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Research Paper

Modeling and Forecasting of Sulfur Dioxide (SO_2) Emissions in Several ASEAN Countries (Using State Space Multivariate Time Series Analysis)

Mustofa Usman[1], Edwin Russel[1*], Nurhanurawati[2], Faiz AM Elfaki[3], Nadya R. Ikhsana[4], Deta Erviana[5], Moni Dwi Fenski[5]

[1]*Department of Mathematics, Universitas Lampung, Bandar Lampung, Lampung, 35141, Indonesia*
[2]*Department of Mathematics Education, Universitas Lampung, Bandar Lampung, Lampung, 35141, Indonesia*
[3]*Department of Mathematics, Statistics and Physics, Qatar University, Doha, 2713, Qatar*
[4]*Departement of Economic Development, Universitas Lampung, Bandar Lampung, Lampung, 35141, Indonesia*
[5]*Graduate Students, Department of Mathematics, Universitas Lampung, Bandar Lampung, Lampung, 35141, Indonesia*
**Corresponding author*: winrush08@gmail.com

Abstract
Sulfur dioxide (SO_2) emissions (ton/year) produced from coal combustion, household heating, motor vehicles, and volcanic eruptions, has been considered as a dangerous air pollutant that causes many respiratory diseases and increases the mortality rate. Many studies have been conducted generally in developed countries and industrialized countries that are aware of the adverse effects of increasing SO_2 emissions in the air. Many studies have been conducted to measure the level of air pollution caused by SO_2 emissions and research on the relationship of SO_2 emissions with public health and mortality rates. The problem in this study is how to build the best State Space Multivariate Time Series model for SO_2 emissions data in several ASEAN countries, Indonesia, Thailand, Philippines and Malaysia. This study aims to build the best State Space Multivariate Time Series model that fits the data and uses the best state space model for forecasting SO_2 emissions for the next few years. The analysis method that will be used is State Space Multivariate Time Series Analysis (Autoregressive Vector modeling, and State Space Model). The results show that SO_2 emissions in Indonesia are significantly influenced by emission conditions in Indonesia four years earlier and SO_2 emissions in Malaysia two and four years earlier; SO_2 emissions in Thailand are significantly influenced by SO_2 emission conditions in Thailand and the Philippines one year prior; SO_2 emissions in the Philippines are significantly influenced by SO_2 emission conditions in Thailand one years prior and SO_2 emission conditions in the Philippines four years prior; SO_2 emissions in Malaysia are significantly influenced by SO_2 emissions conditions in Indonesia two, three, and five years prior, SO_2 emissions conditions in Malaysia four years prior, SO_2 emissions conditions in Thailand and Philippines five years prior. Forecasting results using the state space model indicate a downward trend in SO_2 emissions in Indonesia, Thailand, the Philippines, and Malaysia over the next ten years.

Keywords
Sulfur Dioxide (SO_2) Emissions, Air Pollution, VAR Model, State Space Model, Forecasting

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1. INTRODUCTION

Modeling problems of air pollution using a multivariate time series approach is a topic of interest to many researchers and governments, because it concerns with public health and policies that need to be taken by decision makers in government. Sulfur dioxide is designated as a criteria air pollutant (or equivalent) by nearly all developed countries. When released into the atmosphere, sulfur dioxide forms sulfuric acid and fine particulate matter, secondary pollutants (Seinfeld and Pandis, 2016). That have significant adverse impacts on human health (Lelieveld et al., 2015; Lim et al., 2012; Prüss-Üstün et al., 2016; OECD, 2014), the environment (Seinfeld and Pandis, 2016) , and the economy (OECD, 2014). However, conventional emission inventories used to assess impacts are often incomplete or outdated, particularly for developing countries that lack comprehensive emissions reporting requirements and infrastructure (McLinden et al., 2016).

The oxidation of sulfur dioxide (SO_2) leads to the formation of sulfuric acid and fine particles (Seinfeld and Pandis, 2016), which, when combined, are associated with negative health impacts such as cardiovascular disease and cancer (Lelieveld et al., 2015) as well as ecological impacts on soils, forests, and freshwater (Seinfeld and Pandis, 2016). Sulfur dioxide (SO_2) is considered the most widespread pollutant threatening the environment and human health, contributing to the increasing number of cases of cardiovascular and respiratory diseases (Afif et al., 2008). SO_2 is often present with other pollutants in urban areas, resulting from industrial plant emissions and car exhaust (Yang et al., 2009; Djordjevic et al., 2013) . In particular, sulfate aerosols are an important component of suspended fine particles in urban areas, which have a longer residence time in the atmosphere (Fisher et al., 2011). In addition, SO_2 plays a significant role in the formation of acidic species and sulfate aerosols, which can lead to increased ice nucleation (Francis et al., 2016), initiating a dehydration-greenhouse feedback that can accelerate Arctic warming (Jenner and Abiodun, 2013). Furthermore, SO_2 is a pollutant most closely associated with the economic development of industrialization and urbanization, known as the primary combustion product of fossil fuels such as coal, fuel oil, gasoline, and diesel (Yang et al., 2017).

Air pollution is one of the most significant public health problems worldwide (Kelly and Fussell, 2015). Sulfur dioxide (SO_2), which originates primarily from various industrial processes, transportation and vehicles, power plants, and fuel combustion (coal), is one of the most common and disruptive air pollutants in developing countries and industrialized regions (Craig, 2019; Darynova et al., 2020; Li et al., 2021; Zhao et al., 2021).

Research on modeling and predicting sulfur dioxide (SO_2) emissions is generally conducted by researchers in developed countries and is still very rare in ASEAN. Unal et al. (2000) examined factors influencing variability in SO_2 concentrations in Istanbul; Bell et al. (2004) and Moolgavkar et al. (2012) analyzed SO_2 using a time series analysis approach to analyze the relationship between air pollution and mortality rates. Heng et al. (2016) and Vernier et al. (2013) built volcanic sulfur dioxide (SO_2) emissions modeling using the inverse transport modeling approach; Chang et al. (2019) used the Fuzzy based gray modeling procedure approach for forecasting SO_2 emissions in China; Yang et al. (2024a) conducted analysis and forecasting of air pollution caused by Nitrogen and SO_2 using a deep learning approach for cases in China and Yang et al. (2024b) analyzed air pollution using a deep learning approach for cases in Taiwan; Castelli et al. (2020) and Shen et al. (2020) used a machine learning approach for modeling air quality in California; Nieto et al. (2013) studied air quality with a support vector machine-based regression model approach carried out in Northern Spain; O'Brien et al. (2023) analyzed the relationship between SO_2 and mortality rates using regression time series analysis; Chen and Gao (2021) conducted SO_2 modeling with mathematical modeling; Zhang et al. (2017) conducted an analysis of SO_2 modeling and forecasting using the wavelet-ARIMA/ARIMA model approach for the case of China.

The aforementioned studies, conducted by many researchers in various countries, generally only address SO_2 using a univariate analysis approach. This study will explore a novel approach for data from four ASEAN countries: State Space Multivariate Time Series Analysis, using Vector Autoregressive (VAR) modeling and State Space Models for forecasting.

In this study, the problem is how to build models and forecast sulfur dioxide (SO_2) emissions data in several ASEAN countries: Indonesia, Thailand, Philippines, and Malaysia. The approach to solve this problem is to use a multivariate time series analysis, namely Vector Autoregressive (VAR) modeling and State Space Models for forecasting.

2. EXPERIMENTAL SECTION

One of the important assumptions that must be met for Vector Autoregressive (VAR) modeling is the stationarity assumption. Therefore, before building a model, the data must be checked for stationarity and cross-correlation between variables (Hamilton, 1994; Wei, 2006, 2019; Tsay, 2010; Russel et al., 2023). Data stationarity can be checked through the behavior of the data plot and tested using the Augmented Dickey-Fuller test (ADF test) (Wei, 2006, 2019; Tsay, 2010). The Augmented Dickey-Fuller (ADF test) is performed with the following model:

$$\Delta X_t = c + \alpha_t + \beta X_{t-1} + \sum_{i=1}^{m} \gamma_i \Delta X_{t-i} + e_t \tag{1}$$

The null and alternative hypotheses are as follows:

$$H_0 : \beta = 0 \quad \text{vs} \quad H_1 : \beta < 0$$

The test statistic,

$$\tau = \frac{\beta}{s_\beta} \tag{2}$$

The null hypothesis is rejected if p-value $\leq \alpha$, for $\alpha = 0.05$ (Wei, 2006).

2.1 Model Vector Autoregressive (VAR)

Multivariate time series process with the dimension-k $X_t = [X_{1t}, X_{2t}, \ldots, X_{kt}]'$ is a stationary process if each component series is univariate stationary and its first two moments are time invariant (Wei, 2019). The k-dimensional Autoregressive Vector Model of order p, the VAR(p) model, is given by:

$$X_t = \gamma_0 + \Phi_1 X_{t-1} + \Phi_2 X_{t-2} + \cdots + \Phi_p X_{t-p} + \varepsilon_t \tag{3}$$

where X_t is $k \times 1$ vector time series, γ_0 is $k \times 1$ vector constant, Φ_i is $k \times k$ matrix parameter (for $i > 0, \Phi_p \neq 0$), ε_t is vector shock with mean vector zero, and ε_t is variance covariance matrix Σ_ε. We can use the Maximum Likelihood (ML) method, the Bayesian method, or the Least Squares (LS) method (Tsay, 2014; Wei, 2019).

2.2 Granger Causality Test

One of the interesting problems in studying multivariate time series is determining whether there is a causal influence between the variables under discussion. According to Hamilton (1994); Wei (2006, 2019); Russel et al. (2023) Granger causality analysis is used to determine short-term relationships in the form of reciprocity between the variables under study. For example, we analyze the Granger causality between variables Y and X, and the model for the Granger Causality Test is:

$$Y_t = c_1 + \gamma_1 Y_{t-1} + \gamma_2 Y_{t-2} + \cdots + \gamma_p Y_{t-p} + \beta_1 X_{t-1} + \beta_2 X_{t-2} + \cdots + \beta_p X_{t-p} + a_t \quad (4)$$

By using ordinary least squares (OLS), the null hypothesis is:

$H_0 : \beta_1 = \beta_2 = \cdots = \beta_p = 0$ (X is not a Granger Causal Y) with the alternative H_1: at least one $\beta_i \neq 0$ $i = 1, 2, \ldots, p$, (X Granger Causal Y). The test statistics is:

$$\text{F Test} = \frac{(RSS_0 - RSS_1)/p}{RSS_1/(T - 2p - 1)} \quad (5)$$

Reject the null hypothesis is p-value < 0.05 (Hamilton, 1994). Where

$$RSS_1 = \sum_{t=1}^{T} \hat{a}_t^2 \quad (6)$$

Under the null hypothesis, model (4) can be written as follows:

$$Y_t = c_0 + \gamma_1 Y_{t-1} + \gamma_2 Y_{t-2} + \cdots + \gamma_p Y_{t-p} + u_t \quad (7)$$

and

$$RSS_0 = \sum_{t=1}^{T} \hat{u}_t^2 \quad (8)$$

2.3 State Space Model

The state space model (SSM) of a system is a fundamental concept in control theory and the Kalman filter recursion relationship, and it has a significant impact on time series data (Wei, 2006). The SSM format used here is based on the Akaike method (Akaike, 1976). This model is defined by the following state transition equation:

$$Y_{t+1} = FY_t + Ge_{t+1} \quad (9)$$

The output equation is

$$X_t = HY_t \quad (10)$$

where Y_t is sx1 state vector, F is transition matrix $s \times s$, G is sxk input matrix, e_{t+1} is nx1 vektor innovation, and H is mxk matrix of observation (Wei, 2006).

