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A Forecasting Model on Carrying Capacity for Government's Controlling Measure under Environmental Law in Thailand: Adapting Non-recursive Autoregression Based on the Var-X Model

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ABSTRACT

This research aimed to analyze the relationship of causal factors and forecast CO₂ emissions for a 15 years period from 2020 to 2034 by applying a non-recursive autoregression vector autoregression with an exogenous model (Non-Recursive Var-X model). The Non-Recursive Var-X model has been made available for use in long-term forecasting (2020-2034), particularly in regards to the implementation of the 'Industry 4.0' policy of the Thai government. The study found that the results of the Thai government's efforts or 'governmental power' (GP) will likely lead to levels of CO₂ emissions that exceed the country's carrying capacity as determined under its national strategic plan. The findings of this study show that CO₂ emissions are expected to have a growth rate of 27.23 percent (2020-2034), reaching 95.88 Mt CO₂ Eq by 2034. The Non-Recursive Var-X model provides a mean absolute percentage error (MAPE) of 1.12% and a root mean square error (RMSE) of 1.25%. In this research, the Non-Recursive Var-X model was used and CO₂ emissions were forecasted to rise continuously over the established period. This rise exceeds the carrying capacity of Thailand according to the criteria set by the Thai government.

Keywords: Non-recursive Model, Sustainability Policy, Carrying Capacity, Energy Consumption

JEL Classifications: P28, Q42, Q43, Q47, Q48

1. INTRODUCTION

The Industry 4.0 policy of the Thai government aims to promote economic sustainability in the country, as is the case in many other countries around the world. Currently, this policy is a core component in defining many countries' national strategies. Thailand is incorporating this into both its short-and-long term policies (Achawangkul, 2017). The short term covers a 5-year framework (2020-2024), while the long term covers a 15-year framework (2020-2034). This policy is considered important for national development and to ensure consistency in economic, social and environmental aspects (Office of the National Economic and Social Development Board, 2018), especially in

the formulation of consumption strategies which do not exceed carrying capacity. This has hence become a top priority in the implementation of Industry 4.0 (Achawangkul, 2017; Office of the National Economic and Social Development Board, 2018).

From 1990 until the present (2018), the government has made various efforts to promote the development of the economy and boost national wealth, which has resulted in steady growth in gross domestic product (GDP). Various government policies have been implemented to accelerate development, including increasing export volumes across sectors, strengthening tourism, as well as increasing productivity with high skill-based production, including in the clothing and textile industry, manufacturing

and steel industry, and many other areas. Furthermore, the government has focused on increasing domestic consumption, creating innovations, and increasing revenue for foreign direct investment portfolios (National Statistic Office Ministry of Information and Communication Technology, 2018). Thailand has pursued a proactive policy primarily by reducing levied tax, providing funding to major industries, and expanding production sites to new areas (Office of the National Economic and Social Development Board, 2018).

In regards to social policy, it can be seen that the government has attempted to promote and implement social policies in parallel with economic growth, resulting in greater social development (1990). This attempt has included encouraging the use of technology and the internet, creating new employment opportunities, improving health care, strengthening social security, and promoting consumer protections (Department of Alternative Energy Development and Efficiency, 2018). With the implementation of the aforementioned policies, Thailand has shown clear development in both economic and social aspects; however, it has not come without a cost to the environment due to increased energy consumption. From 1990 to 2018, greenhouse emissions, particularly CO₂, have increased in both industrial and non-industrial sectors. This impact has resulted in a 75.91 percent increase over that period (Department of Alternative Energy Development and Efficiency, 2018, Thailand greenhouse gas management organization (public organization), 2018 Hu et al., 2015). This impact on the carrying capacity of the country has been due, in part, to the lack of a clear and precise measuring tool for the assessment of the environmental impact.

Therefore, in the formation of its Industry 4.0 policy, the government must ensure that the economy, society and environment are all taken into consideration in equal proportion to ensure sustainability (Office of the National Economic and Social Development Board, 2018; Zhao et al., 2016). Lack of accurate environment analysis, however, would make this problematic. This research, therefore, seeks to provide a useful tool for guiding Thailand policies and planning by forecasting CO₂ emissions, especially in regards to long-term forecasting (15 years), which involves a number of complexities (Armeanu et al., 2017; To and Lee, 2017; Gómez et al., 2018). This need has led the researchers to develop the "Non-Recursive Var-X model," with the aim to help the government in defining and determining the most appropriate long-term strategies, as well as add to the existing knowledge and provide a foundation for future studies.

2. LITERATURE REVIEW

This section reviews relevant studies by exploring various available forecasting models and methods used in the area of environmental measurement. There have been a few mainstream studies conducted for various purposes and contexts globally. Terêncio et al. (2019) constructed a Partial Least Squares-Path Model (PLS-PM) to investigate a connection between dam wall heights and biophysical parameters in Portugal. That study indicated that terrain slope, rainfall and sedimentary rock are among the significant variables impacting wall construction, and

that changes in these parameters would affect changes of the dam wall height. Boyd et al. (2019) used an Autoregressive Integrated Moving Average (ARIMA) to forecast daily wastewater influent flow for wastewater treatment plants (WWTPs). In this study, the ARIMA model demonstrated a satisfactory outcome in forecasting daily influent flow. Rezaeianzadeh et al. (2014) optimized the use of Artificial Neural Networks (ANNs), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Multiple Linear Regression (MLR) and Multiple Nonlinear Regression (MNL) in forecasting maximum daily flow of the Khosrow Shirin watershed in Iran. These models produced accurate predictions when the area weighted precipitation and the spatially distributed precipitation were the input for the first group of ANNs and MNL, and the second group of ANFIS and MLR, respectively. Furthermore, Ma and Li (2016) enhanced an accuracy of annual runoff forecasting at the Maduwang station of the Bahe River in China by utilizing a novel hybrid model, using a radial basis function network (RBFN) model to support the study. As a result, the hybrid model was found to enhance the sub-model, RBFN, in the accurate forecast of annual runoff series. In fact, the proposed model is now seen as superior to other forecasting models such as the Auto-Regressive Integrated Moving Average (ARIMA) and back-propagation network (BPNN). Büyükşahin and Ertekin (2019) also attempted to combine the linear and nonlinear models, and their model was proven effective in improving forecasting.

