

FORECASTING INDONESIA'S NON-OIL AND GAS EXPORTS AND IMPORTS USING THE VECTOR AUTOREGRESSIVE INTEGRATED MOVING AVERAGE (VARIMA) MODEL

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ABSTRACT Indonesia's international trade, particularly in the non-oil and gas sector, plays a significant role in the national economy. This study aims to model and forecast Indonesia's non-oil and gas exports and imports using the Vector Autoregressive Integrated Moving Average (VARIMA) model, a multivariate time series method that considers dynamic interdependence between variables. The data used in this study were monthly data from January 2018 to December 2024, consisting of 84 observations divided into 58 training data and 26 testing data. Model order identification was carried out using the Matrix Autocorrelation Function (MACF) for the MA component and the Matrix Partial Autocorrelation Function (MPACF) for the AR component. Parameter estimation was conducted using Maximum Likelihood Estimation (MLE) and refined through a restriction process to retain only statistically significant parameters. Diagnostic tests showed that the residuals met the assumptions of white noise and multivariate normality. Among several candidate models, VARIMA(2,1,2) was selected as the optimal model based on the balance between information criteria, model complexity, parameter stability, and forecasting reliability. The model produced MAPE values of 11.10% for imports, categorized as good, and 8.81% for exports, categorized as very good. The forecast results showed relatively stable fluctuations, with imports projected to range from US\$14.32 million to US\$18.48 million and exports from US\$18.38 million to US\$26.41 million. These findings indicate that the VARIMA(2,1,2) model provides adequate forecasting performance and can serve as a quantitative basis for supporting foreign trade policy planning, particularly in anticipating the dynamics of Indonesia's non-oil and gas exports and imports.

Keywords: exports, forecasting, imports, non-oil and gas, VARIMA

ABSTRAK Perdagangan internasional Indonesia, khususnya pada sektor nonmigas, memiliki peran penting dalam perekonomian nasional. Penelitian ini bertujuan untuk memodelkan dan meramalkan nilai ekspor dan impor nonmigas Indonesia menggunakan model *Vector Autoregressive Integrated Moving Average* (VARIMA), yaitu metode deret waktu multivariat yang mempertimbangkan keterkaitan dinamis antarvariabel. Data yang digunakan merupakan data bulanan periode Januari 2018 hingga Desember 2024, yang terdiri atas 84 observasi dan dibagi menjadi 58 data pelatihan serta 26 data pengujian. Identifikasi orde model dilakukan menggunakan *Matrix Autocorrelation Function* (MACF) untuk komponen MA

dan *Matrix Partial Autocorrelation Function* (MPACF) untuk komponen AR. Estimasi parameter dilakukan menggunakan metode *Maximum Likelihood Estimation* (MLE) dan disederhanakan melalui proses restriksi untuk mempertahankan parameter yang signifikan secara statistik. Hasil uji diagnostik menunjukkan bahwa residual memenuhi asumsi *white noise* dan normalitas multivariat. Dari beberapa kandidat model, VARIMA(2,1,2) dipilih sebagai model optimal berdasarkan keseimbangan antara kriteria informasi, kompleksitas model, stabilitas parameter, dan keandalan peramalan. Model ini menghasilkan nilai MAPE sebesar 11,10% untuk impor dengan kategori baik dan 8,81% untuk ekspor dengan kategori sangat baik. Hasil peramalan menunjukkan fluktuasi yang relatif stabil, dengan proyeksi impor berkisar antara US\$14,32 juta hingga US\$18,48 juta dan ekspor berkisar antara US\$18,38 juta hingga US\$26,41 juta. Temuan ini menunjukkan bahwa model VARIMA(2,1,2) memiliki kinerja peramalan yang memadai dan dapat menjadi dasar kuantitatif dalam mendukung perencanaan kebijakan perdagangan luar negeri, khususnya untuk mengantisipasi dinamika ekspor dan impor nonmigas Indonesia.

Kata-kata kunci: ekspor, impor, nonmigas, peramalan, VARIMA

INTRODUCTION

International trade refers to the exchange of products and services between two or more countries, including exports and imports (Susanto et al., 2024). Exports are the sale of goods and services from a country of origin to another country, while imports refer to the acquisition of goods from abroad and their delivery to the country of origin. Exports can be divided into two methods, namely direct and indirect exports (Ahmad, 2019).

International trade through exports and imports is an important indicator of economic growth (Haryani & Ferdous Azam, 2021). Indonesia, as a country rich in natural resources, utilizes these resources for non-oil and gas export commodities (Aisyah & Renggani, 2021). Based on data from *The World Factbook*, Indonesia is among the 50 countries with the largest export volumes (Septyari, 2021). Meanwhile, the government continues to encourage the strengthening of this sector, considering its more dominant role compared to the oil and gas sector (Suryatin et al., 2024).

In the context of Indonesia's international trade, non-oil and gas exports and imports play an important role in supporting the national economy, contributing 40.63% to total exports (Hotsawadi & Gea, 2024). Indonesia's abundant natural and human resources are used as sources of food and export goods (Apriani & Hayati, 2021). The main commodities include minerals, rubber, electrical machinery, and agricultural products (Rini Silaban & Nurlina, 2022). Ironically, in the oil and gas sector, Indonesia imports more than it exports (Rahayu, 2021).

