IJEEP
INTERNATIONAL JOURNAL OF ENERGY ECONOMICS AND POLICY

International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2021, 11(4), 398-411.

A Forecasting Model in Managing Future Scenarios to Achieve the Sustainable Development Goals of Thailand's Environmental Law: Enriching the Path Analysis-VARIMA-OV_i Model

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Received: 03 April 2020 **Accepted:** 20 March 2021 **DOI:** https://doi.org/10.32479/ijeep.9693

ABSTRACT

The objective of this study is to develop a forecasting model for causal factors management in the future in to order to achieve sustainable development goals. This study applies a validity-based concept and the best model called "Path analysis based on vector autoregressive integrated moving average with observed variables" (Path Analysis-VARIMA-OV_i Model). The main distinguishing feature of the proposed model is the highly efficient coverage capacity for different contexts and sectors. The model is developed to serve long-term forecasting (2020-2034). The results of this study show that all three latent variables (economic growth, social growth, and environmental growth) are causally related. Based on the Path Analysis-VARIMA-OV_i Model, the best linear unbiased estimator (BLUE) is detected when the government stipulates a new scenario policy. This model presents the findings that if the government remains at the current future energy consumption levels during 2020-2034, constant with the smallest error correction mechanism, the future CO_2 emission growth rate during 2020-2034 is found to increase at the reduced rate of 8.62% (2020/2034) or equivalent to 78.12 Mt CO_2 Eq. (2020/2034), which is lower than a carrying capacity not exceeding 90.5 Mt CO_2 Eq. (2020-2034). This outcome differs clearly when there is no stipulation of the above scenario. Future CO_2 emission during 2020-2034 will increase at a rate of 40.32% or by 100.92 Mt CO_2 Eq. (2020/2034). However, when applying the Path Analysis-VARIMA-OV_i Model to assess the performance, the mean absolute percentage error (MAPE) is estimated at 1.09%, and the root mean square error (RMSE) is estimated at 1.55%. In comparison with other models, namely multiple regression model (MR model), artificial neural network model (ANN model), back-propagation neural network model (BP model), fuzzy analysis network process model (FANAP model), gray model (GM model), and gray-autoregressive integrated moving average model (GM-ARIMA model), the Path Analysis-VARIMA-OV_i model is found to be the most suitable tool for a policy management and planning to achieve a sustainability for Thailand.

Keywords: Sustainable Development, Energy Consumption, Managing Future Scenarios, Forecasting Model, Carrying Capacity
JEL Classifications: P28, Q42, Q43, Q47, Q48

1. INTRODUCTION

Thailand has consistently implemented a sustainable development goals from the past (1995) to the present (2019). The Thai government's main objective is to boost the growth and development in three main aspects; economic growth, social growth and environmental growth, under the public policy framework of Thailand. The key national strategy for growth is to develop these aspects simultaneously yet continuously bring in efficient operation for Thailand in order to become a developed nation like many countries in Europe and America (The World Bank: Energy Use [Kg of Oil Equivalent Per Capita] Home Page, 2020) Office of the National Economic and Social Development Council (NESDC), 2020). The Thai government operation is carried out proactively and passively, and to achieve future sustainability. The operation ranges in different terms; namely short-term national development plan (1-5 years), medium-term national development plan (6-10 years), and long-term national development plan (11-20 years). This operation consistently continues till present (NESDC, 2020). The Thai government focuses on promoting economic growth at first to continuously provide revenue for Thailand (NESDC, 2020 National Statistic Office Ministry of Information and Communication Technology, 2020) with a number of measures, including the promotion of foreign investment by reducing taxes while maintaining the confidence of foreign investors, the impose of fees reduction in all sectors to attract customers from major competing countries of Thailand, and the focus to increase production (National Statistic Office Ministry of Information and Communication Technology, 2020). In addition, there are proactive measures to encourage tourists around the world for continuous visit to Thailand as to bring in revenue for the country. This is done via participating in bilateral agreements with key trading partners to attract foreign tourists to visit as many as possible, especially tourists from China (NESDC, 2020). Thailand emphasizes on exports to increase market share and international market exposure while stays competitive with strong product pricing and increased export volumes. In addition, Thailand supports local entrepreneurs and manufacturers to growingly increase their export capabilities and provides them with low interest rates borrowing as to increase their operational flexibility with low tax rates. Furthermore, Thailand tends to lower imports volumes in order to boost self-production while keeping foreign investment positive to complement with the imports (The World Bank: Energy Use (Kg of Oil Equivalent Per Capita) Home Page, 2020). Interestingly, the Thai government also accelerates the investment projects in all public infrastructures, including a number of national mega projects. To name some, Thailand proceeds with the construction of electric trains for larger transportation coverage, and the construction of roads and highways (National Statistic Office Ministry of Information and Communication Technology, 2020).

As for the policy implementation to boost social growth, the Thai government has stipulated a number of policies and measures, as well as followed strict evaluations in various aspects. The policies and measures may include the promotion of employment by continuously reducing unemployment rate (NESDC, 2020). The Thai government monitors education system and ensures full coverage of it throughout the country. Besides, the Thai government is closely monitoring the well-being of people via Health and Illness control measure. At the same time, strict implementation and monitoring of social security policies are put in place (The World Bank: Energy Use [Kg of Oil Equivalent Per Capita] Home Page, 2020) National Statistic Office Ministry of Information and Communication Technology, 2020). Furthermore, the policy of consumer protection is closely monitored and followed up (National Statistic Office Ministry of Information and Communication Technology, 2020).

In fact, the Thai government has focused and emphasized both economic growth and social development since the past (1990) up to the present (2019), and they are believed to have effective implementation. This fact can be proven from the increment of gross domestic production (GDP) at a constant rate every year (The World Bank: Energy Use [Kg of Oil Equivalent Per Capita] Home Page, 2020 NESDC, 2020). The continuing economic growth is also seen to improve social growth, which results in standardized social quality of people throughout the country (NESDC, 2020). Nevertheless, both economic growth and social growth in Thailand are effectively performing. Yet, the sustainable development goal policy is currently functioning with less efficiency and hardly attaining a sustainability (National Statistic Office Ministry of Information and Communication Technology, 2020). The environmental growth is found to steadily decline since the past (1990) to the present (2020). It is argued that the greenhouse gas is steadily increasing, especially CO_2 emission continuously increases in all sectors. Particularly, the electronic and industrial sector is shown with the highest CO_2 emission at an increasing growth rate of 71.5% (2019/1990) (National Statistic Office Ministry of Information and Communication Technology, 2020 Department of Alternative Energy Development and Efficiency, 2020 Thailand Greenhouse Gas Management Organization (Public Organization), 2020).

However, the implementation of the sustainable development goal policy in Thailand has been ongoing, and Thailand has been giving full cooperation with international partners since 1995 during a summit in Italy. The summit touched on Human and Environment, and Thailand presented an attendance in the summit (Thailand Greenhouse Gas Management Organization (Public Organization), 2020 United Nations Framework Convention on Climate Change, UNFCCC, Bonn, Germany, 2016). Later, Thailand failed to achieve its target, as it can be seen from the reduction of environmental quality. While Thailand managed to develop economic growth and social growth (National Statistic Office Ministry of Information and Communication Technology, 2020 Pollution Control Department Ministry of Natural Resources and Environment. Enhancement and Conservation of National Environmental Quality Act, B.E. 2535., 2020 Pollution Control Department Ministry of Natural Resources and Environment. Navigation of Thai Waterways Act, B.E. 2546., 2020 Pollution Control Department Ministry of Natural Resources and Environment. Principle 4: In order to achieve sustainable development, environmental protection shall constitute an integral part of the development process and cannot be considered in isolation from it, 2020). One of the main reasons contributing to this failure is due to the absence of management tool for effective policy implementation. Considering the past management tool, it did not account validity and BLUE quality, and used the estimated outcome for national planning. This application would cause a model spuriousness resulting in the mismanagement of Thailand. Nonetheless, this study manages to realize this gap and weakness, resulting in the development of the proposed forecasting tool for Thailand. It is developed to create efficiency and effectiveness in policy management of Thailand. As of this study, it has reviewed the relevant studies and researches from existing literature and models available locally and internationally. This revision aims to create comprehensive understanding of problems and possible guidance for this particular study and future research.