2.4 Canonical Correlation Analysis

Canonical correlation analysis is a statistical analysis used to examine the relationship between a group of dependent variables and a group of independent variables. According to Akaike (1976) and Wei (2006) the state vector is uniquely determined through canonical correlation analysis between a set of current and past observations and a set of current and future event observations. A discussion of canonical correlation can be found in Wei (2006). Canonical correlation analysis is performed simply between the data spaces:

$$D_n = (X_n', X_{n-1}', \ldots, X_{n-p}')' \quad (11)$$

And the predictor space is:

$$F_n = (X_n', X_{n+1|n}', \ldots, X_{n+p|n}')' \quad (12)$$

The selection of the order p for the VAR model is obtained from the optimal fit of the data to the VAR(p) model which is determined based on the smallest AIC (Akaike's Information Criterion) value. Canonical correlation analysis refers to the Block Hankel matrix of covariance between $D_n = (X_n', X_{n-1}', \ldots, X_{n-p}')'$ and $F_n = (X_n', X_{n+1|n}', \ldots, X_{n+p|n}')'$

$$\widehat{\Gamma} = \begin{bmatrix} \widehat{\Gamma}(0) & \widehat{\Gamma}(1) & \ldots & \widehat{\Gamma}(p) \\ \widehat{\Gamma}(1) & \widehat{\Gamma}(2) & \ldots & \widehat{\Gamma}(p+1) \\ \vdots & \vdots & \ddots & \vdots \\ \widehat{\Gamma}(p) & \widehat{\Gamma}(p+1) & \ldots & \widehat{\Gamma}(2p) \end{bmatrix} \quad (13)$$

where $\widehat{\Gamma}(j)$ is a covariance matrix defined as follows:

$$\widehat{\Gamma}(s) = \frac{1}{n} \sum_{t=1}^{n-s} (X_t - \bar{X})(X_{t+s} - \bar{X})' \quad (14)$$

The steps in building a state vector model in this study use a canonical correlation approach following the procedures given by Akaike (1976) and Wei (2006).

2.5 Forecasting

Forecasting for several periods into the future using a state space model. Consider the State Space model given in (9) and (10), once the State Space model is constructed, the l-step forward forecast from the forecast origin at time t can be calculated as follows Wei (2006):

$$\begin{aligned} \widehat{Y}_t(l) &= E(Y_{t+l} \mid Y_j, j \leq t) \\ &= F\widehat{Y}_t(l-1) \\ &= F.F\widehat{Y}_t(l-2) \\ &\vdots \\ &= F^l \widehat{Y}_t \end{aligned} \quad (15)$$

Hence,

$$\begin{aligned}\widehat{X}_t(l) &= E(X_{t+l} \mid X_j, j \le t)\\ &= H\widehat{Y}_t(l)\\ &= HF^l\widehat{Y}_t\end{aligned}$$

where

$$\widehat{Y}_t = E(Y_t \mid Y_j, j \le t) = Y_t \tag{16}$$

It is clear that, from (15), the accuration of the forecast $\widehat{X}_t(l)$ depend on the quality of the estimation $\widehat{Y}_t$ from state vector Y_t, which summarizes information from the past needed to predict the future. To improve forecasting, when new observations become available, they should be used to update the state vector and thus update the forecast. For this purpose, the Kalman Filter method is available, which is a recursive procedure used to make inferences about the state vector Y_t (Wei, 2006; Gomez, 2016).

3. RESULTS AND DISCUSSIONS

Environmental pollution is a serious problem for human health. This study will discuss the development of pollution caused by sulfur. The data used is data on the development of SO_2 emissions (ton/year) in four ASEAN countries: Indonesia (IND), Thailand (THAI), the Philippines (PHIL), and Malaysia (MLS), from 1940 to 2022. The data was taken from `www.ourworldin.data`. Figure 1 shows the development of SO_2 emissions in the four ASEAN countries: Indonesia, Thailand, the Philippines, and Malaysia. Figure 1 shows the SO_2 emissions in the four ASEAN countries. From 1940 to 1965, the development of SO_2 emissions in the four countries was relatively similar. Figure 1 for the Philippine case: From 1965 to 1980 the development of the amount of SO_2 emissions in the Philippines was higher than the other three ASEAN countries, and from 1980 to 1992 the amount of SO_2 emissions in the Philippines had a downward trend, and from 1992 to 2000 the trend was upward, from 2000 to 2010 the trend of the amount of SO_2 emissions in the Philippines decreased and from 2010 to 2022 it had an upward trend. Figure 1 for the case of Thailand: from 1985 to 1995 the amount of SO_2 emissions in Thailand had an upward trend and reached its peak in 1995, and decreased drastically after that until 2000, and from 2000 to 2022 the amount of SO_2 emissions was relatively stable. Figure 1 for the case of Indonesia, the amount of SO_2 emissions in Indonesia from 1940 to 2022 forms a quadratic curve and the trend continues to rise until 2022. Figure 1 for the case of Malaysia, the amount of SO_2 emissions pollution in Malaysia is relatively low compared to the other three ASEAN countries.

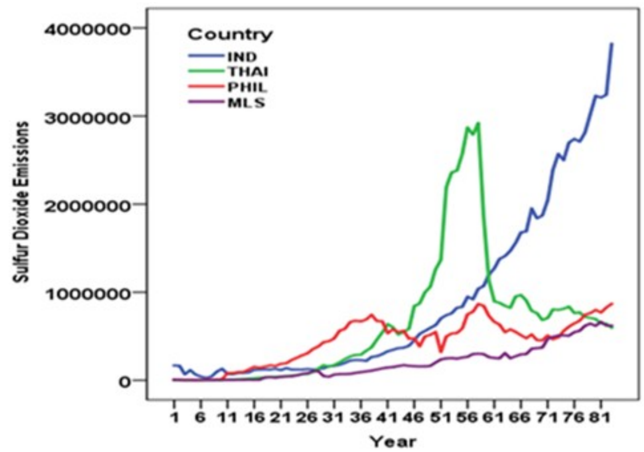


Figure 1. Plot of the Amount of SO_2 Emissions in Indonesia, Thailand, Philippines and Malaysia from 1940 to 2022

3.1 The Stationarity Test, Augmented Dickey-Fuller Test (ADF-Test)

Figure 1 above shows that the SO_2 emissions data in four ASEAN countries, Indonesia, Thailand, the Philippines, and Malaysia, are non-stationary. From the results of the data analysis, Table 1, the ADF test for the SO_2 emissions amount in the four ASEAN countries with the null hypothesis that the data is non-stationary. The test results show that the p-value for the ADF-test is greater than 0.05. Therefore, the null hypothesis is not rejected, and we conclude that the SO_2 emissions data in the four ASEAN countries are non-stationary(Table 1). In addition, with data showing non-stationary and high fluctuations, this implies that if a shock occurs, the impact will take a long time to achieve stability (Parreno, 2024). Therefore, many government leaders who act as decision-makers must be able to plan adaptive energy policies to address urgent needs and non-stationary SO_2 emissions in the long term (Parreno, 2024).

Because the data is non-stationary, it requires a transformation to meet the stationarity assumption. The transformation is performed using differencing (Tsay, 2010). After differencing, the data are reanalyzed using the ADF-Test, with the null hypothesis that the data is non-stationary. The unit root test (ADF-Test) after differencing (d=1) shows a p-value <0.05, thus rejecting the null hypothesis. We can conclude that the data is stationary after differencing once (d=1). To verify cross-correlation of SO_2 emissions data across the four ASEAN countries, cross-correlation analysis was performed up to lag 7. Table 2 shows that cross-correlation exists up to lag 7. The results of the cross-correlation analysis are presented in Table 2.

Table 2, the + sign indicates that at this lag there is a significant positive cross-correlation with a p-value < 0.05; The − sign indicates that at this lag there is a significant negative cross-correlation with a p-value < 0.05. Table 2 shows that there is a cross-correlation up to lag-7. By fulfilling the basic assumption that the data is stationary and there is a cross-correlation, then the time series vector of SO_2 emissions data in Indonesia, Thailand, Philippines and Malaysia up to lag-7, the modeling can use a multivariate time series analysis approach.

Table 1. Dickey-Fuller Unit Root Tests data SO_2 emissions of Indonesia, Thailand, Philippine and Malaysia from 1940 to 2022

Variable	Type	Before Differencing		After Differencing once (d=1)	
		Tau	p-value	Tau	p-value
IND	Zero Mean	6.69	0.9999	-3.07	0.0026
	Single Mean	5.45	0.9999	-4.45	0.0006
	Trend	1.68	0.9999	-8.16	< .0001
THAI	Zero Mean	-1.29	0.1806	-4.55	< .0001
	Single Mean	-1.93	0.3169	-4.53	0.0004
	Trend	-2.04	0.5722	-4.53	0.0025
PHIL	Zero Mean	1.01	0.9163	-4.95	< .0001
	Single Mean	-1.01	0.7446	-5.19	0.0001
	Trend	-1.69	0.7470	-5.15	0.0003
MLS	Zero Mean	3.13	0.9995	-5.12	< .0001
	Single Mean	1.48	0.9992	-5.96	< .0001
	Trend	-1.30	0.8814	-6.40	< .0001

Table 2. Schematic Representation of Cross-Correlation

Variable/Lag	Schematic Representation of Cross Correlations							
	0	1	2	3	4	5	6	7
IND	+...	....	....	....	+...	....	....	+...
THAI	.++.	.+..	..+.	....	..+.	....	....	.-..
PHIL	.++.	.-..	....	....	..+.	.–.	..+-	.–.
MLS	...+	....	+...	....	....	+...	....	+...
+ is > 2× std error, - is < −2× std error, . is between								

3.2 The Selection of the Best Model of VAR(p)

In determining the best model, by only using information criteria (IC) such as AICC, AIC, HQC, and SBC is not enough. In practice, determining the best model using only information criteria does not necessarily produce the best model (Wei, 2019; Tsay, 2014; Nairobi et al., 2022; Warsono et al., 2019). Using the approach suggested by Wei (2019); Tsay (2014); Nairobi et al. (2022); Warsono et al. (2019) in determining the best model by Information Criteria (AICC, AIC, HQC, and SBC), testing the parameters in the VAR(p) model, and the value of R-squares and univariate model ANOVA diagnostics will be considered. Based on the values of the information criteria AICC, AIC, HQC, and BSC (Table 3) for models VAR(1), VAR(2), VAR(3), VAR(4) and VAR(5) the values are not much too different. Although the minimum value occurs in VAR(1). For the VAR(1) model, as seen in Table 4, for the univariate models for IND and MLS there are no significant parameters and with small R-squares, namely 0.0296 and 0.0634, respectively. Based on the results of the test of parameter and R-squares, the VAR(1) model is very poor even though the IC is the smallest. For the VAR(2) model, as seen from Table 4, for the univariate model, for MLS there are no significant parameters with R-squares namely 0.0859. Based on the results of the parameter test and R-squares, the VAR(2) model is relatively better than the VAR(1) model. For the VAR(3) model, as seen from Table 4, for the univariate models all variables IND, THAI, PHIL, and MLS have significant parameters with R-squares namely 0.1857, 0.3648, 0.2158, and 0.1774, respectively. Based on the results of the test of parameters and R-squares, the VAR(3) model is relatively better than the VAR(1) and VAR(2) models. For the VAR(4) model, as seen from Table 4, for the univariate model, all variables IND, THAI, PHIL, and MLS have significant parameters with R-squares of 0.3842, 0.3765, 0.3480, and 0.2315, respectively. Based on the results of the test of parameters and R-squares, the VAR(4) model is better than the VAR(1), VAR(2) and VAR(3) models. For the VAR(5) model, as seen from Table 4, for the univariate model, all variables IND, THAI, PHIL, and MLS have significant parameters with R-squares of 0.4372, 0.3960, 0.3857, and 0.4941, respectively. Based on the results of the test of parameters and R-squares, the VAR(5) model is better than the VAR(1), VAR(2) VAR(3) and VAR(4) models.