Recently, Bai and Pinson (2019) proposed an alternating direction method of multipliers (ADMM) to forecast distributed reconciliation in day-ahead wind power generation in Sardinia, Italy. This method has also been used to solve game theory optimal projection (GTOP). Furthermore, Tao et al. (2017) forecasted monthly precipitation at 138 rain gauge stations in the Yangtze River basin by implementing a hybrid least squares support vector machine (HLSSVM) model. At the same time, the LSSVM-DE was built to provide a comparison tool by combining the LSSVM and differential evolution (DE). Comparing LSSVM with LSSVM-DE, the result using LSSVM-DE proved to be more satisfactory than that of LSSVM. However, the HLSSVM was found to perform best in forecasting monthly precipitation. Nonetheless, Tayyebi et al. (2018) developed a back-cast model and calibration metric to produce historic land use maps in the Ohio River Basin (ORB) of the United States by deploying a high performance computing (HPC) platform. Later, they found that such model can be integrated with other environmental models in order to evaluate the impact of land use on ecosystem services. Jursova et al. (2019) examined the carbon footprint and water footprint of electric vehicles in the Czech Republic by forecasting the electricity generation for the country from 2015 to 2050. Such investigation was done based on the Intergovernmental Panel on Climate Change (IPCC) method and the Water Scarcity method. In the study, electricity generated for charging electric vehicle batteries and passenger car production were found to be the main factors of carbon and water footprints in the Czech Republic. In the area of climate models, Hutchison and Isager (2019) obtained highly accurate cloud cover fraction truth data by utilizing numerical weather prediction and climate models,

the results indicating significant value in assessing cloud model input and output datasets.

Ferreira et al. (2019) applied a multi-layered artificial neural network to forecast consumption with two main considerations of costs and CO₂ emissions of the electrical infrastructure in data centers. In this regards, Brazil was proven to be the “cleanest,” making it the best model on the basis of those considerations. In China, Zhou et al. (2019) developed a novel hybrid model to forecast carbon price by composing an extreme-point symmetric mode decomposition, an extreme learning machine, and a grey wolf optimizer algorithm. The result of this study show its superiority in performance compared to other benchmark methods, making it an effective method for analyzing and predicting carbon price. In Denmark, Karabiber and Xydis (2019) forecasted electricity prices for the Denmark-West region by applying the Autoregressive Integrated Moving Average (ARIMA), Trend and Seasonal Components (TBATS), and Artificial Neural Networks (ANN). In order to improve forecasting results, the study excluded temperature from the analysis. In South Korea, Alsharif et al. (2019) developed a Seasonal Autoregressive Integrated Moving Average (SARIMA) model to forecast the daily and monthly solar radiation in Seoul. Based on the findings, the estimated solar radiation on the monthly average was ranked from 176 to 377 Wh/m². Furthermore, Ma et al. (2018) investigated influencing factors on the growth of energy-related CO₂ emissions in China though the development of a Logarithmic Mean Divisia Index I (LMDI). The results of this study revealed that the main factor correlated with the increase in CO₂ emissions was GDP growth per capita. Inversely, a decrease in energy use intensity, enhancement in energy supply efficiency, or the introduction of non-fossil fuels were found to slow the increase.

The current research attempts to address the weaknesses of past studies, as well as optimize the use of new research methods with the application of advanced statistics, making the research more reliable in estimating results. Furthermore, the study aims to provide a useful tool in shaping Thailand's Industry 4.0 policy by providing additional knowledge. The main distinction of this research is the ability to apply the model in various sectors and contexts. The concept can be described as a Non-Recursive Vector autoregression based on an exogeneous model or “Non-Recursive Var-X” model. The research has utilized the linear structural relations (LISREL) model (Sutthichaimethee and Dockthaisong, 2018). As for its validity, the model was assessed by white noise testing and goodness of fit. The testing results confirm that the model falls within the accepted standards, availing itself to be the most appropriate model for the study (Sutthichaimethee and Kubaha, 2018a; Sutthichaimethee and Ariyasajjakorn, 2018). The research flow is explained below and is shown in Figure 1.

1. Determine a variable framework based on the Non-Recursive Var-X model, which contains both latent variables of the Industry 4.0 policy of the government of Thailand (*GP*), including economic (*ECONO*), social (*SOCIAL*), and environmental (*ENVIRON*) factors, while the observed

variables contain of 13 factors, namely energy consumption (*EC*), energy intensity (*EI*), national income (*NI*), urbanization rate (*UR*), industrial structure (*IS*), balance exports (*E*), indirect foreign investment (*IF*), foreign tourists (*FT*), employment (*EM*), health and illness (*HI*), social security (*SS*), consumer protection (*CP*), and technology (*Tc*)

2. Ensure all observed variables are stationary based on the concept of the Augmented Dickey and Fuller (1981)
3. Analyze the relationship of observed variables by testing co-integration based on the concept of the Johansen and Juselius (Johansen and Juselius, 1990; Johansen, 1995)
4. Measure the validity of the Non-Recursive Var-X model (MacKinnon, 1991; Sutthichaimethee, 2018)
5. Compare the performance of the Non-Recursive Var-X model with other models, namely the regression model (RL model), back propagation neural network model (BP model), artificial neural natural model (ANN model), autoregressive moving average model (ARMA model), and the autoregressive integrated moving average model (ARIMA model), through a performance measure of MAPE and RMSE (Sutthichaimethee and Kubaha, 2018b; Sutthichaimethee and Ariyasajjakorn, 2017a; Sutthichaimethee, 2017)
6. Estimate CO₂ emissions by deploying the Non-Recursive Var-X model for the years of 2020 to 2034, totaling 15 years. The flowchart of the Non-Recursive Var-X model is shown in Figure 1.

3. MATERIALS AND METHODS

3.1. Non-recursive Autoregression Based on Var-X Model

Non-recursive autoregression based on Var-X Model is used to study the influence of independent variables which affect the dependent variables either directly, indirectly or comprehensively as described below (Enders, 2010; Harvey, 1989):

1. The structural equation model demonstrates the cause correlation between exogenous variable and endogenous variable in 2 forms

As can be seen in Figure 2 – recursive model, the feature of the model will be cause and effect in the same direction with no going backward or in the opposite direction where the variables will be able to affect the earlier variable. In Figure 2, it can be seen that the exogenous variable is defined as Instrumental variable: IV, affecting endogenous variables B and C, whereas there is no variation in the analysis of the independent variable and residuals of endogenous variables e_2 and e_3 , which are independent of each other, and the variation is $0; E(e_2)=0, E(e_3)=0$. An equation for Figure 2 can be drawn as follows:

$$B = \beta_0 + \beta_1 A + e_2 \quad (1)$$

$$C = \beta_0 + \beta_1 A + \beta_2 B + e_2 \quad (2)$$

Figure 3 - non-recursive model shows a cause and effect relationship in which each variable can affect the other. In this research, the non-recursive model has been selected.