2. LITERATURE REVIEWS

In this section, it will shed some lights on relevant studies and literature investigating the nexus between concerned variables, forecasting measure and model comparison. For the early discussion, it explores streamline studies examining the relationship of certain factors. Zhang and Broadstock (2016) investigated the causal relationship between energy consumption and GDP for China adopting a time-varying approach. Later, they find out that such a relationship is two-way causal. Within the same context, Zhang and Xu (2012) reexamined the nexus between energy consumption and GDP by extending sectoral and regional analyses based on dynamic panel data. Their study has indicated that economic growth is a cause of the rise in energy consumption at all levels. Yalta and Cakar (2012) tested the causality between the same variables, but specified the GDP into the real characteristic with the use of time series oriented advanced data generation process for 1971 to 2007. Beside these two factors, Zhang and Lin (2012) extended further to estimate urbanization, energy consumption and CO_2 emissions by applying STIRPAT model and provincial panel data from 1995 to 2010 in China. Based on their study, they detect the increment of energy consumption and CO_2 emissions due to urbanization. In Taiwan, Lu (2017) explored the connection between electricity consumption and economic growth for 17 Taiwanese industries, and a long-run equilibrium relationship and a bi-directional Granger causality are found between variables, suggesting a 1% increase in electricity consumption would boost the real GDP by 1.72%. Xu et al. (2014) analyzed factors affecting carbon emissions due to fossil energy consumption in China. Based on their analysis, electricity production, petroleum processing and coking, metal smelting and rolling, chemical manufacture, and non-metal mineral products, are the factors contributing to carbon emissions. Analyzing the impacts of industry structure, economic output, energy structure, energy intensity, and emission factors on the total carbon dioxide emissions, Ren et al. (2014) adopted the Log Mean Divisia Index (LMDI) method for China's manufacturing industry during 1996 to 2010. With their analysis, it illustrates that the increase of CO_2 emissions is due to the increase in economic output. Otherwise, the decrease in energy intensity would help reduce CO_2 emissions. In addition, Dai et al. (2018) proposed a novel model of EEMD-ISFLA-LSSVM (Ensemble Empirical Mode Decomposition and Least Squares Support Vector Machine Optimized by Improved Shuffled Frog Leaping Algorithm) for forecasting the energy consumption in China from 2018 to 2022. As a result, China's energy consumption is projected to have a significant growth. Nonetheless, Liu et al. (2019) carried out a provincial-level analysis to investigate the economic transition, technology change, and energy consumption in China. As of the study's findings, it reveals that GDP share of the tertiary sector has a significant impact in the reduction of energy consumption, a decrease in heavy industry production affects in the reduction of energy demand, and improvement in industrial electricity efficiency helps in the reduction of energy consumption. While Ma et al. (2018) deployed a machine learning forecasting algorithm devoid of massive independent variables and assumptions for forecasting renewable energy consumption (REC) in the US during 2009 to 2016 period. Having said that, the proposed model saves the US about ~2692.62 PJ petajoules (PJ) on hydroelectric (HE-EC) and ~9695.09 PJ on REC from biomass (REC-BMs).

In terms of forecasting and modelling, a number of studies has established different models to measure and estimate various purposes globally. Qin et al. (2019) constructed Autoregressive (AR) model and Long Short-Term Memory (LSTM) model in Python language based on the TensorFlow framework aimed at simulating and predicting the hydrological time series. As of their study's result, the feasibility of the models is captured for the prediction of the hydrological time series. Mosavi et al. (2018) revisited the existing literature and studies to illustrate the state of the art of Machine Learning (ML) models in flood prediction and to investigate the most suitable models. By taking ML models as a benchmark, hybridization, data decomposition, algorithm ensemble, and model optimization are found as the most effective strategies in improving the quality of the flood prediction models. While Lohani et al. (2014) proposed Peak Percent Threshold Statistic (PPTS) as a new model performance criterion to examine the performance of a flood forecasting model using hourly rainfall and discharge data as a sample. They also compared the result of the proposed model with artificial neural networks (ANN), Self-Organizing Map (SOM) based ANN model and subtractive clustering-based Takagi Sugeno fuzzy model (SC-T-S fuzzy model). As of their analysis, the SC-T-S fuzzy model is shown with reasonably accurate forecast coupled with sufficient lead-time. To Xia et al. (2017), they presented a novel surface reconstruction method (SRM) as an efficient and stable hydrodynamic model with novel source term discretization schemes for overland flow and flood. Upon analyzing the study, the presented model can provide correct prediction of mass flux on slopes. Shrestha et al. (2013) examined the quality of precipitation forecasts from four Numerical Weather Prediction (NWP) models, namely ACCESS-G 80 km resolution, ACCESS-R 37.5 km, ACCESS-A 12 km, and ACCESS-VT 5 km, based on the Australian Community Climate Earth-System Simulator (ACCESS). As part of their findings, it presents that the systematic biases in rainfall forecasts has to be removed before using the rainfall forecasts for streamflow forecasting. Jabbari et al. (2020) deployed a numerical weather prediction and a rainfall-runoff model to assess the precipitation and flood forecast for the Imjin River (South and North Korea). As a result, they no result, they notice that the Weather Research and Forecasting (WRF) model underestimates precipitation in point and catchment assessment. In addition, Seguritan et al. (2012) estimated phage structural protein sequences by applying the ANNs model coupled with additional estimates; amino acid frequency, and major capsid and tail proteins. As of their analysis, it is evident of which the above specialized ANNs perform better the structural ANNs. Hughes et al. (2020) adopted information graphs together with predictive values to aid interpretation in the evaluation and comparison of disease forecasts. As part of their findings, such a format is complimentary to the calculation of a receiver operating characteristic (ROC) curve in terms of sensitivity and specificity. Whereas Jabbari and Bae (2020) applied the total least squares (TLS) method and the lead-time dependent bias correction method to improve real-time data of flood forecast. As of their findings, the applied methods help reduce error in real-time flood forecasts in addition to the accuracy improvements.

With further exploration and model development, Manservigi et al. (2020) developed a simulation model accounting for component efficiency and energy balance in order to reduce primary energy consumption. With the proposed model, their findings confirm that it can save primary energy consumption up to 5.1%. Reynolds et al. (2019) optimized artificial neural networks and a genetic algorithm to determine the optimal operating schedule of the heat generation equipment, thermal storage and the heating set point temperature. Considering this holistic optimization, their study illustrates the potential gain when energy is optimally managed. Szul and Kokoszka (2020) explored the possibility of Rough Set Theory (RST) model to estimate the thermal energy consumption of buildings undergoing an energy renovation. As a result, the model is tested positive providing the possible application of the model with quality outcome. To Bourdeau et al. (2019), they modelled and forecasted building energy consumption through a revision of data-driven techniques, and the synthesis of latest technical improvement and research effort is also presented. Biswas et al. (2016) projected residential building energy consumption by employing the technique of neural network. The result of their study has made it comparable to other existing literature. Lü et al. (2015) used a physical statistical approach to model and project energy consumption, and their finding affirms the improvement of forecasting accuracy. Having said that, Costanzo et al. (2018) revisited the quality of the passive behavior of a Passivhaus for thermal comfort parameters temperature and relative humidity and Indoor Environmental quality (IEQ) parameter CO_2 concentrations. They later find that such a Passivhaus Standard can still be a good reference for the design of low-energy and comfortable houses in a Mediterranean climate. Zhang et al. (2019) projected China's energy consumption using a robust principal component analysis (RPCA) algorithm coupled with the Tabu search (TS) algorithm and the least square to support vector machine (LSSVM). In their analysis, a gradual rise of energy consumption from 2017 to 2030 is found, and it will breakthrough 6000 million tons by 2030. In China, Wu et al. (2017) projected China's energy consumption and carbon emissions peaks using an agent-based model driven by enterprises' innovation. Based on the study's analysis, peak energy consumption is expected to happen between 2020 and 2034 while peak carbon emissions are estimated to exist between 2020 and 2032. Under the same context, Yuan et al. (2014) studied peak energy consumption and CO_2 emissions by conducting analytical framework. With their study in place, it shows that peak energy consumption is projected to be at 5200 to 5400 million tons coal equivalent (Mtce) in 2035 to 2040 while peak CO_2 emissions is projected to be at 9200 to 9400 million tons (Mt) in 2030 to 2035. Haddad and Rahman (2012) proposed an approach of Bayesian generalized least squares (BGLS) regression in a region-of-influence (ROI) framework, quantile regression (QR) and parameter regression (PR), for regional frequency analysis (RFFA). Later, the study has proven that both QR and PR in BGLS-ROI framework help increase the accuracy and reliability of estimates for flood quantile and moments. Talking about RFA, Jung et al. [40] developed an improved nonlinear approach integrating a canonical correlation analysis and neural network (CCA-NN)-based regional frequency analysis (RFA) for low-flow estimation. Their study results in the potential of machine learning-based nonlinear techniques to estimate reliable low-flows at ungauged sites.