Based on the results of analysis and the comparision among the results of the models VAR(1), VAR(2), VAR(3) VAR(4) and

VAR(5). Based on the results of the analysis above, the best model to be used is the VAR(5) model.

Table 3. Test for Optimal Lag by Using Minimum Information Criteria Based on AICC, AIC, HQC, and SBC

Model	Information Criteria			
	AICC	AIC	HQC	SBC
VAR(1)	88.92	88.48	89.13	89.48
VAR(2)	89.20	89.09	89.52	90.16
VAR(3)	89.56	89.30	89.93	90.86
VAR(4)	89.66	89.18	90.00	91.23
VAR(5)	89.88	89.07	90.09	91.62

3.3 Model VAR(5) and its Estimate

Model multivariate time series for the relationship among SO_2 emissions of Indonesia, Thailand, Philippines, and Malaysia is given below:

$$\begin{bmatrix} \mathrm{IND}_t \\ \mathrm{THAI}_t \\ \mathrm{PHIL}_t \\ \mathrm{MLS}_t \end{bmatrix} = \Gamma_0 + \Gamma_1 \begin{bmatrix} \mathrm{IND}_{t-1} \\ \mathrm{THAI}_{t-1} \\ \mathrm{PHIL}_{t-1} \\ \mathrm{MLS}_{t-1} \end{bmatrix} + \Gamma_2 \begin{bmatrix} \mathrm{IND}_{t-2} \\ \mathrm{THAI}_{t-2} \\ \mathrm{PHIL}_{t-2} \\ \mathrm{MLS}_{t-2} \end{bmatrix} + \Gamma_3 \begin{bmatrix} \mathrm{IND}_{t-3} \\ \mathrm{THAI}_{t-3} \\ \mathrm{PHIL}_{t-3} \\ \mathrm{MLS}_{t-3} \end{bmatrix} + \Gamma_4 \begin{bmatrix} \mathrm{IND}_{t-4} \\ \mathrm{THAI}_{t-4} \\ \mathrm{PHIL}_{t-4} \\ \mathrm{MLS}_{t-4} \end{bmatrix} + \Gamma_5 \begin{bmatrix} \mathrm{IND}_{t-5} \\ \mathrm{THAI}_{t-5} \\ \mathrm{PHIL}_{t-5} \\ \mathrm{MLS}_{t-5} \end{bmatrix} + E_t \tag{17}$$

The estimate model is

$$\begin{aligned} \begin{bmatrix} \mathrm{IND}_t \\ \mathrm{THAI}_t \\ \mathrm{PHIL}_t \\ \mathrm{MLS}_t \end{bmatrix} &= \begin{bmatrix} 14529.1538 \\ 35440.6754 \\ 1791.1968 \\ 5368.6721 \end{bmatrix} \\ &+ \begin{bmatrix} -0.0440 & -0.0573 & -0.1276 & 0.1685 \\ -0.2112 & 0.5169^* & -1.2831^* & 0.3856 \\ -0.0334 & 0.1130^* & -0.1967 & 0.0247 \\ 0.0254 & 0.0062 & 0.0439 & 0.0690 \end{bmatrix} \begin{bmatrix} \mathrm{IND}_{t-1} \\ \mathrm{THAI}_{t-1} \\ \mathrm{PHIL}_{t-1} \\ \mathrm{MLS}_{t-1} \end{bmatrix} \\ &+ \begin{bmatrix} -0.2687 & -0.0492 & -0.1530 & 1.4164^* \\ -0.0866 & 0.0224 & -0.0545 & -0.1006 \\ 0.0786 & -0.0087 & 0.2143 & -0.0064 \\ -0.0957^* & 0.0032 & -0.0201 & -0.0572 \end{bmatrix} \begin{bmatrix} \mathrm{IND}_{t-2} \\ \mathrm{THAI}_{t-2} \\ \mathrm{PHIL}_{t-2} \\ \mathrm{MLS}_{t-2} \end{bmatrix} \\ &+ \begin{bmatrix} 0.0678 & 0.0446 & -0.1910 & 0.0595 \\ -0.1138 & -0.0464 & -0.1450 & 0.0535 \\ 0.1495 & 0.0850 & 0.0210 & -0.2507 \\ 0.0885^* & -0.0161 & 0.0035 & 0.2095 \end{bmatrix} \begin{bmatrix} \mathrm{IND}_{t-3} \\ \mathrm{THAI}_{t-3} \\ \mathrm{PHIL}_{t-3} \\ \mathrm{MLS}_{t-3} \end{bmatrix} \\ &+ \begin{bmatrix} 0.4685^* & -0.0650 & 0.3643 & 0.4216 \\ 0.1627 & 0.0245 & -0.2156 & 0.2153 \\ -0.0178 & 0.0185 & 0.3909^* & -0.3066 \\ -0.0176 & 0.0297 & -0.0367 & -0.2533^* \end{bmatrix} \begin{bmatrix} \mathrm{IND}_{t-4} \\ \mathrm{THAI}_{t-4} \\ \mathrm{PHIL}_{t-4} \\ \mathrm{MLS}_{t-4} \end{bmatrix} \\ &+ \begin{bmatrix} 0.0356 & -0.0448 & -0.1257 & 1.1952^* \\ -0.0328 & 0.1118 & -0.5941 & -0.2455 \\ -0.0453 & -0.0612 & -0.0291 & -0.3876 \\ 0.0837^* & 0.0599^* & -0.1509^* & 0.1572 \end{bmatrix} \begin{bmatrix} \mathrm{IND}_{t-5} \\ \mathrm{THAI}_{t-5} \\ \mathrm{PHIL}_{t-5} \\ \mathrm{MLS}_{t-5} \end{bmatrix} \end{aligned} \tag{18}$$

Note that the estimate parameter with (*) sign is significant for $\alpha = 0.05$. The covariance innovation is

$$\mathrm{Cov}(E_t) = \begin{bmatrix} 6982113847 & 6657826935 & -348600058 & 145281003 \\ 657826935 & 30325858457 & 3050821104 & 434560889 \\ -348600058 & 3050821104 & 297327008 & -18540241 \\ 145281003 & 434560889 & -18540241 & 357102657 \end{bmatrix}$$

3.4 Diagnostic Model

Model (18) and Table 4 (VAR(5)) from the results of the univariate model analysis (Table 5) for each variable SO_2 emissions Indonesia (IND), SO_2 emissions Thailand (THAI), SO_2 emissions Philippines (PHIL), and SO_2 emissions Malaysia (MLS) each model is significant at α=0.05 with R-square is 0.4372, 0.3960, 0.3857, and 0.4941, respectively. The results of the residual distribution analysis (Table 6) shows that the results of the Jarque-Bera test (Chi-square test) with the null hypothesis that the residual is normally distributed. The test results show that the null hypothesis is rejected, which means the residual is not normally distributed. However, if we look at the residual graph, both the histogram and the QQ plot, it appears that the deviation is not too far from the normal distribution (Figure 2 and Table 6). From the results of the Autoregressive Conditional heteroscedasticity (ARCH) effect test (Table 6) with the null hypothesis that there is no heteroscedasticity, the null hypothesis is not rejected. So there is no heteroscedasticity in the residuals. From the results of the Root AR characteristics polynomial analysis (Table 7) it shows that all modulus are less than one (<1), which can be concluded that model (18) or VAR(5) model is a stable model and can be used for further analysis (Hamilton, 1994; Tsay, 2014; Wei, 2019).

Figure 3 show that the amount of SO_2 emissions in Indonesia at time t (INDt) is significantly influenced by the amount of SO_2 emissions in Malaysia at time (t-2) (MLSt-2) and (t-5) (MLSt-5) and the amount of SO_2 emissions in Indonesia at time (t-4) (IND¬t-4) with p-values of 0.0093, 0.0328 and 0.0065, respectively. Figure 3 show that the amount of SO_2 emissions in Thailand at time t (THAIt) is significantly influenced by the amount of SO_2 emissions in Thailand at time (t-1) (THAIt-1) and the amount of SO_2 emissions in the Philippines at time (t-1) (PHILt-1) with P-values of 0.0005 and 0.0049, respectively. Figure 3 show that the amount of SO_2 emissions in the Philippines at time t (PHILt) is significantly influenced by the amount of SO_2 emissions in Thailand at time (t-1) (THAIt-1), the amount of SO_2 emissions in Philippines at time at time (t-4)(PHILt-4), with P-values of 0.0131 and 0.0062, respectively. Figure 3 show that the amount of SO_2 emissions in Malaysia at time t (MLSt) is significantly influenced by the amount of SO_2 emissions in Indonesia at time (t-2) (INDt-2), at time (t-3) (INDt-3) and at time (t-5) (INDt-5), the amount of SO_2 emissions in Malaysia at time (t-4) (MLSt-4), the amount of SO_2 emissions in Thailand at time t-5 (THAIt-5), the amount of SO_2 emissions in Philippines at time (t-5) (PHILt-5) with p-values of 0.0077, 0.0138. 0.0363, 0.0412, 0.0002, and 0.0052, respectively.

From the estimate VAR(5) model, the influence of significant parameters can be presented in the form of Figure 3 below.

3.5 Impulse Response Function

3.6 Granger Causality Test

From the results of the Granger Causality Test, Table 8, tests the causal relationship between the amount of SO_2 emissions

Table 4. Schematic Representation of Parameter Estimation for VAR(1) to VAR(5) Models

Model	Variables	C	AR1	AR2	AR3	AR4	AR5	Univariate Model ANOVA		
								R-Square	F-Value	P-Value
VAR(1)	IND	+	....					0.0296	0.58	0.6783
	THAI	.	· + −·					0.3554	10.47	< .0001
	PHIL	+	· + ··					0.0908	1.90	0.1197
	MLS	+	....					0.0634	1.29	0.2826
VAR(2)	IND	+	....	...+				0.1100	1.10	0.3758
	THAI	.	· + −·	....				0.3606	5.01	< .0001
	PHIL	.	· + ··	..+.				0.1801	1.95	0.0657
	MLS	+	....	....				0.0859	0.83	0.5761
VAR(3)	IND	.	....	...+	....			0.1857	1.25	0.2667
	THAI	.	· + −·	....	....			0.3648	3.16	0.0013
	PHIL	.	· + ··	..+.	....			0.2158	1.51	0.1415
	MLS	.	....	....	+...			0.1774	1.19	0.3117
VAR(4)	IND	.	....	...+	....	+...		0.3842	2.38	0.0079
	THAI	.	· + −·	....	....	....		0.3765	2.30	0.0102
	PHIL	.	· + −·	....	....	..+.		0.3480	2.03	0.0246
	MLS	.	....	....	+...	....		0.2315	1.15	0.3344
VAR(5)	IND	.	....	...+	....	+...	...+	0.4372	2.18	0.0118
	THAI	.	· + −·	....	....	....	....	0.3960	1.84	0.0388
	PHIL	.	· + ··	....	....	..+.	....	0.3857	1.76	0.0504
	MLS	.	....	- ...	+...	... -	+ + - ·	0.4941	2.73	0.0016

Notes: + (> 2× std error); − (≤ −2× std error); · (in between/not sig)

Table 5. Univariate Model ANOVA Diagnostics

Variable	R-Square	Standard Deviation	F Value	P-value
IND	0.4372	83559.0440	2.18	0.0118
THAI	0.3960	174143.2124	1.84	0.0388
PHIL	0.3857	54527.7001	1.76	0.0504
MLS	0.4941	18897.1600	2.73	0.0016

Table 6. Univariate Model White Noise Diagnostics

Variable	Normality		ARCH	
	Chi-Square	P-Value	F Value	P-value
IND	79.19	< .0001	0.05	0.8243
THAI	1647.47	< .0001	0.12	0.7262
PHIL	116.78	< .0001	0.00	0.9602
MLS	12.21	0.0022	0.15	0.6966

in four ASEAN countries, Indonesia, Thailand, the Philippines, and Malaysia. Test 1. with the null hypothesis that the amount of SO_2 emissions in Indonesia is influenced by its own past data (information) and is not influenced by Thailand's past SO_2 emissins data. The result of the chi-square test is 4.19 with a P-value of 0.7577, so the null hypothesis is not rejected (NS). So we can conclude that Thailand's past SO_2 emissions data does not contribute to the current amount of SO_2 emissions in Indonesia based on the Granger-Causality Test.