Indonesia's export development has fluctuated over time, with a sharp decline during the COVID-19 pandemic due to lockdowns and disruptions to global supply chains (Febrianti et al., 2021). Since 2021, economic recovery has occurred gradually, although economic growth has remained slow due to declining demand in the industrial sector and low commodity prices (Kartikasari, 2017). This condition

indicates that export and import movements need to be analyzed carefully, especially because both variables may influence each other in the context of international trade.

Time series analysis is one approach that can be used to model and forecast export and import movements. Univariate time series involve only one variable observed sequentially, while multivariate time series include several interrelated variables (Iwok & Okpe, 2016). In this context, Indonesia's non-oil and gas exports and imports are economically interconnected because commodity imports may support export-oriented production. In the post-pandemic environment, which is characterized by global uncertainty, this interdependence has become more complex, making a multivariate approach more appropriate.

The vector time series analysis model is an extension of the univariate time series model. While the Autoregressive Integrated Moving Average (ARIMA) model is known to handle non-stationary data in univariate analysis, the Vector Autoregressive Integrated Moving Average (VARIMA) model can handle multivariate data (Nugroho, 2022). VARIMA is a development of VARMA through a differencing process to handle non-stationarity (Warsono et al., 2019). The analysis methods are also different: univariate analysis uses a single ACF/PACF identification, while multivariate analysis requires an ACF/PACF matrix (Nasution & Cipta, 2023).

VARIMA does not stand alone but consists of several related components, namely VAR, VMA, VARMA, and VARIMA (Rusyana et al., 2020). In addition, ARIMA has also developed into other models such as ARCH and SARIMA. The advantage of VARIMA lies in its ability to improve prediction accuracy by considering the interdependence between variables (Ng et al., 2024). Previous studies have largely relied on univariate approaches without adequate out-of-sample evaluation, thus limiting the reliability of predictions. Therefore, this study applies a multivariate VARIMA model to better capture the dependency between non-oil and gas export and import variables.

The main objective of this study is to find the optimal combination of AR, I, and MA parameters to minimize forecasting errors based on the Mean Absolute Percentage Error (MAPE) (Sherly A et al., 2025), where the technique with the lowest error is considered the most accurate (Putri & Halim, 2020). Based on the background described above, this study aims to model multivariate time series using the Vector Autoregressive Integrated Moving Average (VARIMA) method and apply the model to non-oil and gas import and export value data in Indonesia.

METHODS

The data used in this study were monthly data on Indonesia's non-oil and gas trade from January 2018 to December 2024, consisting of 84 observations. The data were divided into 58 training observations and 26 testing observations. The data were obtained from the official websites of the Central Statistics Agency (BPS) and the

Ministry of Trade of the Republic of Indonesia (KEMENDAG). Data analysis was performed using RStudio software through the following stages.

1. Descriptive Statistical Analysis

Descriptive statistical analysis was conducted to examine the general characteristics of the data. This analysis included measures of central tendency, dispersion, and the relationship between variables through correlation and autocorrelation analysis. This stage was used to obtain an initial overview of the patterns of Indonesia's non-oil and gas export and import data.

2. Stationarity Test

The stationarity test was conducted to ensure that the data met the assumptions required for time series modeling. Variance stationarity was examined using the coefficient of variation, while mean stationarity was tested using the Augmented Dickey-Fuller (ADF) test. If the data were not stationary, a differencing process was applied until the stationarity requirements were fulfilled.

3. VARIMA Model Formulation

The Vector Autoregressive Integrated Moving Average (VARIMA) model is an extension of the ARIMA model for multivariate data that considers dynamic relationships between variables. The VARIMA (p, d, q) model consists of three components: p , which represents the autoregressive (AR) order or the influence of past values on current values; d , which represents the differencing order needed to achieve stationarity; and q , which represents the moving average (MA) order or the influence of past errors on current values.

In general, the matrix form of the VARIMA model in lag operator notation is:

$$\Phi_p(B)(1 - B)^d Z_t = \Theta_q(B)a_t$$

where:

$$Z_t$$

is a vector of endogenous variables of size $k \times 1$,

$$\Phi_p(B)$$

is the AR polynomial matrix,

$$\Theta_q(B)$$

is the MA polynomial matrix, and

$$a_t$$

is the error vector or white noise process.

The matrix polynomial form of the VARIMA model can be written as:

$$\Phi(B) = I_k - \Phi_1 B - \Phi_2 B^2 - \dots - \Phi_p B^p$$

and

$$\Theta(B) = I_k + \Theta_1 B + \Theta_2 B^2 + \dots + \Theta_q B^q$$

Thus, the complete matrix equation can be expressed as:

$$(I_k - \Phi_1 B - \dots - \Phi_p B^p)(1 - B)^d Z_t = (I_k + \Theta_1 B + \dots + \Theta_q B^q) a_t$$

4. Identification of the VARIMA Model

Model order identification was conducted using the Matrix Autocorrelation Function (MACF) and Matrix Partial Autocorrelation Function (MPACF). The MACF was used to measure the temporal correlation between variables at various lags and to help identify the MA (q) order. Meanwhile, the MPACF was used to measure direct correlation after eliminating the influence of intermediate lags, thereby helping to identify the AR (p) order.