For additional attempt, Rahman and Rahman (2020) explored the applicability of principal component analysis (PCA) and cluster analysis coupled with Quantile regression technique (QRT) for regional flood frequency analysis in Australia. Effectively, their study shows that the above technique of PCA with QRT model does not perform well. Aziz et al. (2014) adopted a regional flood frequency analysis with the use of artificial neural networks to estimate flood quantiles in Australia, and it has been found that such an analysis with ANN generates more accurate analysis result. Honorato et al. (2019) also applied neuro-wavelet techniques to predict monthly streamflow. These integrated techniques are tested and later found with the accuracy improvement of the models. Graf et al. (2019) forecasted water temperature by integrating a hybrid model of wavelet transforms (WT) and ANN. With this hybrid model, their study presents the outperform of the model in simulating and forecasting river water temperature time series when the linear, non-linear and traditional ANN models are compared. Upon optimizing the ANN model, Suprayogi et al. (2020) developed a groundwater level forecasting model in monitoring the dynamics of land water fluctuations in tropical peatland. Their study later supports that the model is suitable for an application on tropical peatlands. Gursoy and Engin 2019 applied a wavelet neural network approach based on meteorological data in estimating daily river discharge. According to their analysis, it shows a superiority of the hybrid model over conventional ANN model. However, Bashir et al. (2019) proposed a new hybrid method of bootstrap multiple linear regression (BMLR) to examine the potential of bootstrap resampling technique for daily reservoir inflow prediction. Based on their analysis, the hybrid BMLR model is proven to provide better outcome than any other studied models; MLR, wavelet MLR and wavelet bootstrap MLR.

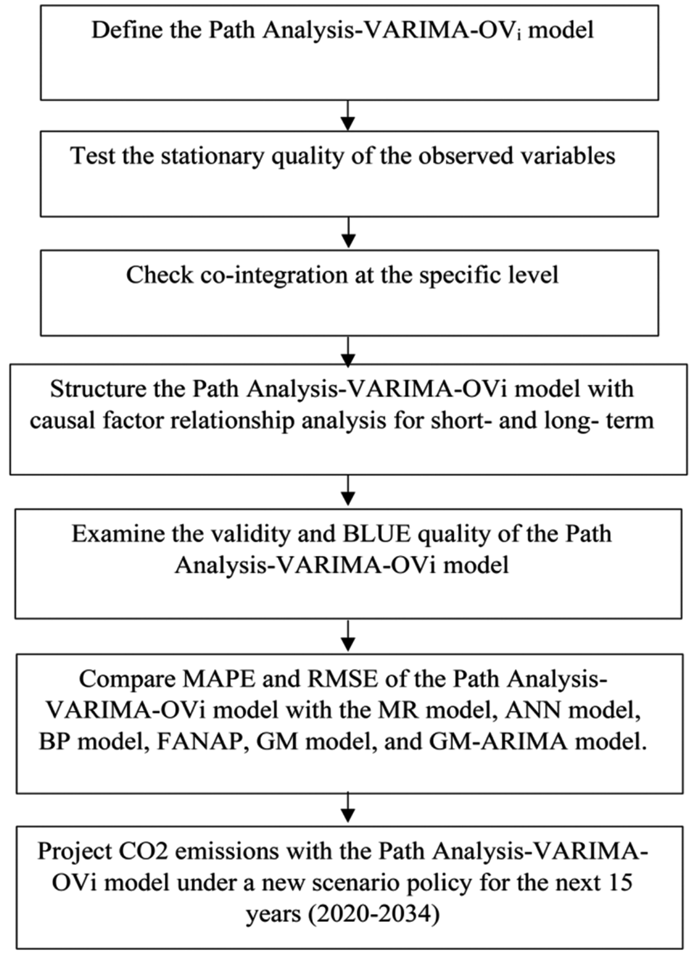
Accounting model comparison, many studies have made extra efforts to compare the available models in the field. In Canada, Adamowski et al. (2012) forecasted urban water demand using wavelet transforms (WA) and ANNs, and later compared the model performance with other existing multiple linear regression (MLR), multiple nonlinear regression (MNLR), autoregressive integrated moving average (ARIMA), ANN. With a combination of WA-ANN models, they are proven to outperform than any other single model for urban water demand forecasting. Mekanik et al. (2013) optimized the application of ANN and MR analysis to forecast long-term seasonal spring rainfall in Victoria, Australia. Here, they find the ANN model outperforming MR model. Valipour et al. (2012) forecasted the monthly inflow of Dez dam reservoir located in Teleh Zang station using Autoregressive Moving Average (ARMA) and Autoregressive Integrated Moving Average (ARIMA) models. With their analysis, ARIMA model is presented with higher accuracy in forecasting compared to ARMA model. While Garmdareh et al. (2018) analyzed regional flood frequency using support vector regression (SVR), adaptive neuro-fuzzy inference system (ANFIS), ANN and nonlinear regression (NLR) techniques coupled with gamma test (GT). Later, their study reveals that GT + ANFIS and GT + SVR models produce better result than any other two models while GT technique improves the model performance. In Iran, Keshtkar et al. (2013) predicted the rainfall for 10 years ranging from 1999 to 2009 by deploying Adaptive Neural Fuzzy Inference System (ANFIS) and ANN together with GT. As a result, the ANFIS model is tested positive indicating a better model performance compared to the ANN model. Roy et al. (2018) estimated heating load in building though a utilization of multivariate adaptive regression splines (MARS), extreme learning machine (ELM), and a hybrid model of MARS and ELM. Upon their analysis, the outperformance of the hybrid model is detected with good quality, high accuracy and less computation time. Geysen et al. (2018) validated operational thermal load forecasting in district heating networks with the use of machine learning and expert system; linear regression, extremely randomized trees regression, feed-forward neural network and support vector machine. Lastly, Song et al. (2020) proposed a framework to quantify uncertainty in machine learning (ML) modelling in order to forecast multi-step time-series using the analysis of variance (ANOVA) theory. Their study also compared LSTM network with simple Recurrent Neutral Networks (RNNs). As of their analysis, it reveals that the proposed framework can indicate uncertainty quantification an indispensable task for a successful application of ML or Deep Learning. In addition, their study shows the superiority of LSTM in discharge simulations while the ML architecture is found as important as the ML approach.

Through the current exploration of the literature, a number of significant areas have been used to benefit this study in its identification of research gaps, research framework and other applicable aspects in the development of this study's contribution. Also, it is worth noting that past studies have used different management models, various analysis concepts, various sample sectors, and different research methods and frameworks. In fact, each model has aimed to create the most suitable model with maximal efficiency in management. However, this study has recognized differences among the studies, which has motivated the development of this study's model for effective management and a better tool to support in the national long-term strategy formulation of Thailand. The applied model is called the "Path Analysis-VARIMA-OV_i model." The model was derived through the following research process.