Test 2. with the null hypothesis that the amount of SO_2 emissions in Indonesia is influenced by its own past data (information) and is not influenced by the past SO_2 emissions data of the Philippines. The result of the chi-square test is 3.82 with a P-value of 0.8006, so the null hypothesis is not rejected (NS). So we can conclude that the past SO_2 emissions data of the Philippines does not contribute to the current amount of SO_2 emissions in Indonesia based on the Granger-Causality Test. Test 3. With the null hypothesis that the amount of SO_2 emissions in Indonesia is influenced by its own past data

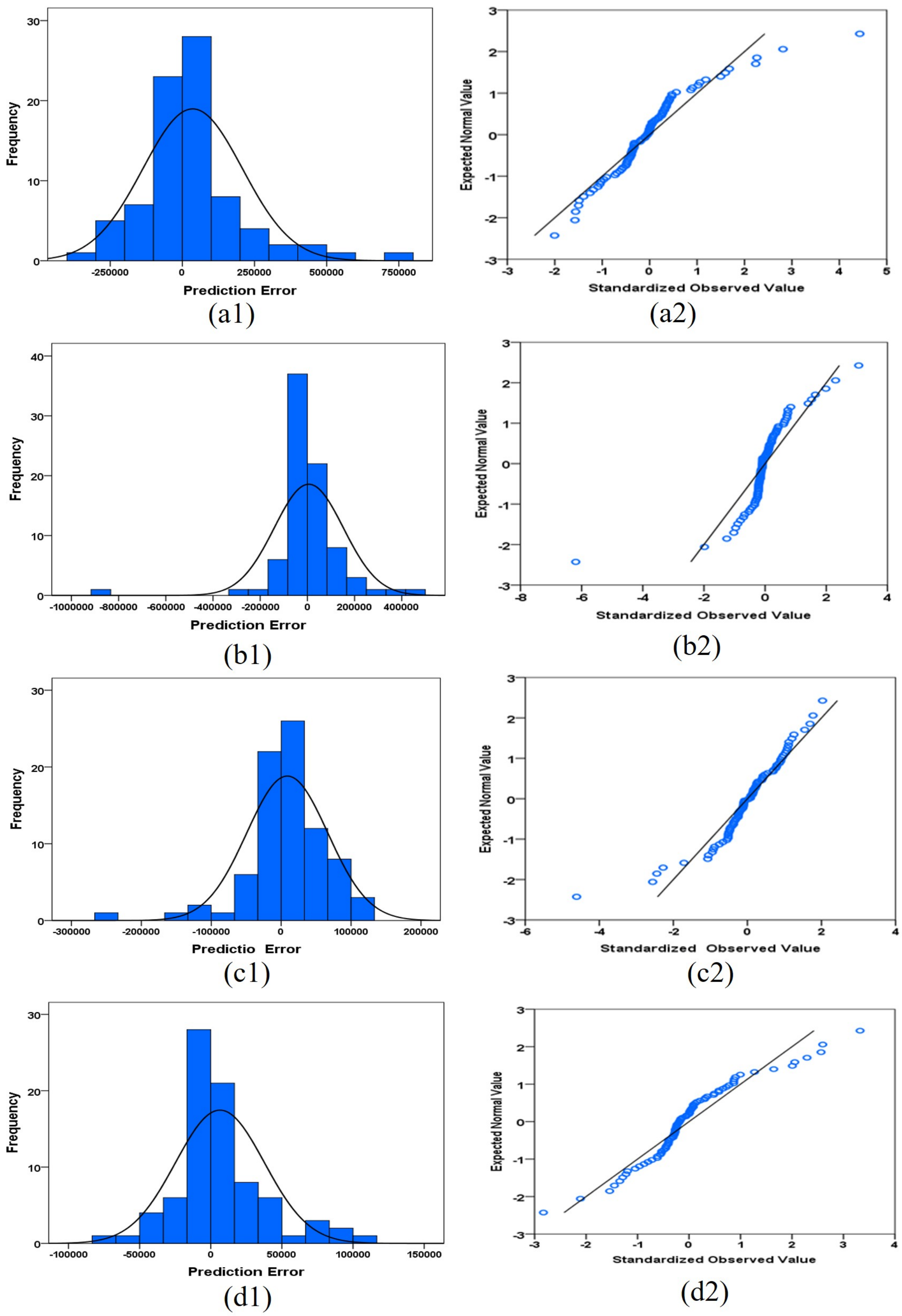


Figure 2. Prediction Error Normality and QQ Plot for Indonesia (a1 and a2), for Thailand (b1 and b2), for Philippines (c1 and c2), and for Malaysia (d1 and d2)

Table 7. Roots of AR Characteristic Polynomial

Index	Real	Imaginary	Modulus	Radian	Degree
1	0.9362	0.0000	0.9363	0.0000	0.0000
2	0.7558	0.2210	0.7875	0.2844	16.2975
3	0.7558	-0.2210	0.7875	-0.2844	-16.2975
4	0.5249	0.6016	0.7985	0.8535	48.8991
5	0.5249	-0.6016	0.7985	-0.8535	-48.8991
6	0.4250	0.2331	0.4847	0.5016	28.7422
7	0.4250	-0.2331	0.4847	-0.5016	-28.7422
8	0.2062	0.7952	0.8215	1.3171	75.4616
9	0.2062	-0.7952	0.8215	-1.3171	-75.4616
10	0.1204	0.0000	0.1204	0.0000	0.0000

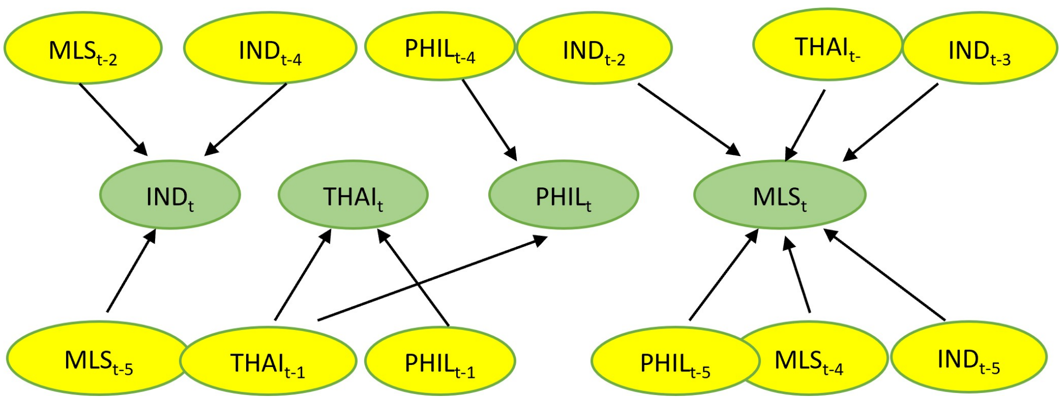


Figure 3. The Sign (X → Y) Shows a Significant Effect from Variable X to Variable Y

(information) and is not influenced by Malaysia's past SO_2 emissions data. The chi-squares test result is 17.72 with a P-value of 0.0133, so the null hypothesis is rejected (significant p-value <0.05). So we can conclude that Malaysia's past SO_2 emissions data contributes to the current amount of SO_2 emissions in Indonesia based on the granger-causality test. Test 4. with the null hypothesis that the amount of SO_2 emissions in Thailand is influenced by its own past data (information) and is not influenced by the past SO_2 emissions data of the Philippines. The chi-squares test result is 16.64 with a p-value of 0.0198, so the null hypothesis is rejected (Significant). So we can conclude that the past SO_2 emissions data of the Philippines contributes significantly to the current amount of SO_2 emissions in Thailand based on the granger-causality test.

Test 5. with the null hypothesis that the amount of SO_2 emissions in Thailand is influenced by its own past data (information) and is not influenced by the past SO_2 emissions data of the Philippines. The result of the chi-squares test is 1.48 with a p-value of 0.9832, so the null hypothesis is not rejected (NS). So we can conclude that the past SO_2 emissions data of Indonesia does not contribute significantly to the current amount of SO_2 emissions in Thailand based on the granger-causality test. Test 6. with the null hypothesis that the amount of SO_2 emissions in Thailand is influenced by its own past data (information) and is not influenced by the past SO_2 emissions data of Malaysia. The result of the chi-squares test is 2.44 with a p-value of 0.9315, so the null hypothesis is not rejected (NS). So we can conclude that the past SO_2 emissions data of Malaysia does not contribute significantly to the current amount of SO_2 emissions in Thailand baesd on the granger-causality test. Test 7. with the null hypothesis that the amount of SO_2 emissions in the Philippines is influenced by its own past data (information) and is not influenced by Thailand's past SO_2 emissions data. The chi-squares test result is 16.44 with a P-value of 0.0214, so the null hypothesis is rejected (Significant). So we can conclude that Thailand's past SO_2 emissions data has a significant contribution to the current amount of SO_2 emissions in the Philippines based on the granger-causality test. Test 8. with the null hypothesis that the amount of SO_2 emissions in the Philippines is influenced by its own past data (information) and is not influenced by Indonesia's past SO_2 emissions data. The chi-squares test result is 3.03 with a p-value of 0.5525, so the null hypothesis is not rejected (NS). So we can conclude that Indonesia's past SO_2 emissions data does not have a significant contribution to the current amount of SO_2 emissions in the Philippines based on the granger-causality test. Test 9. with the null hypothesis that the amount of SO_2 emissions in the Philippines is influenced

