 23.45 % ในปี 2588 และประชากรเพิ่มขึ้น 7.24 % ในขณะเดียวกันก๊าซเรือนกระจกจากการบริโภคในภาคอุตสาหกรรมอาหารจะเพิ่มขึ้น 39.2% สำหรับกรณีของประเทศจีน พบว่า อัตราการเติบโตทางเศรษฐกิจของจีนนั้นยังเพิ่มขึ้นอย่างต่อเนื่องโดย 45.9% ในขณะที่จำนวนประชากรเพิ่มขึ้น 5.32% โดยก๊าซเรือนกระจกจากการบริโภคในภาคอุตสาหกรรมอาหารเพิ่มขึ้น 12.75% อย่างไรก็ตามจากการวิจัยที่ตรวจสอบในภาคอุตสาหกรรมอาหารตั้งแต่ปี 2561 ถึง 2588 แสดงให้เห็นผลกระทบด้านสิ่งแวดล้อมของประเทศไทยได้เพิ่มขึ้นอย่างต่อเนื่องและผลกระทบดังกล่าวสูงกว่าในประเทศจีนมาก เหตุผลหลักคือประเทศจีนมีนโยบายที่เข้มงวดและดำเนินนโยบายกำลังการผลิตอย่างจริงจัง นอกจากนี้ประเทศจีนยังประสบความสำเร็จในการส่งเสริมการบริโภคเทคโนโลยีสะอาด ดังนั้น ประเทศไทยจะต้องมีการกำหนดนโยบายการพัฒนาอย่างยั่งยืนอย่างจริงจัง และพัฒนาขีดความสามารถให้เพิ่มสูงขึ้นอย่างต่อเนื่องต่อไป

คำสำคัญ: การพัฒนาอย่างยั่งยืน การเติบโตของประชากร การเติบโตของ GDP รายได้ต่อหัว ก๊าซเรือนกระจก ขีดความสามารถ เทคโนโลยีสะอาด แผนและนโยบายความยั่งยืน

Introduction

Currently, Thailand has been operating and carrying out on policies in which it aims to ensure on continuous economic growth. Adding to this, the government has boosted in various investment on mega projects, such as electric trains, major heavy industries and other mega projects, as well as encouraged to have a bigger number of both domestic and foreign investors (Asian Development Bank: ADB, 2014) (Office of the National Economic and Social Development Board: NESDB, 2015; Sutthichaimethee, 2017).

As of those various policies implemented, the economy continues to grow, and the people in the country also have a higher per capita income. Population has increased in consumption as there is an indication and measurement from an increased Gross Domestic Product (GDP) index. Particularly, the food industry sector is considered to be an important sector in the national consumption and generation of national revenue. Also, this sector has positioned in the significant top sectors contributing in the national income of Thailand and other ASEAN countries (Sutthichaimethee, 2016; Sutthichaimethee & Sawangdee, 2016; Thailand Development Research Institute: TDRI, 2007).

However, Thailand in the ASEAN region has continued to grow as well. In particular, China has the continuous increment in GDP per capita, and manages to increase relatively in the market share. Both countries share a similarity in term of policies used to accelerate the growth in economy, heavy industrial investment, foreign funding for a production in own country, and supportive investment policy, including investment tax levy and export activities (Sutthichaimethee & Ariyasajjakorn, 2017a, b; Srieakbungrod & Sutthichaimethee, 2018). However, there is also a difference between these two countries in term of energy conservation promotion. In China, there are energy management policies, strict regulations on environmental protection and a special court to oversee the above matter. Unlike China, Thailand has no clear practice in the same matter (Sutthichaimethee & Ariyasajjakorn, 2017 c; Sutthichaimethee, 2018).

As for the current trend of environmental conservation is concerned, many countries have been trying for a long time to do so. Of course, each country has different policies and approaches. There can be a policy of Eco-friendly use and consumption, Clean technology, on-going Corporate Social Responsibility: CSR campaigns as well as the implementation of various penalties for those who destroy the environment. With that, the researcher is, therefore, interested and wants to forecast how much the environment will be possibly destroyed in 2018-2045 due to the economic and social growth. By doing a comparison between two contexts of Thailand and China., Thailand can be possibly at a better sight towards the national development in the sustainable development context (Sutthichaimethee & Ariyasajjakorn, 2017b; Sutthichaimethee & Tanoamchard, 2015).