1. Defining the Path Analysis-VARIMA-OV_i model by identifying the latent variables and observed variables
2. Testing the stationary quality of the observed variables using the augmented Dickey-Fuller concept (Dickey and Fuller, 1981)
3. Examining co-integration at the same level applying the Johansen-Juselius theory (Johansen and Juselius, 1990 MacKinnon, 1991 Johansen, 1995).
4. Structuring the Path Analysis-VARIMA-OV_i model with causal factor relationship analysis, both short-and-long term
5. Checking the validity and BLUE quality of the Path Analysis-VARIMA-OV_i model
6. Assessing the performance using MAPE and RMSE to evaluate the Path Analysis-VARIMA-OV_i model with other models, namely the MR model, ANN model, BP model, FANAP, GM model, and GM-ARIMA model
7. Forecasting CO_2 emissions with the Path Analysis-VARIMA-OV_i model during the period of 2020 -2034 for 15 years in total under a new scenario policy.

The flowchart of the Path Analysis-VARIMA-OV_i model is shown in Figure 1.

Figure 1: The flowchart of the Path Analysis-VARIMA-OVi model



3. THE MATERIAL AND METHOD

The Modern Path Analysis-based on VARIMA-OV_i is a model developed to fill up research gaps of the existing models, and that makes this study to be white noise and not spurious. The Modern Path Analysis -based on VARIMA-OV_i model can be understood as follows. In this model, there are two types of variables, endogenous variable and exogenous variable. Appreciating and comprehension of these variables will help understand the modelling system correctly (Ender, 2010). The exogenous variable is a variable that is changeable due to other external factors, and that can be understood as a variable affecting other factors directly and indirectly. This variable itself is also affected by external influences. Whereas the endogenous variable is a variable within the path and changeable due to exogenous variables or other endogenous variables (Harvey, 1989).

Hypotheses and theories confirm that variable 1, 2, 3 and 4 are related in different paths, as shown below.

Figure 2 indicates the casual factor relationship of the Modern Path Analysis- based on VARIMA-OV_i model (Sutthichaimethee, 2018)

From the above diagram, it can be seen that variable 1 and 2 are exogenous variables, because their variation is not caused by any other factors in the path. In another word, variable 1 and 2 are to affect other variables, which are variable 3 and 4. While these two variables are endogenous variables. This is because variable 3 and 4 are separately affected by external variables (variable 1 and 2). The endogenous variable (variable 3) and the other two exogenous variables (variable 1 and 2) are both independently correlated, and that is known as correlated causes (Sims, 1980 Byrne, 2009 Sutthichaimethee, 2018).

In addition, we can further analyze the diagram by looking at the path (arrows), which can be understood as follows.
1. Variable 3 is directly affected by variable 1 and 2
2. Variable 3 is indirectly affected by variable 2 through variable 1, and it is indirectly affected by variable 1 via variable 2
3. Variable 4 is directly affected by variable 1, 2 and 3
4. Variable 4 is indirectly affected by variable 1 through variable 2 and 3, and they are indirectly affected by variable 2 through variable 1 and 3
5. A and b are residual.

Remarks1. P_{ij} is called as path coefficient used to indicate the influence magnitude of variable j over variable i. For instance, P_{31} means the influence magnitude of variable 1 over variable 3.

2. r_{ij} is the correlation between variable j and variable i

3. In fact, P_{ij} is the population correlation between variable j and variable i, and that means $P_{ij} = \rho_{ij}$. This fact can be easily proven.

The estimation of the Modern Path Analysis – based on VARIMA-OV_i is detailed below.

3.1 The VARIMA – OV_i model at level 1: VARIMA – $OV_{(1)}$

Assuming there are two time series, and both are I (0), affecting each other in the following form (Sutthichaimethee, 2018 Sutthichaimethee, 2016).

$$Y_t = \beta_{10} - \beta_{12} Z_t + \gamma_{11} Y_{t-1} + \gamma_{12} Z_{t-1} + \varepsilon_{yt} \tag{1}$$

$$Z_t = \beta_{20} - \beta_{21} Y_t + \gamma_{21} Y_{t-1} + \gamma_{22} Z_{t-1} + \varepsilon_{zt} \tag{2}$$

Where ε_{yt} and ε_{zt} are the white nose with a mean value of zero while their variance is σ_y^2 and σ_z^2, respectively. These ε_{yt} and ε_{zt} can be called as a Shock of the time series Y_t and Z_t, respectively. Both ε_{yt} and ε_{zt} are assumed not related or written as $Cov(\varepsilon_{yt}, \varepsilon_{zt})=0$.

From Equation (1), the parameter $-\beta_{12}$ indicates the impact of Z_t on Y_t. The parameter $-\beta_{21}$ from Equation (2) shows the impact of Y_t on Z_t. This can be seen that both time series are affected each other. When substituting Equation (1) into (2), it derives the fact that if $-\beta_{21}\neq 0$, then the Shock with time series Y_t (ε_{yt}) will affect indirectly on Z_t. Likewise, substituting Equation (2) into (1), it shows that if $-\beta_{12}\neq 0$, then the Shock with time series Z_t (ε_{zt}) will indirectly affect Y_t, and that can be rewritten as (Sutthichaimethee, 2016):

$$Y_t + \beta_{12} Z_t = \beta_{10} + \gamma_{11} Y_{t-1} + \gamma_{12} Z_{t-1} + \varepsilon_{yt} \tag{3}$$

$$\beta_{21} Y_t + Z_t = \beta_{20} + \gamma_{21} Y_{t-1} + \gamma_{22} Z_{t-1} + \varepsilon_{zt} \tag{4}$$

Here, Equation (3) and (4) can be written in matrix form as:

$$\begin{bmatrix} 1 & \beta_{12} \\ \beta_{21} & 1 \end{bmatrix} \begin{bmatrix} Y_t \\ Z_t \end{bmatrix} = \begin{bmatrix} \beta_{10} \\ \beta_{20} \end{bmatrix} + \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{bmatrix} \begin{bmatrix} Y_{t-1} \\ Z_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{yt} \\ \varepsilon_{zt} \end{bmatrix} \tag{5}$$

Or rewritten as:

$$BX_t = \Gamma_0 + \Gamma_1 X_{t-1} + \varepsilon_t \tag{6}$$

Where

$$B = \begin{bmatrix} 1 & \beta_{12} \\ \beta_{21} & 1 \end{bmatrix},\quad X_t = \begin{bmatrix} Y_t \\ Z_t \end{bmatrix},\quad \Gamma_0 = \begin{bmatrix} \beta_{10} \\ \beta_{20} \end{bmatrix},\quad \Gamma_1 + \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{bmatrix},$$

$$\varepsilon_t = \begin{bmatrix} \varepsilon_{yt} \\ \varepsilon_{zt} \end{bmatrix}$$

From Equation (6), B^{-1} is multiplied, and that would give:

$$X_t = B^{-1}\Gamma_0 + B^{-1}\Gamma_1 X_{t-1} + B^{-1}\varepsilon_t \tag{7}$$

Given that $A_0=B^{-1}\Gamma_0$, $A_1=B^{-1}\Gamma_1$ and $u_t=B^{-1}\varepsilon_t$, then Equation (7) can be written as follows (Sutthichaimethee, 2017).

$$X_t = A_0 + A_1 X_{t-1} + u_t \tag{8}$$

Where $A_0 = \begin{bmatrix} a_{01} \\ a_{02} \end{bmatrix}$, $A_1 = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$ and $u_t = \begin{bmatrix} u_{1t} \\ u_{2t} \end{bmatrix}$

Therefore, Equation (8) can be structured as below.

$$Y_t = a_{10} + a_{21} Y_{t-1} + a_{12} Z_{t-1} + u_{1t} \tag{9}$$

$$Z_t = a_{20} + a_{21} Y_{t-1} + a_{22} Z_{t-1} + u_{2t} \tag{10}$$

It can be seen that Equation (1) and (2) are actually Equation (9) and (10) but different form.