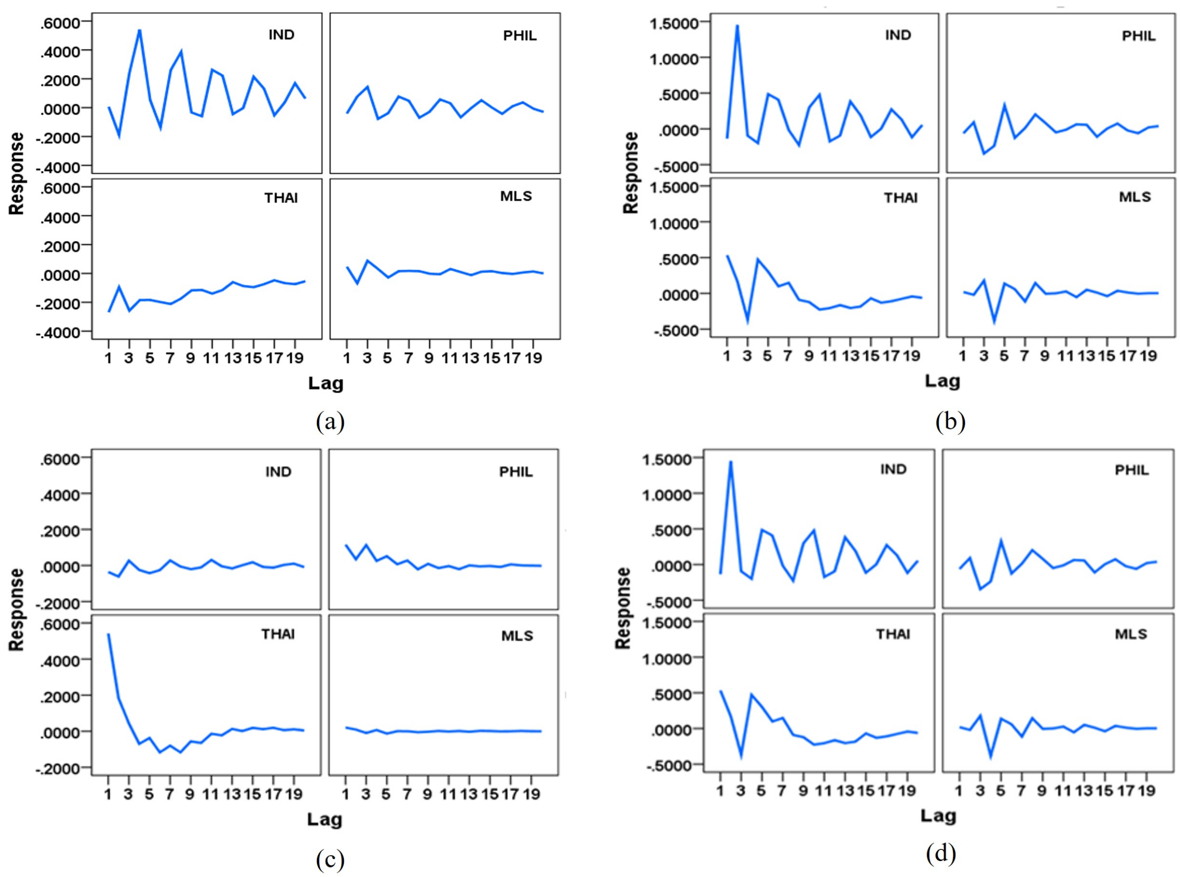


Figure 4. (a) IRF for Shock SO_2 Emissions in Indonesia, (b) IRF for Shock SO_2 Emissions in Thailand, (c) IRF for Shock SO_2 Emissions in Philippines, and (d) IRF for Shock SO_2 Emissions in Malaysia

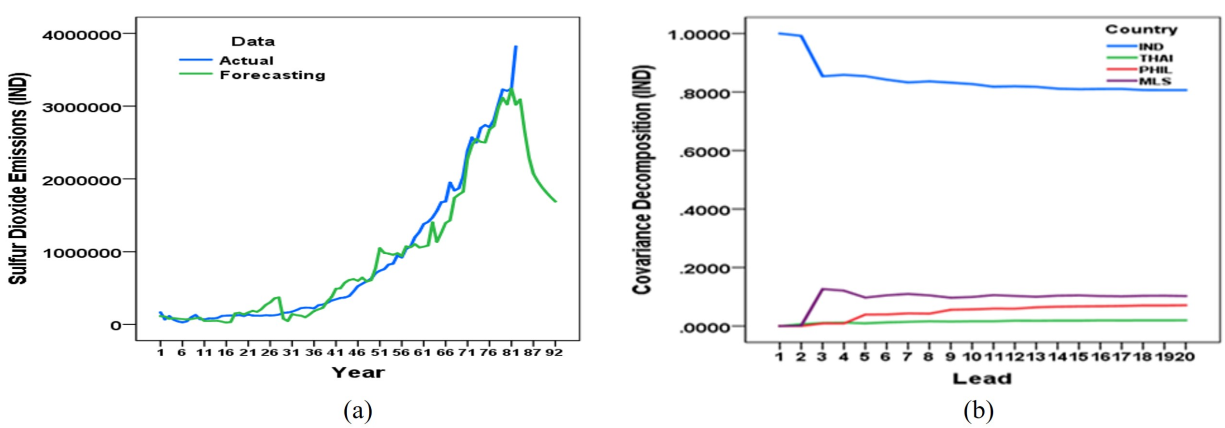


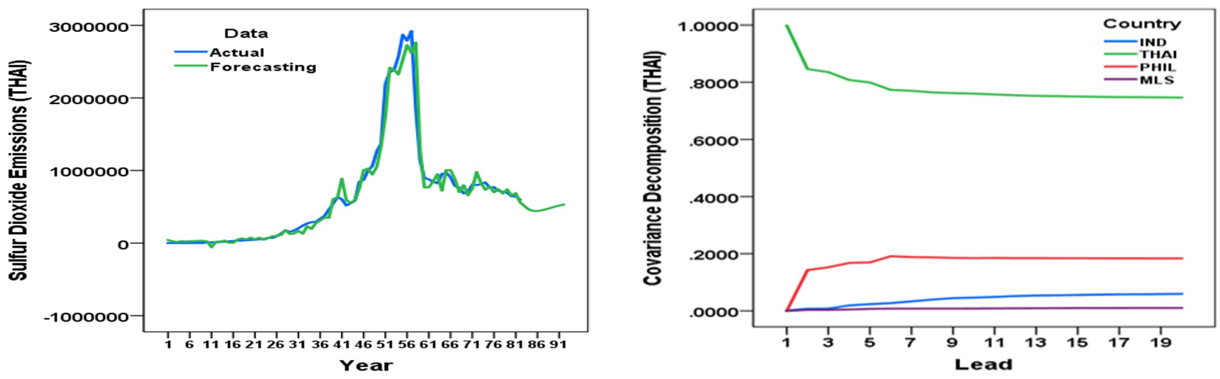
Figure 5. (a) Figure of Predicted Values and Real Values of SO_2 Emissions in Indonesia from 1940 to 2022 and Forecasting Values for the Next 10 Years, and (b) Proportion Prediction Error Covariance Decomposition

by its own past data (information) and is not influenced by Malaysia's past SO_2 emissions data. The chi-squares test result is 4.38 with a p-value of 0.7354, so the null hypothesis is not rejected (NS). So we can conclude that Malaysia's past SO_2 emissions data does not contribute significantly to the current amount of SO_2 emissions in the Philippines based on the granger-causality test. Test 10. with the null hypothesis that the amount of SO_2 emissions in Malaysia is influenced by its own past data (information) and is not influenced by Indonesia's past SO_2 emissions data. The chi-squares test re-

Table 8. Test Granger-Causality

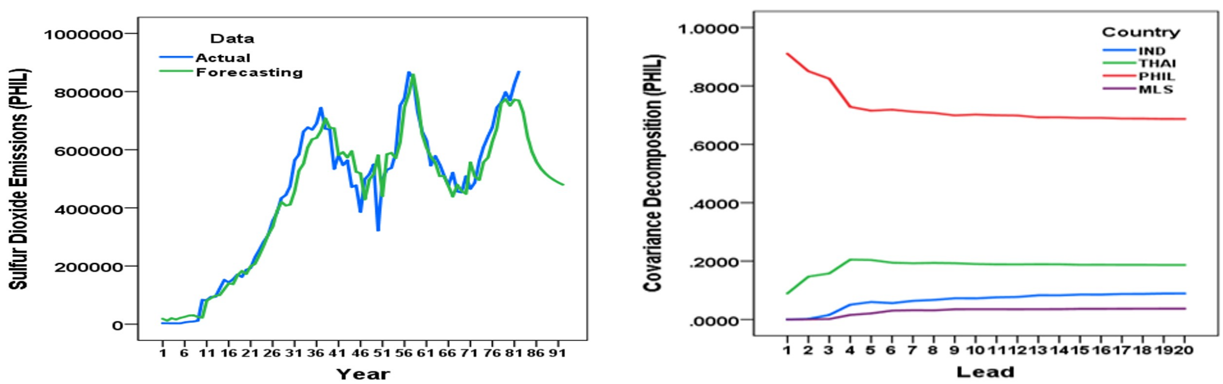
Test	Group Variable	Null Hypothesis (Ho)	Chi-Squares	P-value	Granger cause
1	Group 1: IND Group 2: THAI	The amount of SO_2 emissions in Indonesia is influenced by its own SO_2 emissions and is not influenced by the past SO_2 emissions in Thailand.	4.19	0.7577	NS
2	Group 1: IND Group 2: PHIL	The amount of SO_2 emissions in Indonesia is influenced by its own SO_2 emissions and is not influenced by the past SO_2 emissions in the Philippines.	3.82	0.8006	NS
3	Group 1: IND Group 2: MLS	The amount of SO_2 emissions in Indonesia is influenced by its own SO_2 emissions and is not influenced by the past SO_2 emissions in Malaysia.	17.72	0.0133	Significant
4	Group 1: THAI Group 2: PHIL	The amount of SO_2 emissions in Thailand is influenced by its own SO_2 emissions and is not influenced by the past SO_2 emissions in the Philippines.	16.64	0.0198	Significant
5	Group 1: THAI Group 2: IND	The amount of SO_2 emissions in Thailand is influenced by its own SO_2 emissions and is not influenced by the past SO_2 emissions in Indonesia.	1.48	0.9832	NS
6	Group 1: THAI Group 2: MLS	The amount of SO_2 emissions in Thailand is influenced by its own SO_2 emissions and is not influenced by the past SO_2 emissions in Malaysia.	2.44	0.9315	NS
7	Group 1: PHIL Group 2: THAI	The amount of SO_2 emissions in Philippines is influenced by its own SO_2 emissions and is not influenced by the past SO_2 emissions in Thailand.	16.44	0.0214	Significant
8	Group 1: PHIL Group 2: IND	The amount of SO_2 emissions in Philippines is influenced by its own SO_2 emissions and is not influenced by the past SO_2 emissions in Indonesia.	5.25	0.6300	NS
9	Group 1: PHIL Group 2: MLS	The amount of SO_2 emissions in Philippines is influenced by its own SO_2 emissions and is not influenced by the past SO_2 emissions in Malaysia.	4.38	0.7354	NS
10	Group 1: MLS Group 2: IND	The amount of SO_2 emissions in Malaysia is influenced by its own SO_2 emissions and is not influenced by the past SO_2 emissions in Indonesia.	25.65	0.0006	Significant
11	Group 1: MLS Group 2: THAI	The amount of SO_2 emissions in Malaysia is influenced by its own SO_2 emissions and is not influenced by the past SO_2 emissions in Thailand.	12.48	0.0858	NS
12	Group 1: MLS Group 2: PHIL	The amount of SO_2 emissions in Malaysia is influenced by its own SO_2 emissions and is not influenced by the past SO_2 emissions in Philippines.	8.70	0.2749	NS

sult is 25.65 with a p-value of 0.0006, so the null hypothesis is rejected (Significant). So we can conclude that Indonesia's past SO_2 emissions data contributes significantly to the current amount of SO_2 emissions in Malaysia based on the granger-causality test. Test 11. with the null hypothesis that the amount of SO_2 emissions in Malaysia is influenced by its own past data (information) and is not influenced by Thailand's past SO_2 emissions data. The chi-squares test result is 12.48 with a p-value of 0.0858, so the null hypothesis is not rejected (NS). So we can conclude that Thailand's past SO_2 emissions data does not contribute significantly to the current amount of SO_2 emissions in Malaysia based on the granger-causality test. Test 12. with the null hypothesis that the amount of SO_2 emissions in Malaysia is influenced by its own past data (information) and is not influenced by the past SO_2 emissions data of the Philippines. The chi-squares test result is 1.44 with a p-value



(a) (b)

Figure 6. (a) Figure of Predicted Values and Real Values of SO_2 Emissions in Thailand from 1940 to 2022 and Forecasting Values for the Next 10 Years, and (b) Proportion Prediction Error Covariance Decomposition



(a) (b)

Figure 7. (a) Figure of Predicted Values and Real Values of the Amount of SO_2 Emissions in the Philippines from 1940 to 2022 and Forecasting Values for the Next 10 Years and (b) Proportion Prediction Error Covariance Decomposition

of 0.8373, so the null hypothesis is not rejected (NS). So we can conclude that the past SO_2 emissions data of the Philippines does not contribute significantly to the current amount of SO_2 emissions in Malaysia based on the granger-causality test.