Figure 1: The flowchart of the non-recursive Var-X model

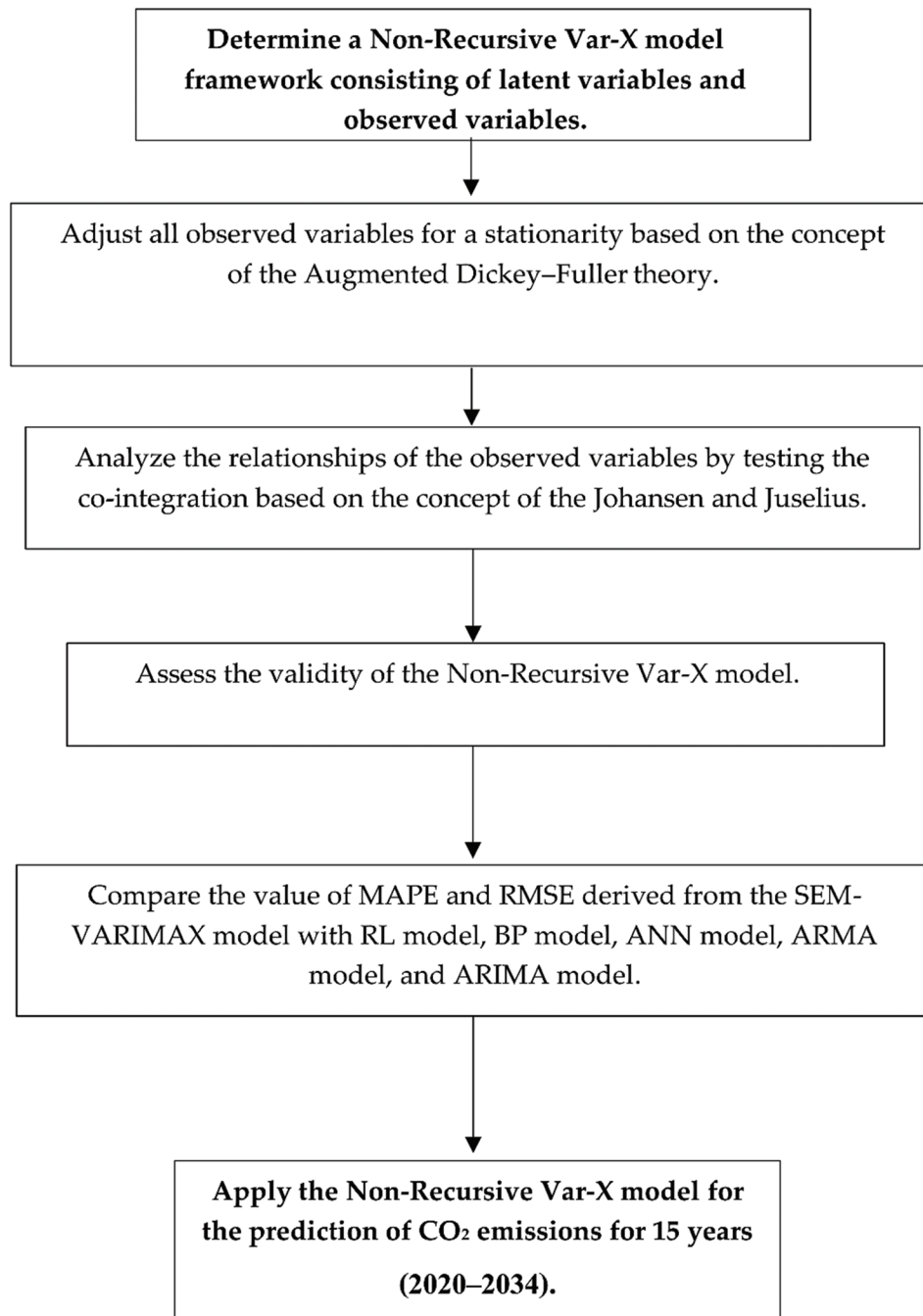
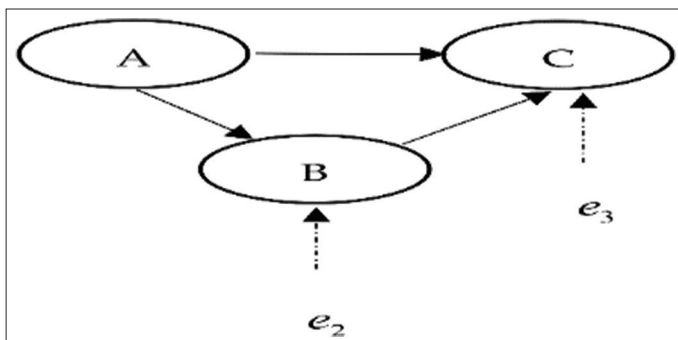


Figure 2: Recursive model



2. Estimation by *VAR-X*

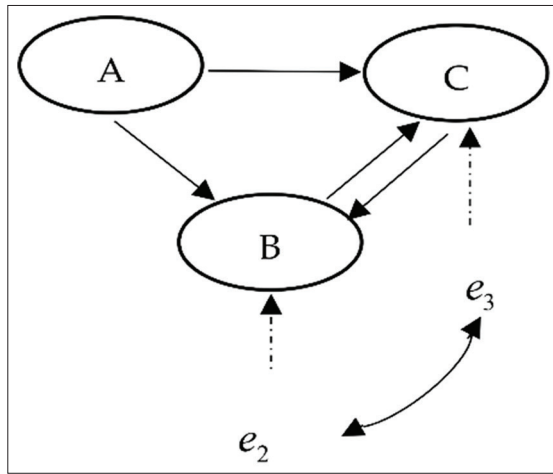
Model *VAR* sequence p : *VAR(p)*

From 2 time series of Y_t and Z_t can be written in *VAR(p)* models as follows:

$$Y_t = a_{10} - a_{11,1}Y_{t-1} + a_{12,1}Y_{t-1} + a_{11,2}Y_{t-2} + a_{12,2}Y_{t-2} + \dots + a_{11,p}Y_{t-p} + a_{12,p}Y_{t-p} + u_{1t} \quad (3)$$

$$Z_t = a_{20} - a_{21,1}Z_{t-1} + a_{22,1}Z_{t-1} + a_{21,2}Z_{t-2} + a_{22,2}Z_{t-2} + \dots + a_{21,p}Z_{t-p} + a_{22,p}Z_{t-p} + u_{2t} \quad (4)$$

Figure 3: Non-recursive model



If we have n sets of time series which are $X_{1t}, X_{2t}, \dots, X_{nt}$ we can write time series in the $VAR(p)$ model as follows (Sutthichaimethee and Ariyasajjakorn, 2017b):

$$X_t = A_0 - A_1 X_{t-1} + A_2 X_{t-2} + \dots + A_p X_{t-p} + u_{1t} \quad (5)$$

where as

$$X_t = \begin{bmatrix} X_{1t} \\ X_{2t} \\ \vdots \\ X_{nt} \end{bmatrix}_{n \times 1}, A_0 = \begin{bmatrix} a_{01} \\ a_{02} \\ \vdots \\ a_{0n} \end{bmatrix}_{n \times 1},$$

$$A_i = \begin{bmatrix} a_{11,i} & \dots & a_{1n,i} \\ a_{21,i} & \dots & a_{2n,i} \\ \vdots & \vdots & \vdots \\ a_{n1,i} & \dots & a_{nn,i} \end{bmatrix}_{n \times n}, i = 1, \dots, p$$

and $u_t = \begin{bmatrix} u_{1t} \\ \vdots \\ u_{nt} \end{bmatrix}_{n \times 1}$

The mean and variation of the $VAR(p)$ model can be done the same as $VAR(1)$ which is not repeated. For the $VAR(p)$ model, a higher parameter value has been found which is the instant parameter with n . The parameter value which has coefficients of $X_{t-1}, X_{t-2}, \dots, X_{t-p}$ have the quantity of $n^2 + n^2 + \dots + n^2 = pn^2$. Therefore, all parameter values in the VAR Model are $n + pn$; the increasing of 1 time series or the increasing of one sequence of VAR delay may increase many parameters. Therefore, in bringing any time series into the Model, there should be a series in which the variables can be described as affecting each other (Sutthichaimethee, 2016a).