- Writing an equation as Equation (1) and (2) is called "Structural Vector Autoregressive Level 1 or shortly written as SVARIMA-$OV_{(1)}$
- Writing an equation as Equation (9) and (10) is called "Vector Autoregressive Level 1 or shortly written as VARIMA-$OV_{(1)}$.

The above model at Level 1 is rooted from slowest variable in Equation (1). Based on the equation of $u_t=B^{-1}\varepsilon_t$, it can be written again as follows (Sutthichaimethee and Ariyasajjakorn, 2017 Sutthichaimethee and Ariyasajjakorn, 2018).

$$\begin{bmatrix} u_{1t} \\ u_{2t} \end{bmatrix} = \begin{bmatrix} 1 & \beta_{12} \\ \beta_{21} & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_{yt} \\ \varepsilon_{zt} \end{bmatrix}$$

$$\begin{bmatrix} u_{1t} \\ u_{2t} \end{bmatrix} = \frac{1}{1-\beta_{21}\beta_{12}} \begin{bmatrix} 1 & \beta_{12} \\ \beta_{21} & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_{yt} \\ \varepsilon_{zt} \end{bmatrix} \tag{11}$$

$$\begin{bmatrix} u_{1t} \\ u_{2t} \end{bmatrix} = \begin{bmatrix} \dfrac{1}{1-\beta_{21}\beta_{12}}(\varepsilon_{yt} - \beta_{12}\varepsilon_{zt}) \\ \dfrac{1}{1-\beta_{21}\beta_{12}}(\varepsilon_{zt} - \beta_{21}\varepsilon_{yt}) \end{bmatrix} \tag{12}$$

$$u_{1t} = \frac{1}{1-\beta_{21}\beta_{12}}(\varepsilon_{yt} - \beta_{12}\varepsilon_{zt}) \tag{13}$$

$$u_{2t} = \frac{1}{1-\beta_{21}\beta_{12}}(\varepsilon_{zt} - \beta_{21}\varepsilon_{yt}) \tag{14}$$

Where u_{1t} and u_{2t} are the error random variable of time series Y_t and Z_t in the VARIMA-OV_i model. The properties of the mean and variance of u_{1t} and u_{2t} are as illustrated below (Sutthichaimethee and Ariyasajjakorn, 2017 Sutthichaimethee and Dockthaisong, 2018 Sutthichaimethee and Kubaha, 2018).

$$E(u_{1t}) = 0 \tag{15}$$

$$E(u_{2t}) = 0 \tag{16}$$

$$Var(u_{1t}) = \left(\frac{1}{1-\beta_{21}\beta_{12}}\right)^2 \left(\sigma_y^2 + \beta_{12}^2\sigma_z^2\right) = \sigma_1^2 \tag{17}$$

$$Var(u_{2t}) = \left(\frac{1}{1-\beta_{21}\beta_{12}}\right)^2 \left(\sigma_z^2 + \beta_{21}^2\sigma_y^2\right) = \sigma_2^2 \tag{18}$$

$$Cov(u_{1t}, u_{2t}) = -\frac{\left(\beta_{21}\sigma_y^2 + \beta_{12}\sigma_z^2\right)}{\left(1-\beta_{21}\beta_{12}\right)^2} = \sigma_{12} \neq 0 \tag{19}$$

Equation (19) tells that u_{1t} and u_{2t} are related, and the covariance matrix of u_{1t} and u_{2t} can be retrieved and represented by Σ as demonstrated below (Sutthichaimethee and Kubaha, 2018 Sutthichaimethee et al., 2015 Valipour et al., 2013).

$$\Sigma = \mathrm{E}\left(u_t u_t'\right) = \mathrm{E}\left(\begin{bmatrix} u_{1t} \\ u_{2t} \end{bmatrix}\begin{bmatrix} u_{1t} & u_{2t} \end{bmatrix}\right)$$

$$= \mathrm{E}\begin{bmatrix} u_{1t}^2 & u_{1t}u_{2t} \\ u_{2t}u_{1t} & u_{2t}^2 \end{bmatrix} = \begin{bmatrix} \mathrm{E}(u_{1t}^2) & \mathrm{E}(u_{1t}u_{2t}) \\ \mathrm{E}(u_{2t}u_{1t}) & \mathrm{E}(u_{2t}^2) \end{bmatrix}$$

$$= \begin{bmatrix} \left(\frac{1}{1-\beta_{21}\beta_{12}}\right)^2 \left(\sigma_y^2 + \beta_{12}^2\sigma_z^2\right) & -\frac{\left(\beta_{21}\sigma_y^2 + \beta_{12}\sigma_z^2\right)}{\left(1-\beta_{21}\beta_{12}\right)^2} \\ -\frac{\left(\beta_{21}\sigma_y^2 + \beta_{12}\sigma_z^2\right)}{\left(1-\beta_{21}\beta_{12}\right)^2} & \left(\frac{1}{1-\beta_{21}\beta_{12}}\right)^2 \left(\sigma_z^2 + \beta_{21}^2\sigma_y^2\right) \end{bmatrix}$$

$$= \mathrm{E}\begin{bmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{21} & u_2^2 \end{bmatrix} \tag{20}$$

Where $\sigma_1^2 = Var(u_{1t})$, $\sigma_2^2 = Var(u_{2t})$, $\sigma_{12}=Cov(u_{1t}, u_{2t})=\sigma_{21}$.

When considering Equation (9) and (10), it is found that the error random variable in each equation has no relation to each other. Therefore, the least squares method in estimating the parameter of both equations will have a variance of the least estimator. Therefore, we will find the mean and variance of the VARIMA-OV_i model as shown in Equation (21) as follows (Enders, 2010 Sutthichaimethee and Kubaha, 2018 Pacheco and Fernandes, 2013):

$$\mathrm{E}(X_t) = \mu = (I - A_1)^{-1} A_0 \tag{21}$$

$$Var(X_t) = \Sigma + A_1 \Sigma A_1' + A_1^2 \Sigma (A_1^2)' + A_1^3 \Sigma (A_1^3)' + \ldots \tag{22}$$

Where $A_1^j \to 0$ when j→∞, and this means the variance of every time series in vector X_t can be estimated via the VARIMA-$OV_{(1)}$ model.

1. u_t is the vector inclusive of the Shock of Y_t and Z_t
2. Each time series in the VARIMA-$OV_{(1)}$ model depends on previous uncertainties of every times series of the model
3. The longer the unexpected event, the lesser the impact on the time series of the VARIMA- $OV_{(1)}$ model.

3.2. The VARIMA-OV(P) Model

There are two sets of time series; Y_t and Z_t, and they are written in the modelling form of the VARIMA-OV(P) model as follow (Harvey, 1989 Sutthichaimethee, 2016 Sutthichaimethee and Ariyasajjakorn, 2018).

$$\begin{aligned} Y_t &= a_{10} + a_{11,1}Y_{t-1} + a_{12,1}Y_{t-1} + a_{11,2}Y_{t-2} + \\ &a_{12,2}Y_{t-2} + \ldots + a_{11,p}Y_{t-p} + a_{12,p}Y_{t-p} + u_{1t} \end{aligned} \tag{23}$$

$$\begin{aligned} Z_t &= a_{20} + a_{21,1}Y_{t-1} + a_{22,1}Y_{t-1} + a_{21,2}Y_{t-2} + \\ &a_{22,2}Y_{t-2} + \ldots + a_{21,p}Y_{t-p} + a_{22,p}Y_{t-p} + u_{2t} \end{aligned} \tag{24}$$

If there are *n* set of time series, X1t, X2t,…, Xnt, they can also be written in the modelling form of the VARIMA-OV(P) model as below.

$$X_t = A_0 + A_1 X_{t-1} + A_2 X_{t-2} + \ldots + A_p X_{t-p} + u_t \tag{25}$$

Where

$$X_t = \begin{bmatrix} X_{1t} \\ X_{2t} \\ \vdots \\ X_{nt} \end{bmatrix}_{n\times 1}, \quad A_0 = \begin{bmatrix} a_{01} \\ a_{02} \\ \vdots \\ a_{0n} \end{bmatrix}_{n\times 1}, \quad A_i = \begin{bmatrix} a_{11,i} & \cdots & a_{1n,i} \\ a_{21,i} & \cdots & a_{2n,i} \\ \vdots & \vdots & \vdots \\ a_{n1,i} & \cdots & a_{nn,i} \end{bmatrix}_{n\times n}, \; i = 1, \ldots, p$$

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

In estimating the mean and variance of the VARIMA-OV(P) model, it can be done the same way as it is for the VARIMA-OV(1) model. Based on the VARIMA-OV(P) model, many parameters are detected at constant for n-number. While the coefficient parameters of $X_{t-1}, X_{t-2}, \ldots, X_{t-p}$ are $n^2+n^2+\ldots n^2=pn^2$-number.