Figures 4(a), 4(b), 4(c), and 4(d) show the impulse response function (IRF) that occurs if a shock occurs in one variable (in standard deviation) and its impact on itself and on the other variables. Figure 4(a) shows the IRF if a shock occurs of one standard deviation of SO_2 emissions in Indonesia (IND), then it will have an effect for several years to come on SO_2 emissions to IND itself, to Thailand (THAI), to the Philippines (PHIL), and to Malaysia (MLS).

Figure 4(a) shows if a shock occurs of one standard deviation in IND and its effect on SO_2 emissions in IND itself (IND→IND) for some coming years fluctuates. After 1 year the effect is relatively small at 0.0064; after 2 years the effect is negative at -0.1899; after 3 to 5 years the effects are positive at 0.2403, 0.5413, and 0.0539, respectively; after 6 years the effect is negative at -0.1354; after 7 and 8 years, the effect are positive at 0.2607 and 0.3862, respectively, and from the 9th year onwards, the impact weakens towards equilibrium. Its impact on SO_2 emissions in Thailand (IND→THAI) are negative, after 1 to 7 years the impact are: -0.2688, -0.0953, -0.2578, -0.1847, -0.1837, -0.1987, and -0;2117, respectively. and from the 8th year onwards, the impact weakens towards equilibrium. Its impact on SO_2 emissions in Philippines (IND→PHIL) are relatively small, after 1 years the impact is negative -0.0411, after 2 and 3 years the impacts are positive 0.0763, and 0.1433, respectively. and from the 4th year onwards, the impact weakens towards equilibrium. Its impact on SO_2 emissions in Malaysia (IND→MLS) are relatively small, after the fisrt 3 years the impact are 0.0465, -0.0675, and 0.0874 , respectively. And from the 4th year onwards, the impact weakens towards equilibrium.

Figure 4(b) shows if a shock occurs of one standard deviation in Thailand and its effect on SO_2 emissions in Indonesia (THAI→IND) for some coming years are relatively small. After the first 2 year the effect are relatively small at -0.0357 and

-0.0615 respectively. And from the 4th year onwards, the impact weakens towards equilibrium. Its impact on SO_2 emissions in Thailand itself (THAI→THAI) are positive for the first 3 year 0.5423, 0.1821, and 0.0434, respectively. And from the 4th year onwards, the impact weakens towards equilibrium. Its impact on SO_2 emissions in Philippines (THAI→PHIL) are positive for the first 3 year 0.1154, 0.0343, and 0.1131, respectively. And from the 4th year onwards, the impact weakens towards equilibrium., Its impact on SO_2 emissions in Malaysia (THAI→MLS) are relatively small, after 1 years the impact is 0.0201, respectively. And from the 2nd year onwards, the impact weakens towards equilibrium.

Figure 4(c) shows if a shock occurs of one standard deviation in Philippine and its effect on SO_2 emissions in Indonesia (PHIL→IND) for some coming years fluctuates. After the first 3 years the effect are negative -0.0225, -0.0916, and -0.0320, respectively, after 4 years the impact is positive 0.3607. And from the 5th year onwards, the impact weakens towards equilibrium. Its impact on SO_2 emissions in Thailand (PHIL→THAI) are negative, after the first 5 years. The impacts are -1.4406, -0.4561, -0.5918, -0.2481, and -0.6778, respectively.And from the 6th years onwards, the impact weakens towards equilibrium. Its impact on SO_2 emissions in Philippines itself (PHIL→PHIL) are fluctuative , after the first 5 years the impact are -0.2640, 0.0799, -0.1085, 0.2129, and -0.2957, respectively. And from the 6th year onwards, the impact weakens towards equilibrium. Its impact on SO_2 emissions in Malaysia (PHIL→MLS) are very small, it can be seen in Figure 4(c) where the response for MLS is relatively flat.

Figure 4(d) shows if a shock occurs of one standard deviation in Malaysia and its effect on SO_2 emissions in Indonesia (MLS→IND) for some coming years fluctuates and long enought. After the first 9 years the impacts are -0.1359, 1.4993, -0.0947, -0.1986, 0.4853, 0.4057, -0.0150,-0.2253, 0.3003, and 0.4757, respectively. After 11 years onwards the impact weakens towards equilibrium. Its impact on SO_2 emissions in Thailand (MLS→THAI) after the first 5 years, the impacts are 0.5329, 0.1680, -0.3675, 0.4719, and 0.3024, respectively. And from the 6th years onwards, the impact weakens towards equilibrium. Its impact on SO_2 emissions in Philippines (MLS→PHIL) are fluctuative , after the first 6 years the impact are -0.0612, 0.0917, -0.3436, -0.2360, 0.3245, and -0.1257, respectively. And from the 7th year onwards, the impact are weakens towards equilibrium. Its impact on SO_2 emissions in Malaysia itself (MLS→MLS) are fluctuative and after the first 8 years the impacts are 0.0184, -0.0199, 0.1778, -0.3828, 0.1369, 0.0589, -0.1134, and 0.1440, respectively. And after 9th years onwards the impact are weakens towards equilibrium.

3.7 Canonical Correlation Analysi and State Space Model

From the results of multivariate time series analysis for the relationship of the amount of SO_2 emissions in four ASEAN countries, Indonesia, Thailand, Philippines and Malaysia, the model used is VAR(5). Based on the VAR(5) model, a state space model for forecasting is built. To determine the state vector, we use the approach suggested by Wei (2006) and Akaike (1976), namely by using canonical correlation. To determine the state vector, it is determined based on the Information Criterion (IC) value, where if the IC value < 0, then the minimum value of the canonical correlation is taken as zero (Wei, 2006), otherwise, it is considered greater than zero. From Table 9, for the first step we take the state vector: $\mathrm{IND}_{t|t}$, $\mathrm{THAI}_{t|t}$, $\mathrm{PHIL}_{t|t}$, $\mathrm{MLS}_{t|t}$, $\mathrm{IND}_{t+1|t}$ and for this set of state vectors, the IC value is positive (2.7494), therefore we include the variable $\mathrm{IND}_{t+1|t}$ in the state vector. In the second step, we consider the set of vectors $\mathrm{IND}_{t|t}$, $\mathrm{THAI}_{t|t}$, $\mathrm{PHIL}_{t|t}$, $\mathrm{MLS}_{t|t}$, $\mathrm{IND}_{t+1|t}$, $\mathrm{THAI}_{t+1|t}$ and for this set of state vectors, the IC value is negative (-4.4549), because the IC value is negative, then we remove the variable $\mathrm{THAI}_{t+1|t}$ from the state vector. In the third step, we consider the set of vectors $\mathrm{IND}_{t|t}$, $\mathrm{THAI}_{t|t}$, $\mathrm{PHIL}_{t|t}$, $\mathrm{MLS}_{t|t}$, $\mathrm{IND}_{t+1|t}$, $\mathrm{PHIL}_{t+1|t}$ and for this set of state vectors, the IC value is negative (-11.4420), because the IC value is negative, then we remove the variable $\mathrm{PHIL}_{t+1|t}$ from the state vector. In the fourth step, we consider the set of vectors $\mathrm{IND}_{t|t}$, $\mathrm{THAI}_{t|t}$, $\mathrm{PHIL}_{t|t}$, $\mathrm{MLS}_{t|t}$, $\mathrm{IND}_{t+1|t}$, $\mathrm{MLS}_{t+1|t}$ and for this set of state vectors, the IC value is negative (-9.9245), because the IC value is negative, then the variable $\mathrm{MLS}_{t+1|t}$ is removed from the state vector. In the fifth step, we consider the set of vectors $\mathrm{IND}_{t|t}$, $\mathrm{THAI}_{t|t}$, $\mathrm{PHIL}_{t|t}$, $\mathrm{MLS}_{t|t}$, $\mathrm{IND}_{t+1|t}$, $\mathrm{IND}_{t+2|t}$ and for this set of state vectors, the IC value is negative (-2.5640), because the IC value is negative, then the variable $\mathrm{IND}_{t+2|t}$ is removed from the state vector. Therefore, based on the results of the canonical correlation analysis, the components of the state vector are:

$$Y_t = \begin{bmatrix} \mathrm{IND}_{t|t} \\ \mathrm{THAI}_{t|t} \\ \mathrm{PHIL}_{t|t} \\ \mathrm{MLS}_{t|t} \\ \mathrm{IND}_{t+1|t} \end{bmatrix} \tag{19}$$

3.8 Estimate State Space Model

From Table 9, the results of canonical correlation analysis and the results of parameters estimate of transition matrix F and input matrix G given in the following state space model:

$$Y_{t+1} = FY_t + GX_{t+1} \tag{20}$$

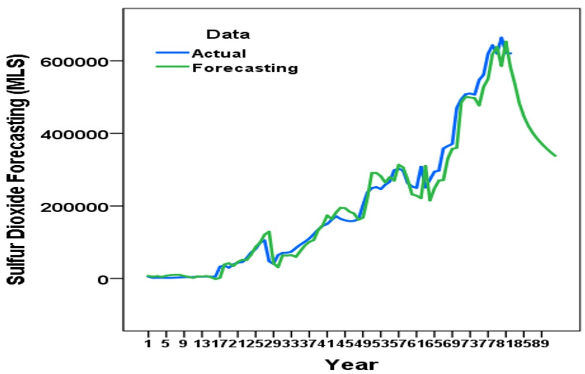
and the estimates state space model is

$$\begin{aligned}\begin{bmatrix} \mathrm{IND}_{t+1|t} \\ \mathrm{THAI}_{t+1|t} \\ \mathrm{PHIL}_{t+1|t} \\ \mathrm{MLS}_{t+1|t} \\ \mathrm{IND}_{t+2|t} \end{bmatrix} &= \begin{bmatrix} 0 & 0 & 0 & 0 & 1 \\ -0.0935 & 0.9073 & -0.6749 & 5.3713 & -0.8529 \\ -0.1651 & 0.0024 & 0.8465 & 0.7040 & 0.0469 \\ -0.1014 & 0.0040 & -0.0141 & 1.0242 & 0.0923 \\ -0.3451 & 0.0668 & -0.0416 & -0.5196 & 1.4075 \end{bmatrix} \begin{bmatrix} \mathrm{IND}_{t|t} \\ \mathrm{THAI}_{t|t} \\ \mathrm{PHIL}_{t|t} \\ \mathrm{MLS}_{t|t} \\ \mathrm{IND}_{t+1|t} \end{bmatrix} \\ &+ \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ -0.2239 & -0.2093 & -0.1064 & 6.1336 \end{bmatrix} \begin{bmatrix} \alpha_{t+1} \\ \beta_{t+1} \\ \gamma_{t+1} \\ \delta_{t+1} \end{bmatrix}\end{aligned} \tag{21}$$