The significance cut-off pattern of the MACF and MPACF was used to determine the possible model order. The symbol (+) indicates a significant positive correlation, (-) indicates a significant negative correlation, and (.) indicates no significant correlation. The significance limit was determined by two times the standard error.

5. Optimal Model Selection

The initial model order was selected based on the MACF and MPACF patterns, supported by the minimum value of Akaike's Information Criterion (AIC). The model with the smallest AIC value was considered the most appropriate candidate model before further parameter estimation and diagnostic testing.

6. Parameter Estimation

Model parameters were estimated using Maximum Likelihood Estimation (MLE). If some parameters were not statistically significant, a restriction process was applied so that only significant parameters were retained in the final model.

7. Model Diagnostic Test

Model diagnostics were conducted to ensure that the selected model satisfied the required assumptions. The white noise assumption was tested using the portmanteau test to examine whether significant autocorrelation remained in the residuals. In addition, a multivariate normality test was conducted to evaluate the distribution of the residuals.

8. Accuracy Evaluation

Model forecasting accuracy was evaluated using Mean Absolute Percentage Error (MAPE) on the testing data. The model with the lowest MAPE value was considered the most accurate model for forecasting Indonesia's non-oil and gas export and import values.

9. Forecasting

The best model obtained from the evaluation stage was then used to forecast Indonesia's non-oil and gas export and import values for the next period.

FINDING AND DISCUSSION

Indonesia's non-oil and gas exports and imports exhibit a specific distribution pattern. Based on Table 1, a descriptive analysis of Indonesia's non-oil and gas exports and imports is conducted.

Table 1. Descriptive Statistics of Non-Oil and Gas Export and Import Data

Variable	Mean	Standard Deviation	Coefficient of Variation	Minimum	Maximum
Import (X1)	13.28305	2.392426	18.01112	7.78110	18.47020
Export (X2)	15.92520	4.274337	26.84009	9.89173	26.26583

Based on Table 1, the average value of imports (X₁) and export (X₂) Non-Oil and Gas are 13.28305 and 15.92520, respectively, indicating that exports tend to be higher than imports. The standard deviation of imports is 2.392426, which is smaller than the standard deviation of exports which reaches 4.274337, indicating that export data has a greater spread from its average value. The coefficient of variation of import data is 18.01%, indicating a fairly stable level of fluctuation, while the coefficient of variation of export data is 26.84%, indicating that export data changes more frequently. Import data ranged from 7.78 to 18.47, while export data ranged from 9.89 to 26.27. All values in this study are expressed in millions of USD to ensure consistency of measurement units across variables. All values are expressed in millions of USD for consistency of measurement and interpretation. These differences in ranges indicate that non-oil and gas exports experienced more variable fluctuations than imports during the study period.

The discussion in Table 1 can be presented visually. The time series plot of non-oil and gas exports and imports tends to form a trend pattern.

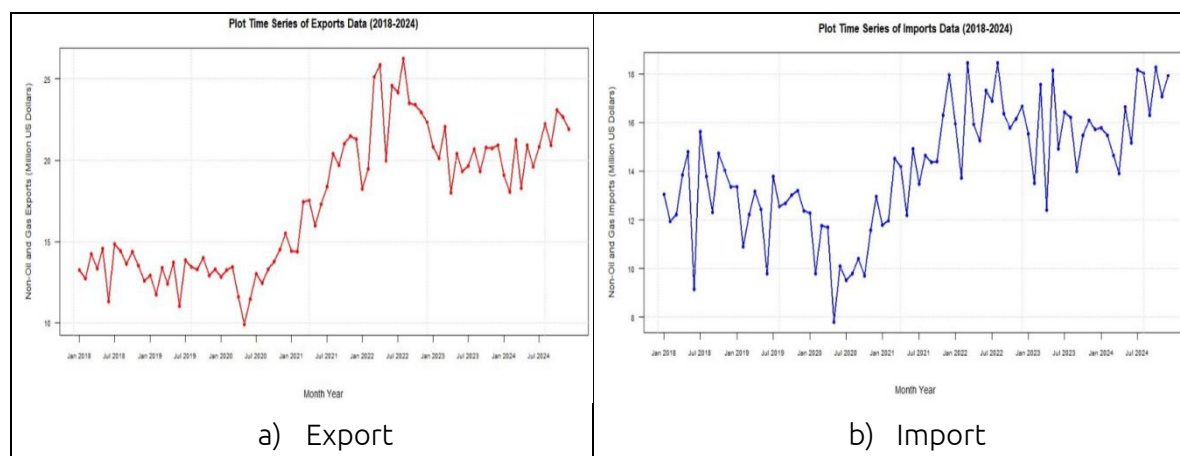


Figure 1. Time Series Plot of Non-Oil and Gas Imports and Exports

Based on Figure 1, Indonesia's non-oil and gas import data shows a relatively stable pattern at the beginning of the 2018-2019 period, with a value of around US\$915 million. However, there was a drastic decline in mid-2020, reaching a low of around US\$8 million, likely due to the impact of the COVID-19 pandemic on international trade activity. After this period, imports experienced a significant recovery and tended to increase consistently, peaking in mid-2022 at around US\$18.5 million.