Therefore, the total parameters in the VARIMA-OV_i model is $n+pn^2$-number. The more the time series is increased by 1 or the level of the VARIMA – OV_i model is increased by 1, the greater the parameter would be. Hence, any time series used for the VARIMA-OV_i model should be series that carry effect.

3.3. Measurement of the Forecasting Performance

In this research, we apply the MAPE and RMSE to evaluate the performance. The calculation equations are shown as follows (Enders, 2010 Harvey, 1989 Sutthichaimethee and Kubaha, 2018 Sutthichaimethee and Kubaha, 2018):

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \tag{26}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\hat{y}_i - y_i\right)^2} \tag{27}$$

4. EMPIRICAL ANALYSIS

4.1. Screening of Influencing Factors for Model Input

This study defines the Path Analysis-VARIMA-OV_i model with three latent variables consisting of Economic growth (*Econgrowth*), Social growth (*Socgrowth*), and Environmental growth (*Econgrowth*), while the observed variables comprise the following 12 indicators: urbanization rate (*URR*), industrial structure (*ISR*), total exports (*EXM*), indirect foreign investment (*IFR*), expenditure government rate (*GER*), employment (*EMR*), health and illness (*HIR*), social security (*SSR*), consumer protection (*CPR*), energy consumption (*ECR*), oil consumption rate (*OCR*), and carbon dioxide emissions (CO_2).

As regards the structural analysis for the Path Analysis-VARIMA-OV_i model, the study selected 12 observed variables to perform stationary tests at the level I (0) and first level I (1) by using the unit root test based on the augmented Dickey-Fuller theory (ADF-test). This study applied only stationary variables at the same level, and it estimated stationary quality at level I (0) and first level I (1) only, as illustrated in Table 1.

According to Table 1, all observed variables were non-stationary at Level I (0), because all of their Tau-test values were lower than the MacKinnon critical value or shown as being non-significant. Therefore, the study carried the first difference at Level I (1), and the results show that all observed variables were then stationary at Level I (1). This is because the Tau test value was greater than the MacKinnon critical value at 1%, 5% and 10%. This result further indicates that all observed variables were significant. Once they were statistically significant, all observed variables at the first difference level I (1) were analyzed for co-integration as proposed by Johansen and Juselius, as shown in Table 2.

Table 1: Unit root test at level I(0) and first difference I (1)

Tau test				MacKinnon critical value		
Variables	Level I(0) Value	Variables	First difference I(1) Value	1%	5%	10%
In (*URR*)	−4.10	Δ In (*URR*)	−5.91***	−4.15	−3.25	−2.10
In (*ISR*)	−4.01	Δ In (*ISR*)	−5.35***	−4.15	−3.25	−2.10
In (*EXM*)	−3.97	Δ In (*EXM*)	−4.74***	−4.15	−3.25	−2.10
In (*IFR*)	−4.11	Δ In (*IFR*)	−5.05***	−4.15	−3.25	−2.10
In (*GER*)	−3.78	Δ In (*GER*)	−4.21***	−4.15	−3.25	−2.10
In (*EMR*)	−3.45	Δ In (*EMR*)	−4.45***	−4.15	−3.25	−2.10
In (*HIR*)	−3.98	Δ In (*HIR*)	−4.60***	−4.15	−3.25	−2.10
In (*SSR*)	−3.61	Δ In (*SSR*)	−4.95***	−4.15	−3.25	−2.10
In (*CPR*)	−3.20	Δ In (*CPR*)	−4.45***	−4.15	−3.25	−2.10
In (*ECR*)	−4.02	Δ In (*ECR*)	−5.85***	−4.15	−3.25	−2.10
In (*OCR*)	−3.79	Δ In (*EIR*)	−5.25***	−4.15	−3.25	−2.10
In (CO_2)	−4.10	Δ In (CO_2)	−6.01***	−4.15	−3.25	−2.10

URR is the urbanization rate, *ISR* is the industrial structure, *EXM* is the total exports, *IFR* is the indirect foreign investment, *GER* is the expenditure government rate, *EMR* is the employment, *HIR* is the health and illness, *SSR* is the social security, *CPR* is the consumer protection, *ECR* is the energy consumption, *OCR* is the oil consumption rate, CO_2 is the carbon dioxide emissions *** denotes a significance, α=0.01, compared to the Tau test with the MacKinnon critical value, Δ is the first difference, and 1n is the natural logarithm

4.2. Analysis of Co-integration

As regards co-integration analysis, this aims to analyze the long-term relationship of observation variables and short-term error correction as explained by the theory of Johansen and Juselius, as illustrated in Table 2.

From Table 2, all observed variables were co-integrated. The trace test was estimated at 220.25 and 95.04, which were greater than the MacKinnon critical value, indicating that they are significant at 1% and 5%. Considering the maximum eigenvalue test, this was valued at 255.01 and 90.20, which were greater than the MacKinnon critical value, and shows that the variables were significant at 1% and 5%. Once all variables were found to be significant, they were further estimated to address error correction mechanisms in the Path Analysis-VARIMA-OV_i model.

4.3. Formation of Analysis Modeling with the Path Analysis-VARIMA-OV_i Model

In the development of the model, the study used three latent variables: Economic growth, social growth, and environmental growth, which were shown to be causally related in modeling the Path Analysis-VARIMA-OV_i model. This model consists of 12 observed variables, which were all co-integrated. The error correction mechanism was also made at the first difference I (1), as shown in Figure 3.

Figure 3 presents the analysis results of the Path Analysis-VARIMA-OV_i model, presenting the causal factor relationship of the latent variables, which are as follows: economic growth (*Econgrowth*) with indicators of urbanization rate (*URR*), industrial structure (*ISR*), total exports (*EXM*), indirect foreign investment (*IFR*), expenditure government rate (*GER*), social growth (*Socgrowth*) with indicators of employment (*EMR*), health and illness (*HIR*), social security (*SSR*), consumer protection (*CPR*), and environmental growth (*Econgrowth*) with indicators of energy consumption (*ECR*), oil consumption rate (*OCR*), and carbon dioxide emissions (CO_2). The above analysis reveals that

Table 2: Co-integration test by Johansen and Juselius

Variables	Hypothesized No of CE(S)	Trace statistic test	Max-Eigen statistic test	MacKinnon critical value	
				1%	5%
Δ In (*URR*), Δ In (*ISR*), Δ In (*EXM*), Δ In (*IFR*), Δ In (*GER*), Δ In (*EMR*), Δ In (*HIR*), Δ In (*SSR*), Δ In (*CPR*), Δ In (*ECR*), Δ In (*OCR*), Δ In (CO_2)	None***	220.25***	255.01***	15.25	10.50
	At Most 1***	95.04***	90.20***	10.50	7.25

***denotes significance α=0.01, **denotes significance α=0.05

latent variables have direct effects, indirect effects, and causal effects. In addition, the Path Analysis-VARIMA-OVi model shows the adjustment ability to equilibrium with different sizes by considering the error correction mechanism ($SECM_{t-1}$). With validity in check, the Path Analysis-VARIMA-OV_i model was found to have BLUE quality, as well as eliminating spuriousness, heteroskedasticity, multicollinearity, and autocorrelation. Thus, findings on the magnitude of the influence of relationship with white noise feature were further revealed, as demonstrated in Table 3.