In the studies of relationship between economic growth, population growth, and environmental betterment as illustrated below, many researches were reviewed and referred. For instance, a study conducted by Mulugeta et al. (2012) has shown that energy consumption is an important driving force towards the economic growth, and the study was investigated by forming an economic growth hypothesis. In Saudi Arabia, Alkhathlan and Javid (2013) examined the relationship between economic growth, energy consumption, and CO_2 emissions. Apparently, they had found that the rise of CO_2 emissions was due to the increment of income per capita. As of a broader study scope, Arouri et al. (2012) has investigated the relationship between the real GDP, CO_2 emissions, and energy consumption in 12 selected Middle East and North African countries (MENA) using a bootstrap panel method. They found a clear evidence indicating that CO_2 emissions are significantly affected by energy consumption. Additionally, Acaravci and Ozturk (2010) studied the causality between various factors, including energy use, economic growth, and CO_2 emissions, with a sample size of 19 European countries. By using a technique of autoregressive distributed lag (ARDL) and the error-correction Granger causality test, they were able to find only the long-run relationship between those factors in certain countries, such as Iceland, Switzerland, Denmark, Portugal, Germany, Greece, and Italy. Furthermore, Menyah and Wolde-Rufael (2010) produced a similar research study on the causality between energy consumption, pollutant emissions, and economic growth in South Africa with the same approach of ARDL. As of their finding, it revealed the long-run relationship between variables. In addition to this, Sulaiman and Abdul-Rahim (2017) conducted an investigation of a three-way linkage relationship between economic growth, CO_2 emissions, and energy consumption in Malaysia during the period of 1975–2015. The study's result presented that the rise of both factors; energy consumption and economic growth, do contribute to the rise of CO_2 emissions.

In connection to CO_2 emissions, many evidences were revealed through different studies of relational focus saying about the influence of CO_2 emissions. Akpan and Akpan (2012) conducted a study pertaining to CO_2 emissions in Nigeria, and later found that an economic growth improves when carbon emissions are rising, and this rise of CO_2 emissions is positively associated with electricity consumption. While Sulaiman (2014) used an application of the Toda and Yamamoto causality test to study in the same area. He later provided a claim that CO_2 emissions do support an economic growth, while energy consumption contributes to the increase of CO_2 emissions. However, Manu and Sulaiman (2017) adapted the simple ordinary least squares (OLS) approach to investigate the relationship between economic growth, energy consumption, and CO_2 emissions in Malaysia. This study covered the period of 1965–2015, and they later found that CO_2 emissions are reduced when the income is raised. In the meantime, it increases when the trade openness increases.

In relation to this study, it is also instrumental and necessary mentioning the Grey system and Autoregressive Integrated Moving Average by Lotfalipour, Falahi, and Bastam (2013). Their study optimized the above models to predict CO_2 emissions in Iran. Their finding has evidenced that the models could produce a more accurate result than any other method, and their estimation was up to 925.68 million tons of carbon dioxide emissions by 2020 in equivalence of 66 percent growth compared to 2010. Whereas Li (2016) evaluated the CO_2 emissions reduction under different scenarios for the year of 2016 and 2020 in Beijing. He applied the Back Propagation (BP) neural network optimized by the improved Particle Swarm Optimization Algorithm. However, his investigation showed that the model was not effective enough to provide high precision. In the meantime, Zhao, Huang, and Yan (2018) forecasted CO_2 emissions in China from 2017 to 2020 with the implementation of some selected models: the single LSSVM model, the LSSVM model enhanced by the particle swarm optimization algorithm (PSO-LSSVM), and the Back Propagation (BP) neural network model. The above prediction verified that structural factors would have a significant impact on CO_2 emissions by 2020. Simultaneously, this allows China to keep its promise to reduce greenhouse gas emissions by 2030. While Dai, Niu, and Han (2018) proposed to adapt the MSFLA-LSSVM model in CO_2 emissions prediction in China from 2018 to 2025. They concluded that China's CO_2 emissions would exhibit a slow growth trend for the next few years. With such finding, it puts China's CO_2 emissions literally in control for the future in which China could start to reduce the greenhouse effect in time.

With various researches and studies put for reviews, the study found that most above discussed literatures have demonstrated in term of the relationship focus with the implementation of old models. In addition to this, there is still a lack of variables reasoning analysis with short-term forecasting capability. Therefore, this study sees such gaps here, and later produces the VARIMAX Model as to serve in the long-term analysis at most efficient for a better future use.

Objective

The objective of this study is to forecast the effects of economic growth along with population growth on Greenhous gas emission in Food Industry sector of Thailand and China resulting from Economic and Social growth based on Sustainable Development policy for 2018-2045.