Despite fluctuations, imports remained at a relatively high level until the end of 2024.

Meanwhile, non-oil and gas export data showed a different trend but a similar recovery pattern. In the 2018-2019 period, exports fluctuated between USD 12-15 million. Similarly, imports also contracted in 2020, reaching a low of around USD 10 million. However, the recovery of exports was more dramatic than imports, with a sharp increase starting in late 2020 and peaking at around USD 26 million in mid-2022. Despite a subsequent decline, exports remained at a higher level than the pre-pandemic period, reaching around USD 1,823 million at the end of the period. Because the time series plot indicated that the data was not yet stationary, a stationarity test was performed. However, before examining the stationarity of the data, the relationship between the non-oil and gas import variables and non-oil and gas exports is shown in Figure 2.

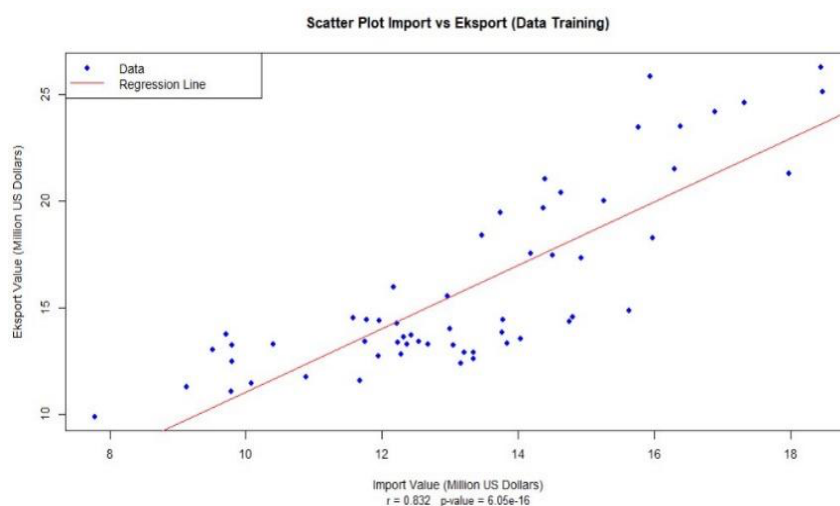


Figure 2. Scatter Diagram between Non-Oil and Gas Imports and Exports

Based on Figure 2, the distribution of the points shows a strong positive correlation pattern between import and export values. This is evident from the tendency of the data points to follow an upward trend line from the bottom left to the top right. The correlation coefficient obtained is 0.832 with a p-value of 6.05e-16 ($p < 0.001$), indicating that the correlation relationship is highly statistically significant. This high correlation strength indicates that an increase in import activity tends to be followed by an increase in export activity, reflecting a close relationship between the two variables in trade activity. To ensure the suitability of the data for VARIMA modeling, an initial test for data stationarity was conducted. The results of this test are presented in Table 2.

Table 2. ADF test for export and import variable before and after differencing

Variable	Before Differencing		After Differencing	
	Dickey Fuller	P-Value	Dickey Fuller	P-Value
Import	-1.0847	0,9171	-5,0766	< 0.01

Variable	Before Differencing		After Differencing	
	Dickey Fuller	P-Value	Dickey Fuller	P-Value
Export	-1.3094	0,8535	-5,1999	< 0.01

Based on Table 2, it is known that the statistical value of the Dickey-Fuller test before differencing for the import and export variables is -1.0847 and -1.3094, respectively, with a p-value > 0.05, which indicates that both variables are not stationary with respect to their average, so it is necessary to transform through differencing to make the data stationary. After differencing, the statistical value is -5.0766 for imports and -5.1999 for exports with a p-value < 0.01, so it can be concluded that the import and export data are stationary at their average. This result is also supported by the analysis through the Matrix Autocorrelation Function (MACF) which shows that before differencing the plot tends to decrease slowly and the autocorrelation sign still appears in several lags, whereas after differencing the pattern disappears, so it can be confirmed that the data has met the stationarity assumption and can be used to build a valid VARIMA model. The following is a schematic image of the MACF plot after differencing:

Table 4. MACF Graph of Non-Oil and Gas Imports and Exports After Differentiation

Variable/Lag	MACF (Multivariate ACF)											
	0	1	2	3	4	5	6	7	8	9	10	
Import	--	.-	++-	.+	.+	--	NA	
Export	--++	NA	

Based on Table 4, the (+) and (-) signs are only significant at some lags for each variable. This condition indicates that the data has been stationary in the mean after differentiation, so that these results serve as a reference in determining the order of the VARIMA model through Matrix Autocorrelation Function (MACF) and Matrix Partial Autocorrelation Function (MPACF) analysis.