Figure 2: Indicates the casual factor relationship of the Modern Path Analysis- based on VARIMA-OV_i model

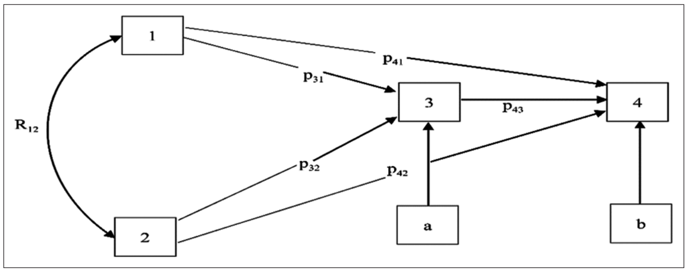


Table 3 shows that the Path Analysis-VARIMA-OV_i model has a validity with BLUE quality, indicating further the absence of model spuriousness. By testing the goodness of fit, the model satisfies the standard of RMSEA and RMR close to 0. The value of GFI and AGFI is close to 1. Therefore, the Path Analysis-VARIMA-OV_i model is deemed suitable for analyzing the causal factor relationship of economic growth (*Econgrowth*), Social growth (*Socgrowth*), and Environmental growth (*Econgrowth*). Upon analyzing the magnitude of the relationship, Economic growth (*Econgrowth*) was detected as having direct effect on social growth (*Socgrowth*) by 54% at the significance level of 1%, indicating that if economic growth (*Econgrowth*) changes by 1%, social growth (*Socgrowth*) will move by 54%. Besides, Social growth (*Socgrowth*) is found with direct effect on Environmental growth (*Econgrowth*) by 26%. This means if Social growth

Figure 3: The results of relationship analysis using the Path Analysis-VARIMA-OV_i model

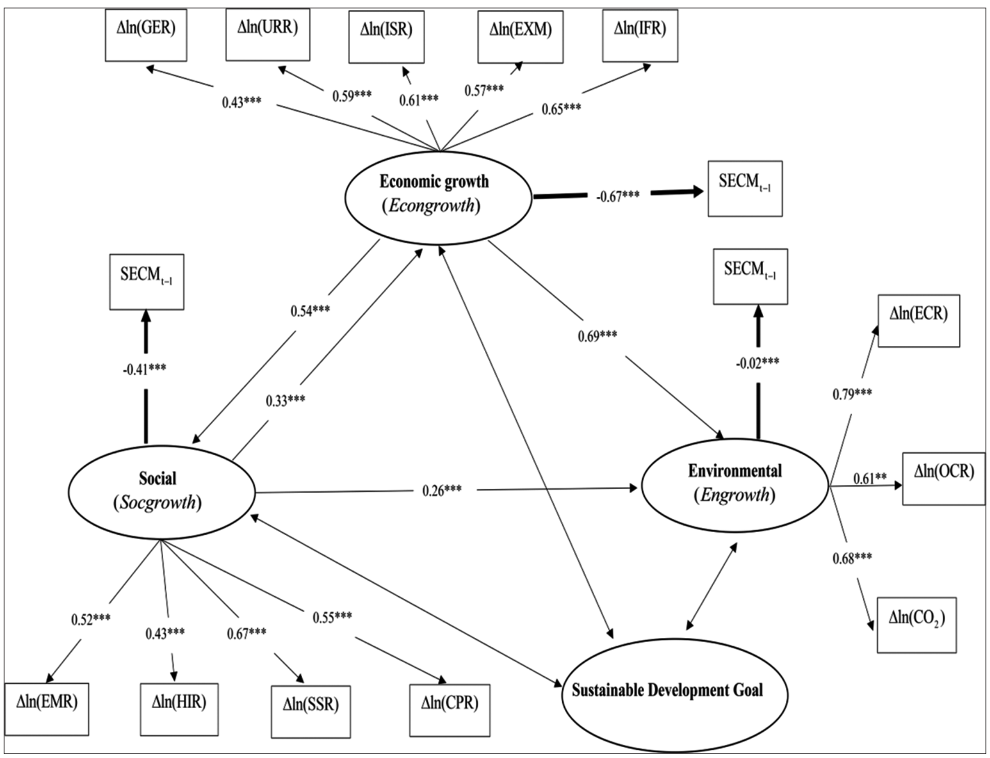


Table 3: Results of relationship size analysis of the Path Analysis-VARIMA-OV_i model

Dependent Variables	Type of effect	Independent VARIABLES			
		Economic growth (*Econgrowth*)	Social growth (*Socgrowth*)	Environmental growth (*Econgrowth*)	Error Correction Mechanism (*$SECM_{t-1}$*)
Economic growth (*Econgrowth*)	DE	-	0.33***	-	−0.67***
	IE	-	-	-	-
Social growth (*Socgrowth*)	DE	0.54***	-	-	−0.41***
	IE	-	-	-	-
Environmental growth (*Econgrowth*)	DE	0.69***	0.26***	-	−0.02**
	IE	0.19***	0.21***	-	-

In the above, ***denotes significance α =0.01, **denotes significance α=0.05, x^2/df is 1.15, RMSEA is 0.01, RMRis 0.003, GFI is 0.95, A GFI is 0.91, R-squared is 0.96, the F-statistic is 131.20 (probability is 0.00), the ARCH test is 20.25 (probability is 0.1), the LM test is 1.22 (probability is 0.10), DE is direct effect and IE is indirect effect

(*Socgrowth*) changes by 1%, Environmental growth (*Econgrowth*) will be changed by 26%, accordingly. Whereas economic growth (*Econgrowth*) is found with direct effect on Environmental growth (*Econgrowth*) by 69%, presenting that if Economic growth (*Econgrowth*) grows by 1%, it will influence environmental growth (*Econgrowth*) to change by 69%. However, as concerns the analysis of economic growth (*Econgrowth*) with social growth (*Socgrowth*) it was found that they are casually related, meaning that social growth (*Socgrowth*) was impact over changes in economic growth (*Econgrowth*) with the relationship size of 33%. This finding indicates that if social growth (*Socgrowth*) changes by 1%, it will affect economic growth (*Econgrowth*) to change by 33% with a positive relationship.

In the case of the error correction mechanism ($SECM_{t-1}$), it is resulted from the Path Analysis-VARIMA-OV_i model. It is the value indicating about the adjustment ability to equilibrium with different sizes. Economic growth (*Econgrowth*) was produced with the error correction mechanism ($SECM_{t-1}$) valued at −0.67 at the significance level of 1%, indicating such an ability of 67%. However, Economic growth (*Econgrowth*) was found to have a better ability compared to social growth (*Socgrowth*) and environmental growth (*Econgrowth*) with the size of −0.41 and −0.02 at the same significance level of 1%.

The above analysis results assert that the Path Analysis-VARIMA-OV_i model has appropriate validity and BLUE quality. The study, however, carried out performance assessment for more complex model performance evaluation by using MAPE and RMSE values. The values of the Path Analysis-VARIMA-OV_i model were compared with other models, namely the MR model, ANN model, BP model, FANAP model, GM model, and GM-ARIMA model. The following results were generated.