Model and Methodology

VARIMAX Model

The VARIMAX Model is a statistical model that is used and applied in advanced statistics as to avoid spurious problems. In the construction of the forecasting model, it is necessary to use time series data, because the data is very accurate when comparing with primary data, also known as information data. Besides, the optimization of such data is very useful for analysis and later forecasting. This is because it can evaluate errors and measure performances of the model, while enabling to produce the model with the Best Linear Unbiased Estimate (BLUE) (Dickey & Fuller, 1981; Enders, 2010) in order to reduce the issue of Heteroskedasticity, Multicollinearity, and Autocorrelation (Sutthichaimethee & Ariyasajjakorn, 2017c).

Vector Autoregressive -Moving Average Model (VARMA Model or VAR Model) explains 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 i th element, $y_{i,t}$, the observation at time "t" of the i th variable. A p-th order VAR, denoted VAR(p), is

$$y_t = \alpha + \beta_1 y_{t-1} + \beta_2 y_{t-2} + ... + \beta_p y_{t-p} + \varepsilon_t$$

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

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 VARIMAX models that allow for the addition of other predictors that are outside the multivariate set of principal interest (Harvey, 1989).

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”(MacKinnon, 1991). 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;

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

From equation (1) 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 Testify the data to be stationary data by Unit root test based on Augment Dickey and Fuller concept.
- 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:

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

$$\text{MAE} = \sum_{i=1}^{n} \left| F_i - A_i \right| / n \tag{3}$$

$$\text{MAPE} = \sum_{i=1}^{n} \left| \left(F_i - A_i \right) // A_i \right| / n \times 100 \tag{4}$$

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 (Harvey, 1989; Cryer & Chan, 2008).

For most Non-stationary data, it shall be justified with Augmented Dickey Fuller method (Dicky & Fuller, 1981) as it is shown below.

$$\Delta Y_t = \delta_1 Y_t + \sum_{i=2}^{p} \beta_i \Delta Y_{t-i+1} + \varepsilon_t$$

(5)

$$\Delta Y_t = \alpha_1 + \delta\ Y_{t-1} + \sum_{i=2}^{p} \beta_i \Delta Y_{t-i+1} + \varepsilon_t$$

(6)

$$\Delta Y_t = \alpha_1 + \alpha_2 T + \delta\ Y_{t-1} + \sum_{i=2}^{p} \beta_i \Delta Y_{t-i+1} + \varepsilon_t$$

(7)

From the mentioned equations, p value is the lagged value of first difference to the variable, and this can be done by estimating the Unit Root and associating with the Augmented Dickey Fuller method as stated below:

$$\Delta Y_t = \alpha_1 + \alpha_2 T + \delta\ Y_{t-1} + \sum_{i=2}^{p} \beta_i \Delta Y_{t-i+1} + \varepsilon_t$$

(8)

From this equation, it considers three problems, specifically the autocorrelation in εt is set to have White Noise property in which the Error Term has 0 mean, and this lies constant with the hypotheses below:

H0 :δ = 0 , Non-Stationary

H1 :δ < 0 , Non-Stationary

If tau-statistics of the efficiency δ are in the absolute term form, more critical values are showing in the ADF table (Dicky & Fuller, 1981), and this rejects the major hypothesis, indicating that time series of variables are stationary. Hence, it is possible to say that ΔY_t Integrated Number d represented by $\Delta Yt \sim I(d)$.

The model must only be the Best Model as to produce a more accurate forecasting result, and the problems of the model shall be tested in order to avoid any potential errors that might occur, following these three tests.

1) Test the Autocorrelation by using Lagrangian Multiplier Test - LM test

- LM Test is applied when there are lagged variables of dependent variables appeared to be independent variables in the equation. In this test, it is not recommended to use Durbin-Watson. In addition, the LM is to find out more whether Error Terms have high level autocorrelation problem. The testing method is demonstrated below:

$$Y_t = \alpha_0 + \alpha_1 X_t + \beta_1 U_{t-1} + \beta_2 U_{t-2} + ... + \beta_p U_{t-p}$$

(9)

If F Critical value is at the designated significant level, while $\chi^2 p$ and $F_{m,n-k}$ – Test Statistic is bigger than the value of Critical χ^2, the major hypothesis is then rejected. In this context, at least one β has the value differing from 0, and this is to say that Autocorrelation problem exists.

2) Test Heteroskedasticity by using ARCH Test

- ARCH Testing is one of the methods to check Heteroskedasticity in time series data. When the Residual is retrieved, the lagged variables of the residual is computed with the Residual by using the value of F and nR^2, that has Chi- Square distribution. Here, if there is Heteroskedasticity, the hypothesis is then rejected. This can be clarified by seeing the critical value of $\chi^2 p$ from the table at the selected significant level has lower in value than the $\chi^2 p$ statistical test.