The (+), (-), and (.) symbols on the MACF and MPACF plots are generated by comparing the correlation value with twice the standard error, i.e.

$$2 \times se(\rho_{ij}(k)) = 2 \times \sqrt{\frac{1}{84-1}} = 0,2195$$

Based on Table 4, the MACF plot shows that the (+) and (-) symbols only appear significantly at certain lags by comparing the correlation value $\rho_{ij}(k)$ to twice the standard error of 0.2195; the value $\rho_{ij}(k) > 0.2195$ indicates a significant positive correlation relationship, while $\rho_{ij}(k) < -0.2195$ indicates a significant negative correlation relationship, and the value $-0.2195 \leq \rho_{ij}(k) \leq 0.2195$ indicates no significant correlation relationship between the variables at that lag.

Based on Table 4, the MACF results show that the (+) symbol only appears in certain lags for import and export variables, which indicates a significant correlation because the correlation value exceeds twice the standard error of 0.2195, so that these lags are used as a reference in determining the MA order in the VARIMA model.

Table 5. MPACF Plot of Non-Oil and Gas Imports and Exports After Differentiation

Variable/Lag	MPACF (Multivariate PACF)										
	0	1	2	3	4	5	6	7	8	9	10
Import	++	--	--	.-	..	.+	.+	.-	.-	.+	.+
Export	++	--	.-	.-	..	.+

Based on Table 5, the MPACF plot for the Import variable shows a significant symbol (++) at lag 0 and (+) at lags 5, 6, 9, and 10, while the Export variable is significant (++) at lag 0 and (+) at lag 5. Because there is a partial correlation that is still significant at these lags, it shows that the VARIMA model for the AR order is carried out by analyzing the MPACF plot. To determine the VARIMA order, information on the smallest AIC (Akaike's Information Criterion) value is required at the Minimum Information Criterion obtained with the help of the software in Table 6.

Table 6. Minimum Information Criterion

Lag	MA 0	MA 1	MA 2	MA 3	MA 4	MA 5
AR 0	NA	216.8698	188.9934	180.7276	177.2022	162.9440
AR 1	216.8698	188.9934	180.7276	177.2022	162.9440	157.8709
AR 2	188.9934	180.7276	177.2022	162.9440	157.8709	160.5221
AR 3	180.7276	177.2022	162.9440	157.8709	160.5221	151.3775
Lag	MA 6	MA 7	MA 8	MA 9	MA 10	
AR 0	157.8709	160.5221	151.3775	141.9560	140.4120	
AR 1	160.5221	151.3775	141.9560	140.4120	142.0439	
AR 2	151.3775	141.9560	140.4120	142.0439	144,8953	
AR 3	141.9560	140.4120	142.0439	144,8953	135.5791	

Based on the estimation results of the VARIMA (2,1,2) model, the parameter coefficients for lags MA (0) to MA (5) range from 216.8698 to 157.8709, with values decreasing as the lag increases, indicating that the impact of shocks from the previous period decreases over time. For lags MA (6) to MA (10), the coefficients reach a minimum value of 135.5791 at AR (3) and MA (10).

Although the Minimum Information Criterion (MIC) indicates that the combination of AR(3) and MA(10) provides the best statistical fit, the selection of the VARIMA(2,1,2) model is more appropriate due to several practical considerations.

First, the VARIMA (3,1,10) model exhibits excessive complexity and is susceptible to overfitting, which can reduce the model's predictive ability on new data. Second, among the pre-defined candidate models, VARIMA (2,1,2) provides the optimal balance between fit accuracy and model stability. Third, models with lower lag orders tend to be more robust and stable in practical applications, especially for non-oil and gas import-export data that exhibit high volatility characteristics. Therefore, the VARIMA (2,1,2) model is selected as the optimal model because it provides the optimal trade-off between goodness of fit and parsimony, while avoiding the risk of overfitting that can reduce the model's generalizability.

Next, using the VARIMA (2,1,2) model, parameter estimates and significance were determined. Parameter estimates were obtained using the Maximum Likelihood Estimation (MLE) method.

Table 7. Parameter Estimation of the VARIMA (2, 1, 2) Model

Variable	Parameter	Estimate	1.5x Standard Error	t	P-Value	Lag Variable
Import	ϕ_{211}	-0.04863	0.27804	-0.26	0.7943	Import(t-1)
	ϕ_{212}	0.32587	0.23148	2.11	0.0387	Export(t-1)
	ϕ_{221}	-0.04863	0.27804	-0.26	0.7943	Import(t-2)
	ϕ_{222}	0.10247	0.19390	0.49	0.6236	Export(t-2)
	θ_{211}	0.04925	0.17758	0.42	0.6789	e1(t-1)
	θ_{212}	0.24731	0.12398	1.98	0.0534	e2(t-1)
	θ_{221}	0.04925	0.17758	0.42	0.6789	e1(t-2)
	θ_{222}	-0.15489	0.13761	-1.00	0.0947	e2(t-2)
Export	ϕ_{211}	-0.04863	0.27804	-0.26	0.7943	Import(t-1)
	ϕ_{212}	0.32587	0.23148	2.11	0.0387	Export(t-1)
	ϕ_{221}	-0.04863	0.27804	-0.26	0.7943	Import(t-2)
	ϕ_{222}	0.10247	0.19390	0.49	0.6236	Export(t-2)
	θ_{211}	0.04925	0.17758	0.42	0.6789	e1(t-1)
	θ_{212}	0.24731	0.12398	1.98	0.0534	e2(t-1)
	θ_{221}	0.04925	0.17758	0.42	0.6789	e1(t-2)
	θ_{222}	-0.15489	0.13761	-1.00	0.0947	e2(t-2)