Table 4: The performance monitoring of the forecasting model

Forecasting model	MAPE (%)	RMSE (%)
MR model	16.49	19.80
ANN model	10.17	12.63
BP model	7.05	8.19
FANAP model	5.11	6.69
GM model	4.01	4.08
GM-ARIMA model	3.64	4.31
Path Analysis-VARIMA-OV_i model	1.09	1.55

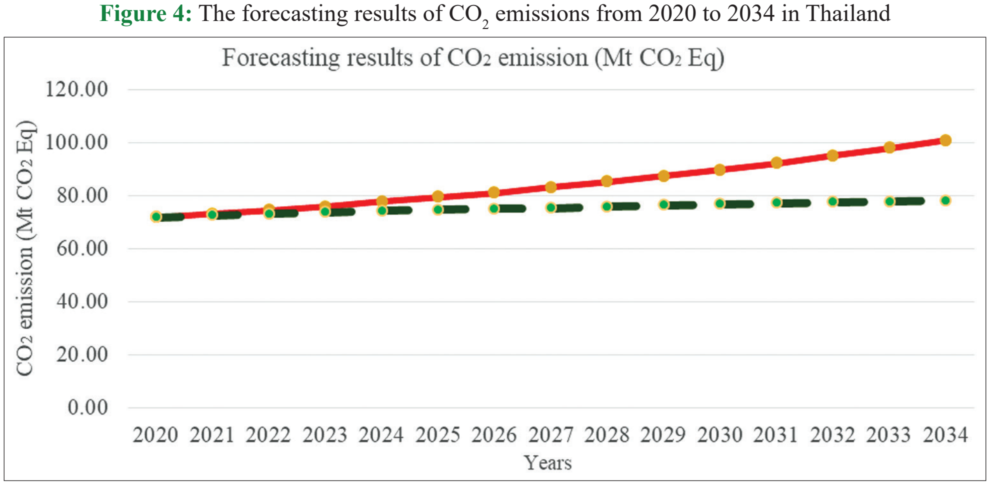
Table 4 indicates that the Path Analysis-VARIMA-OV_i model has the lowest MAPE and RMSE valued at 1.09% and 1.55%, respectively, in comparison with other models. The GM-ARIMA model has MAPE and RMSE values of 3.64% and 4.31%, respectively. The GM model has MAPE and RMSE values of 4.01% and 4.08%, respectively. The FANAP model has MAPE and RMSE values of 5.11% and 6.69%, respectively. The BP model has MAPE and RMSE values of 7.05% and 8.19%, respectively. The ANN model has MAPE and RMSE values of 10.17% and 12.63%, respectively. The MR model has MAPE and RMSE values of 16.49% and 19.80%, respectively. Based on these outcomes, the Path Analysis-VARIMA-OV_i model is believed to be the best and most appropriate model as a forecasting tool to manage policies in order to achieve the sustainable development goals.

4.4. Forecasting Model for CO_2 Emissions based on the Path Analysis-VARIMA-OV_i Model

Based on the analysis, the Path Analysis-VARIMA-OV_i model is the most suitable model for long-term forecasting. Therefore, when the Thai government defines a scenario, the proposed model is able to help determine environmental growth (*Econgrowth*), because the model was found to have the lowest value for the error correction mechanism ($SECM_{t-1}$), and this makes the model work its best to define a new scenario policy by choosing energy consumption (*ECR*). This is because its parameter value is greater than any other indicators under environmental growth (*Econgrowth*). Hence, the Path Analysis-VARIMA-OV_i model can be used to project or predict CO_2 emission for the next 15 years (2020-2034), and forecast CO_2 emission for the next same period length (2020-2034) with the new scenario policy, where energy consumption (*ECR*) remains constant yet doesn't exceed the present value (2019), as shown in Figure 4.

Figure 4 shows that CO_2 emissions over the next 15 years from 2020 to 2034 in Thailand will rise by a rate of 40.32% (2034/2020), and CO_2 emissions are estimated to have a higher carrying capacity of 90.5 Mt CO_2 Eq. (2020-2034). However, the study accounts for a new scenario policy, where energy consumption (ECR) is

Figure 4: The forecasting results of CO_2 emissions from 2020 to 2034 in Thailand



constant and doesn't exceed the present value (2019). This new consideration results in CO_2 emissions over the next 15 years from 2020 to 2034 in Thailand being predicted to also rise by the reduced growth rate of 8.62% (2034/2020) or increase by 78.12 Mt CO_2 Eq. (2020/2034).

5. CONCLUSIONS AND DISCUSSION

This study developed the Path Analysis-VARIMA-OV_i model based on causal factor relationship, and it is believed to consist of the features of the best model. The relationship was analyzed as regards the latent variables of economic growth (*Econgrowth*) with five indicators. They consist of urbanization rate (URR), industrial structure (*ISR*), total exports (*EXM*), indirect foreign investment (*IFR*), expenditure government rate (*GER*). Social growth (*Socgrowth*) comprises four indicators: employment (*EMR*), health and illness (*HIR*), social security (*SSR*), consumer protection (*CPR*). Lastly, environmental growth (*Econgrowth*) consists of three indicators: energy consumption (*ECR*), oil consumption rate (*OCR*), and carbon dioxide emissions (CO_2). As concerns the study's findings, all the observed variables were found to be stationary at the first difference level, I(1). When testing co-integration, they all were found co-integrated at the first difference level, I(1). Therefore, the proposed model of the Path Analysis-VARIMA-OV_i was developed for long-term forecasting. The model further accounts for the error correction mechanism ($SECM_{t-1}$). According to the estimated value of such a mechanism, environmental growth (*Econgrowth*) has the lowest ability for error correction, and this sector is given priority by the government for support in national planning for the future national strategy. Environmental growth (*Econgrowth*) should be carefully understood, because it can be causally affected by the economic growth (*Econgrowth*). This impact has a direct influence on the environmental growth (*Econgrowth*) and the social growth (*Socgrowth*), respectively. The study also presents evidence that environmental growth (*Econgrowth*) has no impact on the other sectors at all.

When the Path Analysis-VARIMA-OV_i model is used for the purpose of long-term forecasting (2020-2034) coupled with the performance assessment in comparison with other models (MR model, ANN model, BP model, FANAP model, GM model, and GM-ARIMA model), it was found that the Path Analysis-VARIMA-OV_i model is the best forecasting tool for future prediction and long-term projection in particular. In addition, the proposed model ensured the absence of heteroskedasticity, multicollinearity, and autocorrelation.

Therefore, the study confirms the high quality and proper capacity of the Path Analysis-VARIMA-OV_i model to stipulate the sustainable development goal with high efficiency. In the case of new scenario policy determination, this depends on environmental growth (*Econgrowth*) and the long-term prediction of carbon dioxide emissions over 15 years (2020-2034). The study also made comparison of the forecasting scenario with the new scenario policy and without it. By accounting for the carrying capacity aspect, it shows that future CO_2 emissions (2020-2034) will rise with a reduced growth rate of 78.12 Mt CO_2 Eq. (2020/2034), and that the expectation is lower than the carrying capacity set at 90.5 Mt CO_2 Eq. (2020-2034). This outcome is based on the new scenario policy and the Thai government's future energy consumption (2020-2034) remaining constant due to the lowest value of the error correction mechanism. Nevertheless, if the Thai government does consider a new scenario policy, future CO_2 emissions (2020-2034) are predicted to increase at a growth rate of 40.32% or 100.92 Mt CO_2 Eq. (2020/2034), which is higher than the stipulated standard. This increase will severely affect the environment, because environmental growth (*Econgrowth*) has the lowest adjustment ability, and this will lead to future failure in attaining sustainability (United Nations Framework Convention on Climate Change, UNFCCC, Bonn, Germany, 2014) United Nations. Urbanization and sustainable development in Asia and the Pacific: linkages and policy implications, 2020).

However, following the review of the related research, this study distinguishes itself from other research in the past in several ways. One of the main differences is the development of the Path Analysis-VARIMA-OV_i model coupled with the application of various concepts and theories. The study also strengthens the weaknesses of past research as it is made applicable for other sectors as a tool for national policy formulation. In this study, LISREL software coupled with EVIEWS was optimized to create high quality and precision in analysis.

As concerns recommendations in applying this study's findings, the observed variables must be completely defined and actual for the latent variables. Validity testing is also required together with BLUE checking in order to minimize any potential errors. As for long-term forecasting, the study provides strict monitoring in terms of the modelling process and white noise analysis so as to generate the best results for national policy formulation and planning.

In terms of study limitations, Thailand lacks sustainable development goals and a new scenario policy for the next 20-year plan. Also, the country is not ready with scenario planning, making the nation fail to achieve effective and efficient policy management. Therefore, the application of this study's contribution will help Thailand with planning and policy formulation, and enable the country to stay focused with a defined direction in order to achieve sustainability in the near future.

6. ACKNOWLEDGMENTS

This research is supported by Rachadapisek Sompote Fund for Postdoctoral Fellowship, Chulalongkorn University.

7. CONFLICTS OF INTEREST

The authors declare no conflict of interest

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