3.2. Estimation of Parameters in the VAR Model

As shown in Equation (5), the Model is as follows (Sutthichaimethee, 2016a Sutthichaimethee, 2016b Gulum et al., 2018):

$$X_t = A_0 - A_1 X_{t-1} + A_2 X_{t-2} + \dots + A_p X_{t-p} + u_{1t} \quad (5)$$

whereas

X_t is vector dimension $n \times 1$ of time series n sets which have all attributes as $I(0)$

A_0 is vector dimension $n \times 1$ of instant value

A_i is metric dimension $n \times n$ of co-efficient of $X_{t-i} (i=1, \dots, p)$

u_t is vector dimension $n \times 1$ of random errors variable

n sets of time series to be brought into vector X_t of VAR model should have a correlation with each other which is the main objective of VAR model analysis, which is to find out the correlation between each variable of the time series in X_t . Therefore, in sequential selection (p), which will be used in the VAR model, it should be the appropriate value which is neither too large or too small and should be able to describe the correlation of each variable in the time series of the model. The principle to select the sequence (p) of the VAR model in the first step can be that the p sequence should be sequence which has the lowest Akaike Information Criterion AIC according to the following formula:

$$AIC(p) = -2 \left(\frac{l}{T} \right) + \frac{2}{T} k \quad (6)$$

Whereas l is the probability value of multivariate normal distribution which is calculated from the estimation value of parameters in the $VAR(p)$ model, T is the number of samples in estimation of value in the model and k is the number of parameters for estimation in the VAR model which is equal to $n + pn^2$, with n as the time series in the VAR model.

In the second step, we examine if the selected p sequence in the first step is appropriate enough when there is no correlation problem of error random variable in the $VAR(p)$ model. Once the problem exists, the next sequence closer to the original can be selected i.e. to increase 1 or 2 sequences to test the VAR model. The hypothesis testing can be done as follows:

H_0 : None correlation problem within u_t or $E(u_t u'_{t-1}) = 0, i = 1, \dots, h$ where $h > p$

H_1 : None correlation problem within u_t or $E(u_t u'_{t-1})$ at least 1 variable is not zero

The statistic value which is used to test the above hypothesis is *Ljung Box* Q_h which is calculated by using the following formula:

$$Q_h = T \sum_{j=1}^h \text{tr}(\hat{C}'_j \hat{C}_0^{-1} \hat{C}_j \hat{C}_0^{-1}) \sim X^2_{(n^2(h-p))} \quad (7)$$

Whereas $\hat{C}'_i = T^{-1} \sum_{t=i+1}^T e_t e'_{t-i}$

e_t is the vector of residual value from the $VAR(p)$ model
 n is the number of time series in the $VAR(p)$ model

The estimation of parameter value in each equation of the VAR model can be calculated by using the least square method or the most probability method for which the results will provide both

consistent and asymptotically efficient attributes. Mostly, it was found the in the estimation of the VAR model that many coefficients will have no significance due to the independence in the VAR model which has high multicollinearity and likely lower t value than its real value. Therefore, the t value should not be used in the range to eliminate independent variables of the VAR model. Moreover, the main objective of the VAR model is to determine the correlation of time series in the model, rejecting independence variable of the VAR Model that is not appropriate as it may not contain the key information (Sutthichaimethee, 2016b).

3.3. Residual Coefficient and Direct, Indirect and Overall Effects

As shown in Figure 4, X_1 and X_2 are exogenous variables, X_3 and Y_4 are endogenous variables, where X_1 , X_2 and X_3 have an impact on Y_4 with coefficient path values of p_{41} , p_{42} and p_{43} respectively with e_3 and e_4 as residual variables of variables X_3 and Y_4 .

1. Calculation of residual value to the variable in the model defines the endogenous variable as $j = \sqrt{1 - R_{j,1,2,\dots,i}^2}$ which $R_{j,1,2,\dots,i}^2$ is square of endogenous variable coefficient j and variable $1,2,\dots,i$ which have influence on j . Therefore, according to Figure 4, the coefficient path value from e_3 to variable X_3 is equal to $\sqrt{1 - R_{3,1,2}^2}$, and coefficient path value from to variable X_4 is equal to $\sqrt{1 - R_{4,1,2}^2}$

2. Total effect analysis, direct and indirect effect
The calculation of Total Effect: TE is equal to addition of Direct Effect: DE and Indirect Effect: IE. Based on Figure 4, the results are as follow (Sutthichaimethee, 2016a):

Path 1 (X_1 to X_3)

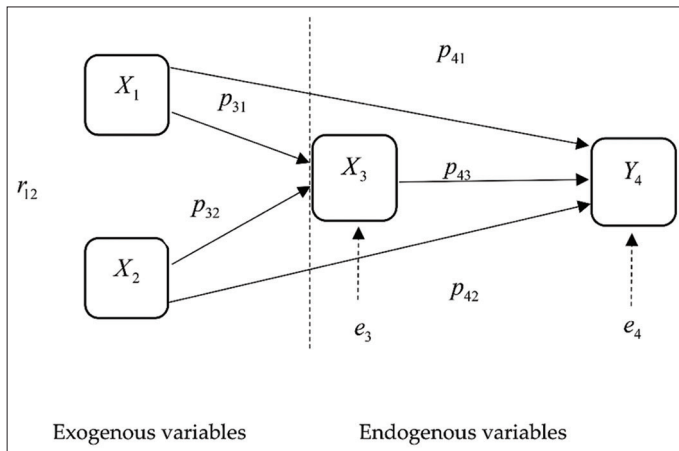
$$DE = p_{31}, IE = r_{12}p_{32}, TE = p_{31} + r_{12}p_{32} \quad (8)$$

Path 2 (X_1 to Y_4)

$$DE = p_{41}, IE = p_{31}p_{43} + r_{12}p_{32}p_{43} + r_{12}p_{42},$$

$$TE = p_{41} + p_{31}p_{43} + r_{12}p_{32}p_{43} + r_{12}p_{42} \quad (9)$$

Figure 4: Direction of the relationship of causal factors



Path 3 (X_2 to X_3)

$$DE = p_{32}, IE = r_{12}p_{31}, TE = p_{32} + r_{12}p_{31} \quad (10)$$

Path 4 (X_2 to Y_4)

$$DE = p_{42}, IE = p_{32}p_{43} + r_{12}p_{31}p_{43} + r_{12}p_{41},$$

$$TE = p_{42} + p_{32}p_{43} + r_{12}p_{31}p_{43} + r_{12}p_{41} \quad (11)$$

Path 5 (X_3 to Y_4)

$$DE = p_{43}, IE = -, TE = p_{43} \quad (12)$$

3.4. Measurement of the Forecasting Performance

In this research, we evaluated the performance of the Non-Recursive Var-X model by using MAPE and RMSE. These two values are compared to the same types of values of other existing models, like the regression model (RL model), back propagation neural network model (BP model), artificial neural natural model (ANN model), autoregressive moving average model (ARMA model), and the autoregressive integrated moving average model (ARIMA model). The calculation equations are shown as follows (Enders, 2010; Harvey, 1989; Albatayneh et al., 2018; Sohail, 2017):