3) Test Multicorrelinearity by applying a correlation test and responses from Correlogram value compared to chi-square value.

The components of VARIMAX Model

To this VARIMAX Model, it considers four main elements, namely Auto Regressive (AR), Moving Average (MA), Exogenous Variable and Integrated (I) (Sutthichaimethee, 2017; Cryer & Chan, 2008; Dong, Coa, & Lee, 2015). The model is shown as follows.

1. Auto Regressive (AR) has the following characteristics:

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + ... + \beta_p Y_{t-p} + \varepsilon_t$$

(10)

Where $\beta_1 ... \beta_p$ denotes as parameters, α goes as a content, and ε_t is the random variable (white noise).

2. Moving Average (MA) uses the error term from the forecasting to see the differences between variables that actually happen (Y Actual) with the dependent variables (Y Forecast) or $\varepsilon_t = Y_{at} - Y_{ft}$ in the past to help in forecasting the variables required needed in the future. This can be seen below.

$$Y_t = \delta + \varepsilon_t - \gamma_1 \varepsilon_{t-1} - \gamma_2 \varepsilon_{t-2} - ... - \gamma_q \varepsilon_{t-q} \quad (11)$$

Where Moving Average of Order q or MA(q) by q means that the last order of error value is used.

3. Integrated (I) is to see the difference of variables. It is very crucial to know the difference, because the VARIMA is non-stationary. With that, it is later possible to convert it to stationary with the difference in p order.

Results and Discussion

The results of the forecasting model of the Greenhouse gas (GHG), Population growth, and Real GDP are classified by each category of the production. This research can be summarized as follows:

The result of VARIMAX Model

(1) VARIMAX Model 1 (2,1,2) for Thailand

$$\begin{aligned}\Delta \ln(GHG)_t = & -0.22 + 4.75\Delta \ln(GHG)**_{t-1} + 2.17\Delta \ln(GHG)**_{t-2} + \\ & 4.69\,\Delta \ln Population \; **_{t-1} + \\ & 3.08\,\Delta \ln(GDP)**_{t-1} + 2.03MA*_1 + 2.05MA*_2 + \\ & 4.01ECM**\end{aligned}$$

$$\begin{aligned}\Delta \ln(Population)_t = & -0.22 + 6.04\Delta \ln(Population)**_{t-1} + \\ & 3.99\Delta \ln(Population)*_{t-2} + 3.01\,\Delta \ln(GHG)**_{t-1} + \\ & 4.12\,\Delta \ln(GDP)**_{t-1} + 2.57MA**_1 + 2.13MA*_2 + \\ & 3.14ECM**\end{aligned}$$

$$\begin{aligned}\Delta \ln(GDP)_t = & -0.11 + 2.54\Delta \ln(GDP)**_{t-1} + 4.34\Delta \ln(GDP)**_{t-2} + \\ & 2.19\,\Delta \ln Population \; **_{t-1} + \\ & 5.72\,\Delta \ln(GHG)**_{t-1} + 2.01MA**_1 + 2.05MA*_2 + \\ & 2.09ECM*\end{aligned}$$

Where ** is significance α = 0.01, * is significance α = 0.05, R-squared is 0.95, Adjusted R-squared is 0.93, Durbin-Watson stat is 2.01, F-statistic is 319.05 (Probability is 0.00), ARCH-test is 20.95 (Probability is 0.10), LM – test is 1.05 (Probability is 0.11) and response test ($\chi^2 > critical$) is significance.

(2) VARIMAX Model 1 (2,1,2) for China

$$\Delta \ln(GHG)_t = -0.35 + 2.94\Delta\ln(GHG)^{**}_{t-1} + 4.15\Delta\ln(GHG)^{**}_{t-2} + 3.09\Delta\ln Population^{**}_{t-1} + 2.75\Delta\ln(GDP)^{**}_{t-1} + 2.76MA^{*}_{1} + 1.05MA^{*}_{2} + 3.51ECM^{**}$$

$$\Delta \ln(Population)_t = -0.34 + 5.06\Delta\ln(Population)^{**}_{t-1} + 2.59\Delta\ln(Population)^{*}_{t-2} + 2.75\Delta\ln(GHG)^{**}_{t-1} + 2.59\Delta\ln(GDP)^{**}_{t-1} + 2.57MA^{**}_{1} + 2.13MA^{*}_{2} + 3.14ECM^{**}$$

$$\Delta \ln(GDP)_t = -0.21 + 5.19\Delta\ln(GDP)^{**}_{t-1} + 4.11\Delta\ln(GDP)^{**}_{t-2} + 2.41\Delta\ln Population^{**}_{t-1} + 6.54\Delta\ln(GHG)^{**}_{t-1} + 2.54MA^{**}_{1} + 1.95MA^{*}_{2} + 2.09ECM^{*}$$

Where ** is significance α = 0.01, * is significance α = 0.05, R-squared is 0.94, Adjusted R-squared is 0.92, Durbin-Watson stat is 2.02, F-statistic is 199.06 (Probability is 0.00), ARCH-test is 20.15 (Probability is 0.10), LM – test is 1.97 (Probability is 0.11) and response test ($\chi^2 > critical$) is significance.