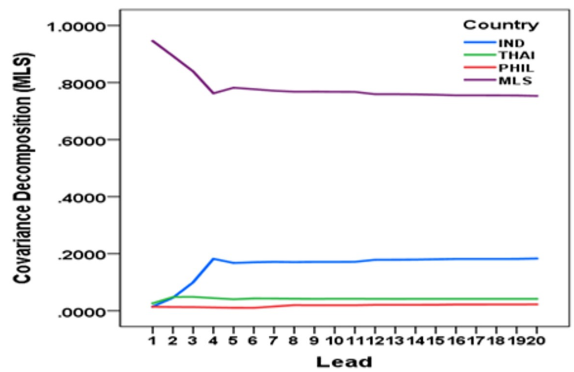
And the covariance innovation is

Table 9. Analysis Canonical Correlation

State Vector	Canonical Correlation	IC	Chi-Square	DF
$IND_{t\|t}$ $THAI_{t\|t}$ $PHIL_{t\|t}$ $MLS_{t\|t}$ $IND_{t+1\|t}$	1 1 1 1 0.4496	2.7494	17.8459	8
$IND_{t\|t}$ $THAI_{t\|t}$ $PHIL_{t\|t}$ $MLS_{t\|t}$ $IND_{t+1\|t}$ $THAI_{t+1\|t}$	1 1 1 1 0.6023 0.3295	-4.4549	9.1425	7
$IND_{t\|t}$ $THAI_{t\|t}$ $PHIL_{t\|t}$ $MLS_{t\|t}$ $IND_{t+1\|t}$ $PHIL_{t+1\|t}$	1 1 1 1 0.5072 0.1742	-11.4420	2.4501	7
$IND_{t\|t}$ $THAI_{t\|t}$ $PHIL_{t\|t}$ $MLS_{t\|t}$ $IND_{t+1\|t}$ $MLS_{t+1\|t}$	1 1 1 1 0.4608 0.2188	-9.9245	3.9036	7
$IND_{t\|t}$ $THAI_{t\|t}$ $PHIL_{t\|t}$ $MLS_{t\|t}$ $IND_{t+1\|t}$ $IND_{t+2\|t}$	1 1 1 1 0.4557 0.3587	-2.5640	10.9537	7



(a)



(b)

Figure 8. (a) Figure of Predicted Values and Real Values of the Amount of SO_2 Emissions in the Malaysia from 1940 to 2022 and Forecasting Values for the Next 10 Years and (b) Proportion Prediction Error Covariance Decomposition

$$\mathrm{Var}\begin{bmatrix}\alpha_{t+1}\\ \beta_{t+1}\\ \gamma_{t+1}\\ \delta_{t+1}\end{bmatrix}=\begin{bmatrix}8.412E10 & 6.4576E9 & 1.351E10 & 1.326E10\\ 6.4576E9 & 2.869E10 & 5.9202E9 & 1.9883E9\\ 1.351E10 & 5.9202E9 & 6.5909E9 & 2.5507E9\\ 1.326E10 & 1.9883E9 & 2.5507E9 & 2.6858E9\end{bmatrix}$$

3.9 Forecasting with a State Space Model and Proportion Prediction Error Covariance Decomposition

To obtain forecasted SO_2 emissions in four ASEAN countries: Indonesia, Thailand, the Philippines, and Malaysia for the next 10 periods, the State Space Model and Kalman Filter techniques will be used. Parameter estimates for the state space model are given in and Equation (21). This model will be used to forecast SO_2 emissions in the four ASEAN countries for the next 10 periods. Figure 5(a) shows a plot of real data and predictions using the state space model for SO_2 emission in Indonesia the prediction values and the real values are close to each other, this indicate that the model is very reliable to be used for forecasting. The forecasted SO_2 emissions in Indonesia for the next 10 years show a downward trend. The values are 3092448 ton, 2659296 ton, 2386246 ton, 2202243 ton, 2069199 ton, 1966375 ton, 1882261 ton, 1810334 ton, 1746802 ton and 1689402 ton, respectively. From Figure 5(b) the Proportion Prediction Error Covariance Decomposition for forecasting the next one year SO_2 emissions in Indonesia 100% of the variation of SO_2 emissions in Indonesia are explained by the information of SO_2 Indonesia itself; for forecasting the next two-year SO_2 emissions in Indonesia 99.2% of the variation of SO_2 emissions in Indonesia are explained by the information of SO_2 Indonesia itself, 0.7% is explained by the information of SO_2 emission of Thailand, and 0.1% is explained by the information of SO_2 emission in Malaysia; for forecasting the next three-year SO_2 emissions in Indonesia 85.4% of the variation of SO_2 emissions in Indonesia are explained by the information of SO_2 emissions of Indonesia itself, 1.0% is explained by the information of SO_2 emission of Thailand, and 1% is explained by the information of SO_2 emission of Philippines, and 12.6% variation is explained by SO_2 emissions of Malaysia; for forecasting the next four-year and on the the composition of the variation given by information of SO_2 emissions in Indonesia, Thailand, Philippine and Malaysia show stable (Figure 5(b)). Where about 82% of the variation of SO_2 emissions in Indonesia are explained by the information of SO_2 Indonesia itself, 2% is explained by the information of SO_2 emission of Thailand, and 6% is explained by the information of SO_2 emission in Philippines, and 10% variation is explained by SO_2 emissions of Malaysia.

Figure 6(a) shows a plot of real data and predictions using the state space model for SO_2 emission in Thailand the prediction values and the real values are close to each other, this indicate that the model is very reliable to be used for forecasting. The forecasted SO_2 emissions in Thailand for the next 10 years show a downward trend for the first four-year and upward trend for the next the fifth to the tenth year. The values are 510186 ton, 462436 ton, 443036 ton, and 442009 ton for the first four-year, and 451785 ton, 467057 ton, 484337 ton, 501475 ton, 517256 ton and 531085 ton for the last six-year. From Figure 6(b) the Proportion Prediction Error Covariance Decomposition for forecasting the next one year SO_2 emissions in Thailand 100% of the variation of SO_2 emissions in Thailand are explained by the information of SO_2 Thailand itself; for forecasting the next two-year the variation of SO_2 emissions 84.6% of the variation of SO_2 emissions are explained by the information of SO_2 Thailand itself, 0.8% is explained by the information of SO_2 emission of Indonesia, 14.2% is explained by the information of SO_2 emission of Philippines, and 0.3% is explained by the information of SO_2 emission of Malaysia; for forecasting the next three-year SO_2 emissions in Thailand 83.5% of the variation of SO_2 emissions are explained by the information of SO_2 Thailand itself, 0.8% is explained by the information of SO_2 emission of Indonesia, 15.3% is explained by the information of SO_2 emission of Philippines, and 0.4% is explained by the information of SO_2 emission of Malaysia; for forecasting the next four-year SO_2 emissions in Thailand 80.8% of the variation of SO_2 emissions are explained by the information of SO_2 Thailand itself, 2% is explained by the information of SO_2 emission of Indonesia, 16.8% is explained by the information of SO_2 emission of Philippines, and 0.4% is explained by the information of SO_2 emission of Malaysia; for forecasting the next fifth-year and on (long term forecasting) the the composition of the variation given by information of SO_2 emissions in Indonesia, Thailand, Philippines and Malaysia show stable (Figure 6(b)). Where about 76% of the variation of SO_2 emissions are explained by the information of SO_2 Thailand itself, 4% is explained by the information of SO_2 emission of Indonesia, and 19% is explained by the information of SO_2 emission of Philippines, and 1% variation is explained by SO_2 emissions of Malaysia.

Figure 7(a) shows a plot of real data and predictions using the state space model for SO_2 emission in Philipinnes the prediction values and the real values are close to each other, this indicate that the model is very reliable to be used for forecasting. The forecasted SO_2 emissions in Philippines for the next 10 years show a downward trend. The values are 728477 ton, 644913 ton, 592857 ton, 558930 ton, 535674 ton, 518859 ton, 506038 ton, 495776 ton, 487213 ton, and 479829 ton respectively.

From Figure 7(b) the Proportion Prediction Error Covariance Decomposition for forecasting the next one year SO_2 emissions 91% of the variation of SO_2 emissions are explained by the information of SO_2 emissions of Philippines itself and 9% of the variation of SO_2 emissions are explained by the information of SO_2 emissions of Thailand ; for forecasting the next two-year the variation of SO_2 emissions 85% of the variation of SO_2 emissions are explained by the information of SO_2 Philippines itself, 0.2% variation is explained by the information of SO_2 emission of Indonesia, 14.8% is explained by the information of SO_2 emission of Thailand; for forecasting the next three-year SO_2 emissions in Philippines 82.4% of the variation of SO_2 emissions are explained by the information of SO_2 Philippines itself, 1.6% is explained by the information of SO_2 emission of Indonesia, 16% variation is explained by the information of SO_2 emission of Thailand; for forecasting the next four-year SO_2 emissions in Philippines 72.8% of the variation of SO_2 emissions are explained by the information of SO_2 Philippines itself, 5% is explained by the information of SO_2 emission of Indonesia, 20.6% is explained by the information of SO_2 emission of Thailand, and 1.6% is explained by the information of SO_2 emission of Malaysia; for forecasting the next fifth-year and on (long term forecasting) the the composition of the variation given by information of SO_2 emissions of Indonesia, Thailand, Philippines and Malaysia show stable (Figure 7(b)). Where about 70% of the variation of SO_2 emissions are explained by the information of SO_2 emissions Philippines itself, 8% is explained by the information of SO_2 emission of Indonesia, and 19% is explained by the information of SO_2 emissions of Thailand, and 3% variation is explained by SO_2 emissions of Malaysia.

Figure 8(a) shows a plot of real data and predictions using the state space model for SO_2 emission in Malaysia the prediction values and the real values are close to each other, this indicate that the model is very reliable to be used for forecasting. The forecasted SO_2 emissions in Malaysia for the next 10 years show a downward trend. The values are 536631ton, 483353 ton, 447375 ton, 421420 ton, 401465 ton, 385241 ton, 371444 ton, 359306 ton, 348368 ton, and 338345 ton, respectively.

From Figure 8(b) the Proportion Prediction Error Covariance Decomposition for forecasting the next one-year SO_2 emissions 94.5% of the variation of SO_2 emissions are explained by the information of SO_2 emissions of Malaysia itself and 1.5% of the variation of SO_2 emissions are explained by the information of SO_2 emissions of Indonesia, 2.6% of the variation are explained by the information of SO_2 emissions of Thailand, and 1.4% of the variation are explained by the information of SO_2 emissions of Philippines ; for forecasting the next two-year the variation of SO_2 emissions 89.3% of the variation of SO_2 emissions are explained by the information of SO_2 of Malaysia itself, 4.6% variation is explained by the information of SO_2 emission of Indonesia, 4.8% variation is explained by the information of SO_2 emission of Thailand and 1.3% variation is explained by the information of SO_2 emission of Philippine; for forecasting the next three-year SO_2 emissions in Malaysia, 84% of the variation of SO_2 emissions are explained by the information of SO_2 of Malaysia itself, 10% is explained by the information of SO_2 emission of Indonesia, 4.8% variation is explained by the information of SO_2 emission of Thailand, and 1.2% variation is explained by the information of SO_2 emission of Philippine ; for forecasting the next four-year and on (long term forecasting) the the composition of the variation given by information of SO_2 emissions of Indonesia, Thailand, Philippines and Malaysia show stable (Figure 7(b)). Where about 76.8% of the variation of SO_2 emissions are explained by the information of SO_2 emission of Malaysia itself, 17% variation is explained by the information of SO_2 emission of Indonesia, and 4.2% variation is explained by the information of SO_2 emission of Thailand, and 2% variation is explained by SO_2 emissions of Philippines.