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{\hat{y}_i - y_i}{y_i} \right| \quad (13)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)^2} \quad (14)$$

4. EMPIRICAL ANALYSIS

4.1. Screening Influencing Factors for Model Input

This study used the Non-Recursive Var-X model to investigate the relationship of causal factors and predict CO₂ emissions over a 15 years period (2020-2034). The observed variables in terms of economic indicators (ECONO) are national income (NI), urbanization rate (UR), industrial structure (IS), balance exports (E), indirect foreign investment (IF), foreign tourists (FT). The social indicators (SOCIAL) of the observed variables are employment (EM), health and illness (HI), social security (SS), consumer protection (CP) and technology (Tc). Whereas the environmental indicators (ENVIRON) of the observed variables are energy consumption (EC), energy intensity (EI) and carbon emission (CO₂). All variables were used in constructing the non-recursive Var-X model and for forecasting CO₂ emissions for use in guiding the Industry 4.0 policy of the Thai government (GP). Furthermore, only stationary variables at the same level were considered in creating the non-recursive Var-X model. These variables were compared with MacKinnon Critical Value at level I(0), level I(1) and level I(2) based on the Augmented Dickey-Fuller theory. In this study, all variables were initially

non-stationary at level $I(0)$, yet they became stationary at level $I(1)$, as illustrated in Table 1.

Table 1 shows that all factors were stationary at the first difference resulting from the calculating of the Tau test of every causal factor used in the modelling. The Tau test gives a value greater than MacKinnon critical value indicating the stationarity of the variables at a significance level of 1%, 5%, and 10%. Once the variables were confirmed with stationarity at first difference, we then tested them for co-integration as proposed by Johansen and Juselius and shown in Table 2.

4.2. Analysis of Co-integration

Table 2 shows the results of the co-integration test of Johansen and Juselius, which indicate that all causal factors are stationary at first difference in the non-recursive Var-X model with a long-term relationship at significance levels of 1% and 5%. The Trace statistic test was 199.25, and the Maximum Eigen statistic test was 120.05. Both values are greater than MacKinnon critical values at significance levels of 1% and 5%. Therefore, all causal factors are co-integrated, and underwent impact analysis using the Non-Recursive Var-X model as shown in Figure 5 and Table 3.

4.3. Formation of Analysis Modeling with Non-recursive Autoregression Based on the Var-X Model

The Non-Recursive Var-X model is a model that reflects on the relationship of every stationary yet co-integrated causal factor

at the same level. According to this study's findings, each latent variable has a different impact on the others as explained below.

Figure 5 shows the impact of the causal factor relationships revealed by the non-recursive Var-X model by providing an analysis of the latent variables relationships likely to exist under the Industry 4.0 policy if the government of Thailand (*GP*). The latent variables include economic (*ECONO*), social (*SOCIAL*), and environmental factors (*ENVIRON*), while the observed variables consist of national income (*NI*), urbanization rate (*UR*), industrial structure (*IS*), balance exports (*E*), indirect foreign investment (*IF*), foreign tourists (*FT*), employment (*EM*), health and illness (*HI*), social security (*SS*), consumer protection (*CP*), technology (*Tc*), energy consumption (*EC*), energy intensity (*EI*), and carbon dioxide emissions (*CO₂*). This study has calculated the value of error correction mechanism (ECT_{t-1}) to analyze the ability of adjustment toward equilibrium of latent variables, which can be seen in Table 3.

Table 3 illustrates the parameters of the non-recursive Var-X model at statistical significance levels of 1% and 5%. When the validity of the non-recursive Var-X model is tested, the value of the goodness of fit was found to be within the standard range; RMSEA and RMR were near 0, while the GFI and AGFI values approached 1. Furthermore, after testing the features of the most appropriate model, the Non-Recursive Var-X model was found to fit the best model function, and to be workable for future forecasting. Moreover, the model was confirmed to be absent of heteroskedasticity, multicollinearity, and autocorrelation. Therefore, the Non-Recursive Var-X model is able to determine the effect direction of the factors; be it direct or indirect. This study also provides the influence magnitude of the relationship in percentage. The direct effects found can be explained as follows. The economic factor (*ECONO*) has a direct effect on the environmental factor (*ENVIRON*) at about 91% with a significance level of 1%, the economic factor (*ECONO*) has a direct effect on the social factor (*SOCIAL*) at about 77% with a significance level of 1%, the social factor (*SOCIAL*) has a direct effect on the environmental factor (*ENVIRON*) at about 21% with a significance level of 5%, the environmental factor (*ENVIRON*) has a direct effect on the social factor at about 29% with a significance level of 5%, and lastly, the environmental factor (*ENVIRON*) has a direct effect on the economic factor (*ECONO*) at about 29% with a significance level of 5%. In addition, the Non-Recursive Var-X model further provides the ability of adjustment toward equilibrium of latent variables, which can be understood from the value generated from the error correction mechanism (ECT_{t-1}). When looking at the ability aspect of each factor, the economic factor (*ECONO*) has the strongest ability among any concerned factors with the magnitude of -0.42 at a significance level of 1% amounting to 42%, while the second next factor is the social factor (*SOCIAL*) with the magnitude of -0.21 at a significance level of 1% amounting to 21%, and the environmental factor (*ENVIRON*) ranks last with -0.04 magnitude at a significance level of 1% amounting to 4%.

The non-recursive Var-X model was also tested for performance with results shown in MAPE and RMSE for comparison against existing models, including the RL model, BP model, ANN model, ARMA model, and ARIMA model, as shown in Table 4.

Table 1: Stationary test at first difference I (1)

Stationary at first difference I(1)		MacKinnon critical value		
Variables	Tau test	1%	5%	10%
$\Delta \ln (NI)$	-5.45***	-4.11	-3.05	-2.15
$\Delta \ln (UR)$	-5.19***	-4.11	-3.05	-2.15
$\Delta \ln (IS)$	-5.05***	-4.11	-3.05	-2.15
$\Delta \ln (E)$	-5.44***	-4.11	-3.05	-2.15
$\Delta \ln (IF)$	-4.91***	-4.11	-3.05	-2.15
$\Delta \ln (FT)$	-4.87***	-4.11	-3.05	-2.15
$\Delta \ln (EM)$	-4.65***	-4.11	-3.05	-2.15
$\Delta \ln (HI)$	-4.34***	-4.11	-3.05	-2.15
$\Delta \ln (SS)$	-4.79***	-4.11	-3.05	-2.15
$\Delta \ln (CP)$	-4.85***	-4.11	-3.05	-2.15
$\Delta \ln (Tc)$	-5.10***	-4.11	-3.05	-2.15
$\Delta \ln (EC)$	-5.56***	-4.11	-3.05	-2.15
$\Delta \ln (EI)$	-5.02***	-4.11	-3.05	-2.15
$\Delta \ln (CO_2)$	-5.94***	-4.11	-3.05	-2.15