Table 7 displays the estimated parameters of the VARIMA (2,1,2) model before restrictions were applied. In this model, it appears that not all parameters are statistically significant for the movement of the Import or Export variables. This can be seen from the p-value, where only a few parameters are below the 5%

significance level ($p < 0.05$). For example, in the Import equation, the parameter ϕ_{212} (Import to Export $t-1$) has an estimate of 0.32587 with a p-value of 0.0387, indicating a significant positive effect. Meanwhile, many other parameters have p-values well above 0.05, thus considered insignificant. This condition indicates that the full model contains many parameters whose contribution to the prediction is not strong, thus potentially causing overfitting and reducing model efficiency. The restrict results and final estimates are shown in Table 8.

Table 8. Parameter Estimation of the VARIMA (2, 1, 2) Restrict Model

Variable	Parameter	Estimate	1.5x Standard Error	t	P-Value	Lag Variable
Import	ϕ_{211}	0.21847	0.10246	3.05	0.0317	Import($t-1$)
Import	ϕ_{221}	0.23829	0.08833	3.36	0.0429	Import($t-2$)
Import	θ_{211}	-0.14484	0.14043	2.28	0.0140	e1($t-1$)
Import	θ_{222}	-0.10974	0.08148	2.72	0.0138	e2($t-2$)
Export	ϕ_{211}	-0.11190	0.14814	3.05	0.0310	Import($t-1$)
Export	ϕ_{221}	0.23643	0.14373	2.97	0.0182	Import($t-2$)
Export	θ_{211}	0.12718	0.12553	2.19	0.0336	e1($t-1$)
Export	θ_{222}	-0.16252	0.10986	2.62	0.0291	e2($t-2$)

Table 8 displays the estimation results after parameter restrictions using the special Iterative Adjustment method. This process aims to maintain the VARIMA (2,1,2) structure but only leaves statistically significant parameters. Iterative Adjustment is carried out by gradually adjusting the p-value, so that initially insignificant parameters can be optimized, or eliminated if they do not meet the criteria. From the restrict results, it can be seen that all remaining parameters have a p-value < 0.05 , indicating strong statistical significance. For example, in the Import equation, ϕ_{211} (Import to Import $t-1$) of 0.21847 (p-value 0.0317) and ϕ_{221} (Import to Import $t-2$) of 0.23829 (p-value 0.0429) have a positive and significant effect. Similarly, in the Export equation, the parameter ϕ_{211} (Exports to Imports $t-1$) is -0.11190 with a p-value of 0.0310, indicating a significant negative effect. By applying the restrict model, a simpler and more efficient model form is obtained, and it focuses on the relationships between variables that are proven to be significant, thereby increasing the accuracy and validity of the prediction results.

Thus, the parameters identified as statistically significant are structured within the VARIMA (2,1,2) model as follows:

$$\phi_1 = \begin{bmatrix} 0.21847 & 0 \\ -0.11190 & 0 \end{bmatrix}, \phi_2 = \begin{bmatrix} 0.23829 & 0 \\ 0.23643 & 0 \end{bmatrix},$$

$$\theta_1 = \begin{bmatrix} -0.14484 & 0 \\ 0.12718 & 0 \end{bmatrix}, \theta_2 = \begin{bmatrix} 0 & -0.10974 \\ 0 & -0.16252 \end{bmatrix}$$

Thus, the VARIMA (2,1,2) model equation can be expressed in matrix form as follows:

$$\left(\begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} - \begin{bmatrix} 0.21847 & 0 \\ -0.11190 & 0 \end{bmatrix} B - \begin{bmatrix} 0.23829 & 0 \\ 0.23643 & 0 \end{bmatrix} B^2 \right) \begin{bmatrix} Z_{1,t} \\ Z_{2,t} \end{bmatrix} \\ = \left(\begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} + \begin{bmatrix} -0.14484 & 0 \\ 0.12718 & 0 \end{bmatrix} B + \begin{bmatrix} 0 & -0.10974 \\ 0 & -0.16252 \end{bmatrix} B^2 \right) \begin{bmatrix} a_{1,t} \\ a_{2,t} \end{bmatrix}$$

From the matrix equation above, the following is obtained:

$$Z_{1t} = 0.21847Z_{1,t-1} + 0.23829 Z_{1,t-2} - 0.14484a_{1,t-1} - 0.10974a_{2,t-2} + a_{1t}$$

$$Z_{2t} = -0.11190Z_{1,t-1} + 0.23643 Z_{1,t-2} + 0.12718 a_{1,t-1} - 0.16252a_{2,t-2} + a_{2t}$$

These results indicate that the VARIMA (2,1,2) model meets the requirements for significant variables and is able to represent the functional relationship between import and export variables. The model structure also shows the inter-variable influences and temporal relationships that can be used for forecasting and economic policy analysis. The results show that previous period imports have a positive effect on current exports, which indicates trade dependence.