The result obtained from the Food industry sectors prediction from the year 2018 until 2045 with the use of VARIMAX Model has shown that, in the upcoming year of 2045, Thailand's economic growth rate increases continuously to 23.45%, while the growth in population slightly changes to 7.24%. Surprisingly, the change of Greenhouse gas consumption in the food industry sector continues to grow at a rate of 39.2%. For China, the country continues to rise economic growth rate up to 45.9%. The increment in the population is only 5.32%. Whereas, the Greenhouse gas from the food industry sector consumption increases up to 12.75%, indicating the fast and high rising difference of Thailand to China.

The results of this study reflect that there is a continuous growth in the Food Industry sector of Thailand accounting for 23.45 per cent during the forecasted year of 2018 to 2045, while Thailand's economic growth is still lesser than China's economic growth by 45.9 percent. This obviously shows that China has a higher economic growth compared to Thailand. In comparison with the environmental effect (greenhouse gas), Thailand has a potential environmental impact due to GDP growth and population growth by 39.2 percent. Whereas China was only affected by 12.75 percent. As of this finding, it demonstrates that China has set up a more effective sustainable development policy as compared to Thailand, while the policy could really protect the environment at higher effective than Thailand. Moreover, Thailand's population growth is higher than in China indicating the continuous growing in Thai population and bringing a potential effect on the environment.

Therefore, Thailand must ensure to a strict policy and supportive enforcement towards Carrying Capacity and the consumption of Clean technology, for instance. If Thailand aims to achieve a greater level of the sustainable development, there must be a right implementation and adaptation of Carrying Capacity, and take an action towards those who tend to destroy the environmental surrounding. Moreover, Thailand must establish more stringent laws governing and enforcing the above policies as to fulfill the national sustainable development goals.

As many literature reviews were briefly discussed, the study is able to identify an opportunity to develop another area to explore, and that allows the study to illustrate the gap, which requires a fill and differs from other research studies in term of long-term forecasting model. The above gap is evidenced by the failure of consideration of causal factors in all variables as this might create a spuriousity and error in the implementation process in particular contexts. In a policy formation and planning, it is very crucial to obtain a study finding, that can be effectively applicable to other sectors. Although existing studies, such Alkhathlan and Javid (2013), Arouri et al. (2012), Menyah and Wolde-Rufael (2010), Sulaiman and Abdul-Rahim (2017), Akpan and Akpan (2012), Sulaiman (2014), Li (2016), Meanwhile, Zhao, Huang, and Yan (2018), and Dai, Niu, and Han (2018), were able to provide a consistency in term of relational change; the economic and social growth is improved and the environment betterment drops, there still shows the failure to response towards Sustainable Development policy. Therefore, as to increase in effectiveness towards the sustainable policy formation and planning in Thailand, this study's model has to be implemented according to particular context in each sector.

As of suggestions for any interested individuals, to align with certain context of a particular country, the exogeneous variables are to be studied and optimized in the model analysis. Also, it is crucial to perceive other influential factors, which may affect dependent variables. In addition, the set of data used shall be stationary in order to acquire the best model, and clean from Heteroskedasticity, Multicollinearity, and Autocorrelation. Those additional variables may consist of Oil Price, Industrial Structure, Carbon Intensity, Labor and Investment or other variables in line with Sustainable Development of a country where it fits.

Conclusion

In this research, with the utilization of the VARIMAX Model in the forecast, there has been given a finding of, in between 2018 to 2045, the stated rate in the result steadily rises. Besides, it indicates the sign of well-growing economy of Thailand with a positive change of population growth. Contradictable, the environmental system is prone to a destruction as the Greenhouse gas keeps increasing. Whereas, China has a rise in economy and population, but its Greenhouse gas slightly changes in rate compared to Thailand. Hence, it is obvious and necessary for Thailand to take serious actions and initiatives to ensure that the environments, economy and societies are well-developed and well-nurtured as to enhance in the sustainable developments and mitigate the possibility of any destruction to secure those assurances.

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