NI is national income, *UR* is urbanization rate, *IS* is industrial structure, *E* is net exports, *IF* is indirect foreign investment, *FT* is foreign tourists, *EM* is employment, *HI* is health and illness, *SS* is social security, *CP* is consumer protection, *EC* is energy consumption, *EI* is energy intensity, and *CO₂* is carbon dioxide emissions, ***Denotes a significance, $\alpha = 0.01$, compared to the Tau test with the MacKinnon critical value, Δ is the first difference, and \ln is the natural logarithm

Table 2: Co-integration test of Johansen and Juselius

Variables	Co-integration value	MacKinnon Critical value	
$\Delta \ln (NI)$, $\Delta \ln (UR)$, $\Delta \ln (IS)$, $\Delta \ln (E)$, $\Delta \ln (IF)$, $\Delta \ln (FT)$, $\Delta \ln (EM)$, $\Delta \ln (HI)$, $\Delta \ln (SS)$, $\Delta \ln (CP)$, $\Delta \ln (Tc)$, $\Delta \ln (CO_2)$, $\Delta \ln (EC)$, $\Delta \ln (EI)$	Trace statistic test 199.25***	Max-Eigen statistic test 120.05***	1% 5% 16.05 12.25

***Denotes significance $\alpha = 0.01$, **denotes significance $\alpha = 0.05$

Table 4 provides the values of MAPE and RMSE arranged upwards from lowest to highest for comparison with other models' values. The non-recursive Var-X model had results of 1.12% and 1.25%, respectively. The second model in the ranking was the ARIMA model with MAPE and RMSE of 4.65 and 6.18, respectively. Following that was the ANN model with MAPE and RMSE of 10.11 and 12.40, respectively. The ARMA model had a MAPE and RMSE of 14.64 and 15.96, respectively. The BP model had a MAPE and RMSE of 14.71 and 15.82, respectively. Finally, the RL model has the highest values for MAPE and RMSE at 14.64 and 15.96, respectively.

Thus, the Non-Recursive Var-X model can be deemed as the most appropriate to be used to forecast CO₂ emissions in the long term, as explained below.

4.4. A Forecasting CO₂ Emission Based on the Non-recursive Var-X Model

In this forecasting, the non-recursive Var-X model is used to predict CO₂ emission for the next 15 years (2020-2034) as to show the carrying capacity in order to compare with the future national measure set by the government (2034), as illustrated in Figure 6.

Table 3: Results of relationship size analysis of the non-recursive autoregression based on Var-X model

Dependent variables	Type of effect	Independent variables			
		Economic (ECON)	Social (SOCL)	Environmental (ENV)	Error correction mechanism (ECT _{t-1})
Economic (ECON)	DE	-	0.53***	0.29**	-0.42***
	IE	-	0.03***	0.05**	-
Social (SOCL)	DE	0.77***	-	0.21**	-0.21***
	IE	0.22***	-	0.11**	-
Environmental (ENV)	DE	0.91***	0.49***	-	-0.04***
	IE	0.05***	0.11***	-	-

In the above, ***denotes significance $\alpha=0.01$, **denotes significance $\alpha=0.05$, χ^2/df is 1.25, $RMSEA$ is 0.05, RMR is 0.001, GFI is 0.91, $AGFI$ is 0.95, R-squared is 0.96, the F-statistic is 199.75 (probability is 0.00), the ARCH test is 21.05 (probability is 0.1), the LM test is 1.25 (probability is 0.10), DE is the direct effect, and IE is the indirect effect

Figure 5: Causal relationships in non-recursive autoregression based on Var-X model

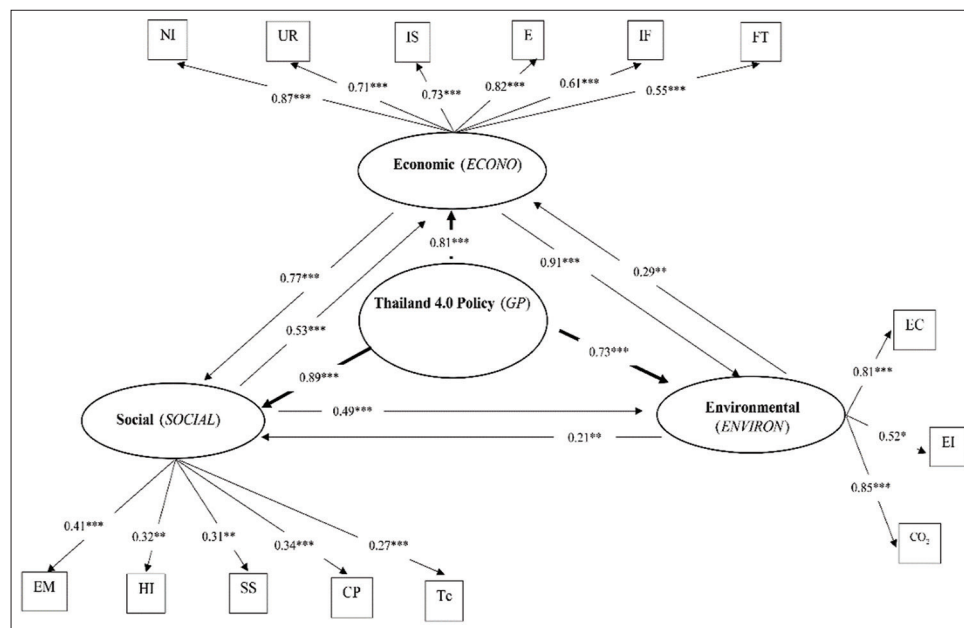


Figure 6: Forecasting results for CO₂ emissions from 2020 to 2034 in Thailand

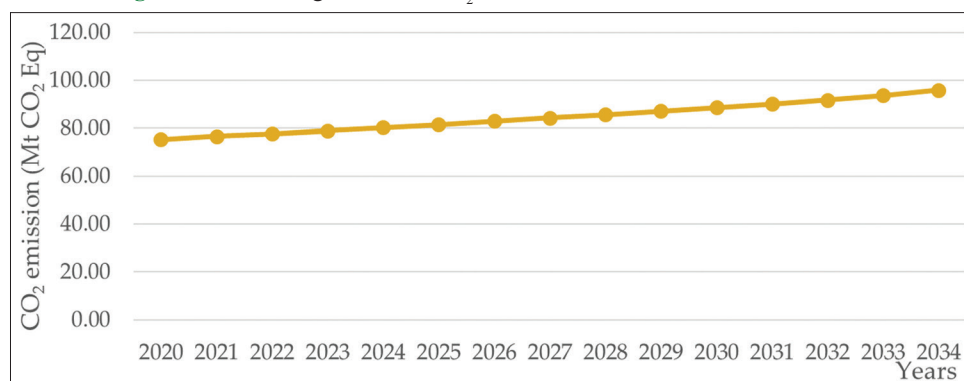


Table 4: The performance monitoring of the forecasting models

Forecasting model	MAPE (%)	RMSE (%)
RL model	21.44	22.93
BP model	14.71	15.82
ARMA model	14.64	15.96
ANN model	10.11	12.40
ARIMA model	4.65	6.18
Non-recursive Var-X model	1.12	1.25

Figure 6 indicates that CO₂ emissions from 2020-2034 under the Industry 4.0 policy of the Thai government will steadily increase at a growth rate of 27.23% of over the entire period, amounting 95.88 Mt CO₂ Eq. by 2034. This figure implies that after implementing the Industry 4.0 policy, CO₂ emissions will exceed the estimated carrying capacity of the country as established by the government of 80 Mt CO₂ Eq. for CO₂ emissions.