Next, these residuals need to be tested. For the white noise test, we use the Portmanteau Test to test the overall significance of the residual autocorrelation.

Table 9. Portmanteau Test

Lag	DF	P-Value
4	16	0.9856
5	20	0.8976
6	24	0.7371
7	28	0.8624
8	32	0.8724
9	36	0.8359
10	40	0.7033

The results of the white noise assumption test using the Portmanteau Test show that all lags have a p-value > 0.05, ranging from 0.7033 to 0.9856. This indicates that the residuals meet the white noise assumption and do not show autocorrelation. With this assumption met, the VARIMA (2,1,2) model is considered suitable for forecasting because the residuals are random and do not show a particular pattern. Furthermore, the multivariate normality assumption must also be met by examining the multivariate normal plot to ensure that the best model can be selected for use.

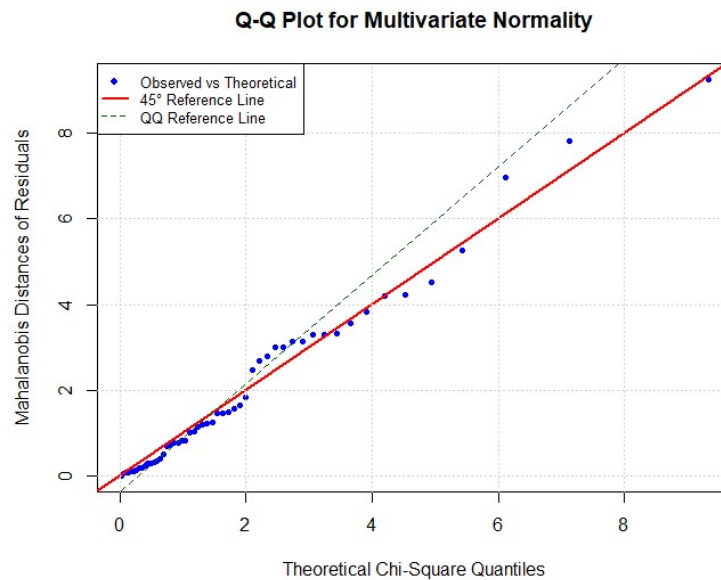


Figure 3. Multivariate Normal Plot

The QQ plot shows that the observation points for multivariate normality align closely with the reference line, although some deviations are observed at the extreme points of the distribution. This indicates that the residuals have met the assumption of multivariate normality. The proportion of residuals that conform to a multivariate normal distribution is acceptable for forecasting purposes, thus allowing the use of the VARIMA(2,1,2) model.

Furthermore, to check the correctness and accuracy of the forecast results based on data from the model obtained, the Mean Absolute Percentage Error (MAPE) can be used.

Table 10. Comparative Evaluation Indonesia's Non-Oil and Gas of Models

VARIMA Model	Imports	Exports
VARIMA (1,1,0)	9.43	6.86
VARIMA (1,1,1)	11.10	8.81
VARIMA (2,1,0)	11.10	8.81
VARIMA (2,1,1)	10.91	8.46
VARIMA (1,1,2)	10.91	8.46
VARIMA (2,1,2)	11.55	8.64

The evaluation results of the six tested VARIMA models showed relatively uniform performance with insignificant differences in MAPE values. MAPE values for non-oil and gas imports ranged from 9.43% to 11.55%, while for non-oil and gas exports they ranged from 6.86% to 8.81%. Statistically, the VARIMA (1,1,0) model demonstrated the highest accuracy with MAPE values of 9.43% for imports and

6.86% for non-oil and gas exports. However, this study determined VARIMA (2,1,2) as the best model based on several appropriate considerations. Statistically, the VARIMA (1,1,0) model exhibits the lowest MAPE value, indicating slightly higher short-term prediction accuracy. However, this study selects the VARIMA (2,1,2) model as the best model due to its superior parameter stability and ability to capture more comprehensive dynamic relationships between variables. Models with high-order AR and MA components are better able to represent the lag structure and adjustment mechanisms in economic time series, which are crucial for long-term forecasting. In contrast, simpler models such as VARIMA (1,1,0) may not fully capture these dynamics, potentially limiting their robustness when applied to future periods characterized by structural change and economic uncertainty.