4. CONCLUSIONS

With the increasing development of industry and the number of vehicles in various countries, particularly in ASEAN, the development of SO_2 emissions, one of the elements that causes air pollution, is interesting to analyze because SO_2 emissions has a significant impact on human health. Furthermore, understanding changes in SO_2 emissions in a country is crucial for governments to formulate policies to reduce SO_2 emissions in the air. SO_2 emissions data in Indonesia, Thailand, the Philippines, and Malaysia are non-stationary, so any shocks to SO_2 emissions will have a long-lasting effect. The best relationship pattern among SO_2 emissions in the four ASEAN countries using a multivariate time series analysis approach is a 5^{th}-order VAR model [VAR(5)]. Based on the results of the Granger causality test, the past SO_2 emissions in Malaysia will influence the current SO_2 emissions in Indonesia, and vice versa. Thus, there is a reciprocal Granger causality between Indonesia and Malaysia. Granger causality analysis results indicate that Malaysia is also influenced by historical SO_2 emissions from Thailand and the Philippines. This is likely due to the proximity of Malaysia and Thailand. Based on the Granger causality analysis, the past SO_2 emissions in Thailand will influence the current SO_2 emissions in the Philippines, and vice versa. Thus, there is a reciprocal Granger causality between Thailand and the Philippines. The results of the forecasting analysis of SO_2 emisions in Indonesia, Thailand, the Philippines, and Malaysia for the next 10 periods (10 years) using a state space model approach indicate that SO_2 emission in Indonesia, the Philippines, and Malaysia is predicted to decline over the next 10 years, while SO_2 emissions in Thailand will tend to remain constant over the next 10 years.

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REFERENCES

Afif, C., C. Chelala, A. Borbon, M. Abboud, J. Adjizian-Gerard, W. Farah, C. Jambert, R. Zaarour, N. Badaro Saliba, P. E. Perros, and T. A. Rizk (2008). SO_2 in Beirut: Air Quality Implication and Effects of Local Emissions and Long-Range Transport. *Air Quality, Atmosphere & Health*, **1**; 167–178

Akaike, H. (1976). Canonical Correlation Analysis of Time Series and the Use of an Information Criterion. In R. K. Mehra and D. G. Lainiotis, editors, *Systems Identification: Advances and Case Studies*. Academic Press, New York

Bell, M. L., J. M. Samet, and F. Dominici (2004). Time-Series Studies of Particulate Matter. *Annual Review of Public Health*, **25**; 247–280

Castelli, M., F. M. Clemente, A. Popovič, S. Silva, and L. Vanneschi (2020). A Machine Learning Approach to Predict Air Quality in California. *Complexity*, **2020**; 8049504

Chang, C., G. Li, S. Zhang, and K. Yu (2019). Employing a Fuzzy-Based Grey Modeling Procedure to Forecast China's Sulfur Dioxide Emissions. *International Journal of Environmental Research and Public Health*, **16**; 2504

Chen, J. and M. Gao (2021). Prediction Method of Sulfur Dioxide Emission. *IEEE Access*, **PP**; 1–1

Craig, K. (2019). A Review of the Chemistry, Pesticide Use, and Environmental Fate of Sulfur Dioxide, as Used in California. *Reviews of Environmental Contamination and Toxicology*, **246**; 33–64

Darynova, Z., M. Amouei Torkmahalleh, T. Abdrakhmanov, S. Sabyrzhan, S. Sagynov, P. K. Hopke, and J. Kushta (2020). SO_2 and HCHO Over the Major Cities of Kazakhstan from 2005 to 2016: Influence of Political, Economic and Industrial Changes. *Scientific Reports*, **10**(1); 12635

Djordjevic, P., D. Nikolic, I. Jovanovic, I. Mihajlovic, M. Savic, and Z. Zivkovic (2013). Episodes of Extremely High Concentrations of SO_2 and Particulate Matter in the Urban Environment of Bor, Serbia. *Environmental Research*, **126**; 204–207

Fisher, J. A., D. J. Jacob, Q. Wang, R. Bahreini, C. C. Carouge, M. J. Cubison, J. E. Dibb, T. Diehl, J. L. Jimenez, E. M. Leibensperger, Z. Lu, M. B. Meinders, H. O. Pye, P. K. Quinn, S. Sharma, D. G. Streets, A. van Donkelaar, and R. M. Yantosca (2011). Sources, Distribution, and Acidity of Sulfate–Ammonium Aerosol in the Arctic in Winter–Spring. *Atmospheric Environment*, **45**; 7301–7318

Francis, T., M. M. Sarin, and R. Rengarajan (2016). Atmospheric SO_2 Oxidation Efficiency Over a Semi-Arid Region: Seasonal Patterns from Observations and GEOS-Chem Model. *Atmospheric Environment*, **125**; 383–395

Gomez, V. (2016). *Multivariate Time Series with Linear State Space Structure*. Springer, New York

Hamilton, H. (1994). *Time Series Analysis*. Princeton University Press, Princeton, New Jersey

Heng, Y., L. Hoffmann, S. G. Griessbach, T. Rössler, and O. Stein (2016). Inverse Transport Modeling of Volcanic Sulfur Dioxide Emissions Using Large-Scale Simulations. *Geoscientific Model Development*, **9**; 1627–1645

Jenner, S. and B. J. Abiodun (2013). The Transport of Atmospheric Sulfur Over Cape Town. *Atmospheric Environment*, **79**; 248–260

Kelly, F. J. and J. C. Fussell (2015). Air Pollution and Public Health: Emerging Hazards and Improved Understanding of Risk. *Environmental Geochemistry and Health*, **37**; 631–649

Lelieveld, J., J. S. Evans, M. Fnais, D. Giannadaki, and A. Pozzer (2015). The Contribution of Outdoor Air Pollution Sources to Premature Mortality on a Global Scale. *Nature*, **525**(7569); 367–371

Li, Z., Y. Wang, Z. Xu, and Y. Cao (2021). Characteristics and Sources of Atmospheric Pollutants in Typical Inland Cities in Arid Regions of Central Asia: A Case Study of Urumqi City. *PLoS ONE*, **16**(4); e0249563

Lim, S. S., T. Vos, A. D. Flaxman, G. Danaei, K. Shibuya, H. Adair-Rohani, and P. M. Pelizzari (2012). A Comparative Risk Assessment of Burden of Disease and Injury Attributable to 67 Risk Factors and Risk Factor Clusters in 21 Regions, 1990–2010: A Systematic Analysis for the Global Burden of Disease Study 2010. *The Lancet*, **380**(9859); 2224–2260

McLinden, C. A., V. E. Fioletov, M. W. Shephard, N. A. Krotkov, C. Li, R. V. Martin, M. D. Moran, and J. Joiner (2016). Space-Based Detection of Missing Sulfur Dioxide Sources of Global Air Pollution. *Nature Geoscience*, **9**; 496–500

Moolgavkar, S. H., R. O. McClellan, A. Dewanji, J. Turim, E. G. Luebeck, and M. Edwards (2012). Time-Series Analyses of Air Pollution and Mortality in the United States: A Subsampling Approach. *Environmental Health Perspectives*, **121**; 73–78

Nairobi, A., E. Russel, S. Paujiah, D. N. Pratama, Wamiliana, and M. Usman (2022). Analysis of Data Inflation Energy and Gasoline Price by Vector Autoregressive Model. *International Journal of Energy Economics and Policy*, **12**(2); 120–126

Nieto, P. J., E. F. Combarro, J. J. Díaz, and E. Montañés (2013). A SVM-Based Regression Model to Study the Air Quality at Local Scale in Oviedo Urban Area (Northern Spain): A Case Study. *Applied Mathematics and Computation*, **219**; 8923–8937

O'Brien, E. P., P. Masselot, F. Sera, D. Royé, S. Breitner, C. F. Ng, M. De Sousa Zanotti Stagliorio Coelho, J. Madureira, A. Tobías, A. M. Vicedo-Cabrera, M. Bell, E. Lavigne, H. Kan, and A. Gasparrini (2023). Short-Term Association between Sulfur Dioxide and Mortality: A Multicountry Analysis in 399 Cities. *Environmental Health Perspectives*, **131**(3); 037002

OECD (2014). *The Cost of Air Pollution: Health Impacts of Road Transport*. OECD Publishing

Parreno, S. J. E. (2024). Assessing the Stationarity of Per Capita Electricity Consumption: Time Series Analysis in ASEAN Countries. *International Journal of Energy Economics and Policy*, **14**(2); 46–52

Prüss-Üstün, A., J. Wolf, C. Corvalán, R. Bos, and M. Neira (2016). *Preventing Disease through Healthy Environments: A Global Assessment of the Burden of Disease from Environmental Risks*. World Health Organization

Russel, E., Wamiliana, Warsono, Nairobi, M. Usman, and F. A. M. Elfaki (2023). Analysis Multivariate Time Series Using State Space Model for Forecasting Inflation in Some Sectors of Economy in Indonesia. *Science and Technology Indonesia*, **8**(1); 144–150

Seinfeld, J. H. and S. N. Pandis (2016). *Atmospheric Chemistry and Physics: From Air Pollution to Climate Change*. John Wiley & Sons, New York

Shen, J., D. Valagolam, and S. McCalla (2020). Prophet Forecasting Model: A Machine Learning Approach to Predict the Concentration of Air Pollutants ($PM_{2\cdot5}$, PM_{10}, O_3, NO_2, SO_2, CO) in Seoul, South Korea. *PeerJ*, **8**

Tsay, R. S. (2010). *Analysis of Financial Time Series*. John Wiley & Sons, New York

Tsay, R. S. (2014). *Multivariate Time Series Analysis*. John Wiley & Sons, New York

Unal, Y. S., S. Incecik, Y. Borhan, and S. Mentes (2000). Factors Influencing the Variability of SO_2 Concentrations in Istanbul. *Journal of the Air & Waste Management Association*, **50**(1); 75–84

Vernier, J. P., L. W. Thomason, T. D. Fairlie, P. Minnis, R. Palikonda, and K. M. Bedka (2013). Comment on: Large Volcanic Aerosol Load in the Stratosphere Linked to Asian Monsoon Transport. *Science*, **339**; 647–647

Warsono, E. Russel, Wamiliana, Widiarti, and M. Usman (2019). Modeling and Forecasting by the Vector Autoregressive Moving Average Model for Export of Coal and Oil Data (Case Study from Indonesia over the Year 2002–2017). *International Journal of Energy Economics and Policy*, **9**(4); 240–247

Wei, W. W. S. (2006). *Time Series Analysis: Univariate and Multivariate Methods*. Addison-Wesley Publishing Company, California

Wei, W. W. S. (2019). *Multivariate Time Series Analysis and Application*. John Wiley & Sons, New York

Yang, C., P. Chen, C. Wu, C. Yang, and L. Chuang (2024a). Deep Learning-Based Air Pollution Analysis on Carbon Monoxide in Taiwan. *Ecological Informatics*, **80**; 102477

Yang, C., P. Chen, C. Yang, and L. Chuang (2024b). Analysis and Forecasting of Air Pollution on Nitrogen Dioxide and Sulfur Dioxide Using Deep Learning. *IEEE Access*, **12**; 165236–165252

Yang, S., W. Yuesi, and Z. Changchun (2009). Measurement of the Vertical Profile of Atmospheric SO_2 during the Heating Period in Beijing on Days of High Air Pollution. *Atmospheric Environment*, **43**(2); 468–472

Yang, X., S. Wang, W. Zhang, D. Zhan, and J. Li (2017). The Impact of Anthropogenic Emissions and Meteorological Conditions on the Spatial Variation of Ambient SO_2 Concentrations: A Panel Study of 113 Chinese Cities. *Science of the Total Environment*, **584–585**; 318–328

Zhang, H., S. Zhang, P. Wang, Y. Qin, and H. Wang (2017). Forecasting of Particulate Matter Time Series Using Wavelet Analysis and Wavelet-ARMA/ARIMA Model in Taiyuan, China. *Journal of the Air & Waste Management Association*, **67**; 776–788

Zhao, C., Y. Sun, Y. Zhong, S. Xu, Y. Liang, S. Liu, X. He, J. Zhu, T. Shibamoto, and M. He (2021). Spatio-Temporal Analysis of Urban Air Pollutants throughout China during 2014–2019. *Air Quality, Atmosphere & Health*, **14**; 1619–1632