5. CONCLUSIONS AND DISCUSSION

For this study, the non-recursive Var-X model was developed using advanced statistics incorporating specific causal factors, making it adaptable to real contexts. The model was validated via various forms of testing determine the goodness of fit for long-term forecasting and in terms applicability to different contexts and sectors. The reliability of the model is demonstrated by the absence heteroskedasticity, multicollinearity, and autocorrelation, making it reflective of the relationship of all causal factors. The latent variables in terms of the economic factor aspect (*ECONO*) consisted of the observed variables of national income (*NI*), urbanization rate (*UR*), industrial structure (*IS*), balance exports (*E*), indirect foreign investment (*IF*), foreign tourists (*FT*). The latent variables in the social factor aspect (*SOCIAL*) were comprised of the observed variables of employment (*EM*), health and illness (*HI*), social security (*SS*), consumer protection (*CP*) and technology (*Tc*). The latent variables in the environmental factor aspect (*ENVIRON*) were inclusive of the observed variables, including energy consumption (*EC*), energy intensity (*EI*) and carbon emissions (CO₂). LISREL was used in the study as it is generally considered the most appropriate option for advanced statistical analysis. This study was conducted according to standard research principles, considering various aspects and characteristics of the causal factors important to create a long-term forecasting model. All causal factors were found to be stationary at the first difference level of 1%, 5%, and 10%, while overall, all factors were co-integrated at the same level. Hence, the causal factors were deemed the most important components in the construction of the non-recursive Var-X model. Validity testing results confirmed the validity of the model in both direct and indirect effects. The study's findings indicate that the latent variable of economy (*ECONO*) had both direct and indirect effects on each variable, while the social (*SOCIAL*) and environmental (*ENVIRON*) variables had a significance level of 1% and 5%, respectively. Furthermore, the latent variable in society (*SOCIAL*) has also had both direct effect and indirect effects on every other variable. The latent variables of economy (*ECONO*) and environment (*ENVIRON*) had a significance level of 1% and 5%, respectively, while the latent variable in environment (*ENVIRON*) had both a direct and indirect

effect for each variable. The latent variables of social (*SOCIAL*) and economic (*ECONO*) factors had a significance level of 1% and 5%, respectively.

When the performance of the non-recursive Var-X model was tested, it showed that the model had the best performance compared to other models, including the RL model, BP model, ANN model, ARMA model, and ARIMA model. For the long-term forecasting (2020-2034), the model was found to be appropriate, predicting carbon emissions rising at a continuous rate over the period of 2020 to 2034, and exceeding the estimated carrying capacity of Thailand (No more than 80 Mt CO₂ Eq.). Using the Non-Recursive Var-X model, carbon emissions (CO₂) are estimated to increase to 95.88 Mt CO₂ Eq. by 2034. The adjustment ability toward equilibrium of the environment (*ENVIRON*) is considered to be slower than economic (*ECONO*) and social (*SOCIAL*) aspects, respectively. Hence, the proposed Industry 4.0 policy of the Thai government (*GP*) is considered insufficient as it exceeds the country's estimated carrying capacity. This highlights the non-recursive Var-X model's relevance for public policy making and planning for the upcoming 2020-2034 period, as well as its suitability for other applications.

As for recommendations for future research, individual researchers should rely on in-depth knowledge of modeling relationships between causal factor variables. At the same time, the causal factors must be carefully selected for their consistency and relevancy with the policy being examined. Researchers should avoid using the general models which do not take validity and appropriateness into account. In analyzing the direction of effects, be it direct or indirect, the model must also reflect the real relationship, avoiding spuriousity.

A limitation of this research is that there are certain causal factors that are not appropriate for inclusion using this model. An example would be cases of full government intervention in areas such as setting prices for diesel fuel. Such interventions by the government do occur from time to time. They do not however reflect real market forces and are unpredictable; therefore, the researchers were not able to incorporate this factor into the modelling.

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REFERENCES

- Achawangkul, Y. (2018), Thailand's Alternative Energy Development Plan. Available from: http://www.unescap.org/sites/default/files/moe%20_%20ae%20policies.pdf. [Last accessed on 2019 Oct 20].
- Albatayneh, A., Alterman, D., Page, A., Moghtaderi, B. (2018), The significance of building design for the climate. *Environmental and Climate Technologies*, 22(1), 165-178.
- Alsharif, M.H., Younes, M.K., Kim, J. (2019), Time series ARIMA model for prediction of daily and monthly average global solar radiation:

- The case study of Seoul, South Korea. *Symmetry*, 11(2), 240.
- Armeanu, D.S., Vintilă, G., Gherghina, S.C. (2017), Does renewable energy drive sustainable economic growth? Multivariate panel data evidence for EU-28 countries. *Energies*, 10(3), 381.
- Bai, L., Pinson, P. (2019), Distributed reconciliation in day-ahead wind power forecasting. *Energies*, 12(6), 1112.
- Boyd, G., Na, D., Li, Z., Snowling, S., Zhang, Q., Zhou, P. (2019), Influent forecasting for wastewater treatment plants in North America. *Sustainability*, 11(6), 1764.
- Büyükhahin, Ü.Ç., Ertekin, Ş. (2019), Improving forecasting accuracy of time series data using a new ARIMA-ANN hybrid method and empirical mode decomposition. *Neurocomputing*, 361, 151-163.
- Department of Alternative Energy Development and Efficiency. (2019), Climate Change in Thailand. Available from: http://www.dede.go.th/ewtadmin/ewt/dede_web/ewt_news.php?nid=47140. [Last accessed on 2019 Oct 20].
- Dickey, D.A., Fuller, W.A. (1981), Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica*, 49, 1057-1072.
- Enders, W. (2010), *Applied Econometrics Time Series*; Wiley Series in Probability and Statistics. Tuscaloosa: University of Alabama.
- Ferreira, J., Callou, G., Josua, A., Tutsch, D., Maciel, P. (2019), An artificial neural network approach to forecast the environmental impact of data centers. *Information*, 10(3), 113.
- Gómez, M., Ciarreta, A., Zarraga, A. (2018), Linear and nonlinear causality between energy consumption and economic growth: The case of Mexico. *Energies*, 11(4), 784.
- Gulum, M., Onay, F.K., Bilgin, A. (2018), Evaluation of predictive capabilities of regression models and artificial neural networks for density and viscosity measurements of different biodiesel-diesel-vegetable oil ternary blends. *Environmental and Climate Technologies*, 22(1), 179-205.
- Harvey, A.C. (1989), *Forecasting, Structural Time Series Models and the Kalman Filter*. Cambridge: Cambridge University Press.
- Hu, Y., Guo, D., Wang, M., Zhang, X., Wang, S. (2015), The relationship between energy consumption and economic growth: Evidence from China's industrial sectors. *Energies*, 8(9), 9392-9406.
- Hutchison, K.D., Iisager, B.D. (2019), Creating truth data to quantify the accuracy of cloud forecasts from numerical weather prediction and climate models. *Atmosphere*, 10(4), 177.
- Johansen, S. (1995), *Likelihood-Based Inference in Cointegrated Vector Autoregressive Models*. Oxford: Oxford University Press.
- Johansen, S., Juselius, K. (1990), Maximum likelihood estimation and inference on cointegration with applications to the demand for money. *Oxford Bulletin of Economics and Statistics*, 52, 169-210.
- Jursova, S., Burchart-Korol, D., Pustejovska, P. (2019), Carbon footprint and water footprint of electric vehicles and batteries charging in view of various sources of power supply in the Czech Republic. *Environments*, 6(3), 38.
- Karabiber, O.A., Xydis, G. (2019), Electricity price forecasting in the Danish day-ahead market using the TBATS, ANN and ARIMA methods. *Energies*, 12(5), 928.
- Ma, C., Li, Y. (2016), Improving Forecasting Accuracy of Annual Runoff Time Series Using RBFN Based on EEMD Decomposition. 2nd International Conference on Energy, Materials and Manufacturing Engineering (EMME 2016). p211-216.
- Ma, L., Chong, C., Zhang, X., Liu, P., Li, W., Li, Z., Ni, W. (2018), LMDi decomposition of energy-related CO₂ Emissions based on energy and CO₂ allocation Sankey diagrams: The method and an application to China. *Sustainability*, 10(2), 344.
- MacKinnon, J. (1991), In: Engle, R., Granger, C., editors. *Critical Values for Cointegration Test in Long-Run Economic Relationships*. Oxford: Oxford University Press.
- National Statistic Office Ministry of Information and Communication Technology. (2018), Data for Plan in Thailand. Available from: <http://www.web.nso.go.th/index.html>. [Last accessed on 2019 Aug 02].
- Office of the National Economic and Social Development Board. (2018), Economic, Social and Environmental. Available from: http://www.nesdb.go.th/nesdb_en/more_news.php?cid=154&filename=index. [Last accessed on 2019 May 12].
- Rezaeianzadeh, M., Tabari, H., Yazdi, A., Isik, S., Kalin, L. (2014), Flood flow forecasting using ANN, ANFIS and regression models. *Neural Computing and Applications*, 25(1), 25-37.
- Sohail, M. (2017), An attempt to design a naturally ventilated tower in subtropical climate of the developing country; Pakistan. *Environmental and Climate Technologies*, 21(1), 47-67.
- Sutthichaimethee, P. (2016a), Model of environmental problems priority arising from the use of environmental and natural resources in machinery sectors of Thailand. *Environmental and Climate Technologies*, 17(1), 18-29.
- Sutthichaimethee, P. (2016b), Modeling environmental impact of machinery sectors to promote sustainable development of Thailand. *Journal of Ecological Engineering*, 17(1), 18-25.
- Sutthichaimethee, P. (2017), Varimax model to forecast the emission of carbon dioxide from energy consumption in rubber and petroleum industries sectors in Thailand. *Journal of Ecological Engineering*, 18(3), 112-117.
- Sutthichaimethee, P. (2018), Forecasting economic, social and environmental growth in the sanitary and service sector based on Thailand's sustainable development policy. *Journal of Ecological Engineering*, 19(1), 205-210.
- Sutthichaimethee, P., Ariyasajjakorn, D. (2017a), Forecasting model of GHG emission in manufacturing sectors of Thailand. *Journal of Ecological Engineering*, 18(1), 18-24.
- Sutthichaimethee, P., Ariyasajjakorn, D. (2017b), The revised input-output table to determine total energy content and total greenhouse gas emission factors in Thailand. *Journal of Ecological Engineering*, 18(6), 166-170.
- Sutthichaimethee, P., Ariyasajjakorn, D. (2018), Forecast of carbon dioxide emissions from energy consumption in industry sectors in Thailand. *Environmental and Climate Technologies*, 22(1), 107-117.
- Sutthichaimethee, P., Dockthaisong, B. (2018), A relationship of causal factors in the economic, social, and environmental aspects affecting the implementation of sustainability policy in Thailand: Enriching the path analysis based on a GMM model. *Resources*, 7(4), 87.
- Sutthichaimethee, P., Kubaha, K. (2018a), A relational analysis model of the causal factors influencing CO₂ in Thailand's industrial sector under a sustainability policy adapting the VARIMAX-ECM model. *Energies*, 11(7), 1704.
- Sutthichaimethee, P., Kubaha, K. (2018b), The efficiency of long-term forecasting model on final energy consumption in Thailand's petroleum industries sector: Enriching the LT-ARIMAXS model under a sustainability policy. *Energies*, 11(8), 2063.
- Tao, L., He, X., Wang, R.A. (2017), A hybrid LSSVM model with empirical mode decomposition and differential evolution for forecasting monthly precipitation. *Journal of Hydrometeorology*, 18, 159-176.
- Tayyebi, A., Tayyebi, A.H., Pekin, B.K., Omrani, H., Pijanowski, B.C. (2018), Modeling historical land use changes at a regional scale: Applying quantity and locational error metrics to assess performance of an artificial neural network-based back-cast model. *Journal of Environmental Informatics*, 31(2), 74-86.
- Terêncio, D.P.S., Fernandes, L.F.S., Cortes, R.M.V., Moura, J.P., Pacheco, F.A.L. (2019), Can land cover changes mitigate large floods? A

- reflection based on partial least squares-path modeling. *Water*, 11(4), 684.
- Thailand Greenhouse Gas Management Organization (Public Organization). (2019), *Energy Consumption and Climate Change in Thailand*. Available from: <http://www.tgo.or.th/2015/thai/content.php?s1=7&s2=16&sub3=sub3>. [Last accessed on 2019 May 05].
- To, W.M., Lee, P.K.C. (2017), Lee energy consumption and economic development in Hong Kong, China. *Energies*, 10(11), 1883.
- Zhao, H., Zhao, H., Han, X., He, Z., Guo, S. (2016), Economic growth, electricity consumption, labor force and capital input: A more comprehensive analysis on North China using panel data. *Energies*, 9(11), 891.
- Zhou, J., Huo, X., Xu, X., Li, Y. (2019), Forecasting the carbon price using extreme-point symmetric mode decomposition and extreme learning machine optimized by the grey wolf optimizer algorithm. *Energies*, 12(5), 950.