The determination of the VARIMA (2,1,2) model as the best model is based on four main criteria. First, the margin of error between the selected model and the most accurate model is still within acceptable tolerance limits, namely a difference of 2.12% for non-oil and gas imports and 1.78% for non-oil and gas exports. Second, this model provides an optimal balance between the level of complexity and accuracy of predictions through a comprehensive parameter structure. The AR (2) component allows for analysis of the influence of the two previous periods, while the MA (2) component analyzes the impact of residual errors in depth. Third, the more complete parameter configuration facilitates the identification of complex dynamic relationships between Indonesian non-oil and gas import variables. Fourth, based on the MAPE interpretation standard where a value <10% indicates very good accuracy and a range of 10-20% indicates good accuracy, the VARIMA (2,1,2) model demonstrates adequate performance with the category "good" for non-oil and gas imports (11.55%) and "very good" for non-oil and gas exports (8.64%).

The MAPE values presented in this study are calculated based on testing data using an out-of-sample evaluation approach that divides the dataset into a training set for model development and a testing set of 26 observations for performance evaluation. This separate evaluation methodology provides an objective assessment of the model's predictive ability on previously unanalyzed data, in accordance with standard practices for evaluating reliable forecasting models. Therefore, the VARIMA (2,1,2) model is suitable for representing Indonesia's future non-oil and gas export-import forecasts and provides a strong basis for formulating appropriate trade policies.

Table 11. Indonesia's Non-Oil and Gas Import and Export Forecast Results

Period	Import (Million USD)	Export (Million USD)
Nov 2022	18.4782	26,4078
Dec 2022	16.9641	24.9969
Jan 2023	15.3297	22.8219

Period	Import (Million USD)	Export (Million USD)
Feb 2023	16.2658	21.8373
Mar 2023	15.7333	20.9439
Apr 2023	16.1861	20.8844
May 2023	14.4233	20.4757
June 2023	14.4899	20.8757
Jul 2023	15.5974	21.3843
Aug 2023	15.0688	21.8322
Sep 2023	15.8774	21.3827
Oct 2023	15.1862	21.4631
Nov 2023	15.1862	21.0974
Dec 2023	15.5974	20,8648
Jan 2024	15.3928	20.3932
Feb 2024	15.6567	20.2365
Mar 2024	15.2849	19.9902
Apr 2024	15.6443	19.6282
May 2024	15.6899	19.2571
June 2024	15.5772	18,7934
Jul 2024	14.9744	18,3789
Aug 2024	14,3184	19,5042
Sep 2024	14.8835	20.1036
Oct 2024	16.1322	21.1315
Nov 2024	15.5312	22.1964
Dec 2024	16.6342	22.9314

The forecast results presented in the table show the projected value of non-oil and gas imports and exports from November 2022 to December 2024. Non-oil and gas imports are expected to fluctuate between USD 14.32 and USD 18.48 million, with the highest predicted value occurring in November 2022 (USD 18.48 million) and the lowest in August 2024 (USD 14.32 million). In comparison, non-oil and gas exports are expected to range between USD 18.38 and USD 26.41 million, peaking in November 2022 (USD 26.41 million) and reaching a low point in July 2024 (USD 18.38 million). The forecast pattern shows a relatively stable trend with mild fluctuations. The forecast results can be seen from the time series plot in Figure 4

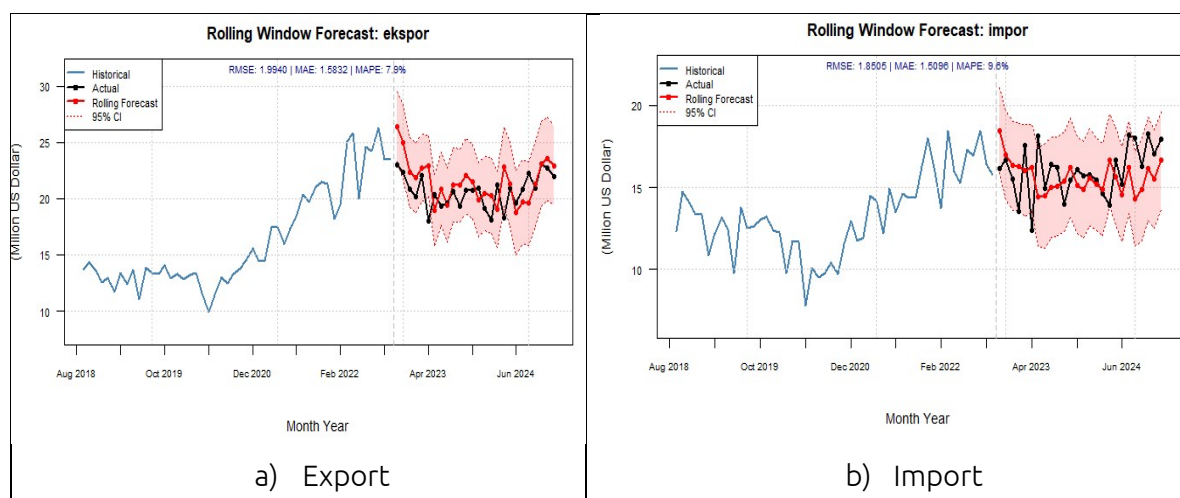


Figure 4. Time Series Plot of Non-Oil and Gas Import and Export Forecasting

The VARIMA (2,1,2) model predicts non-oil and gas imports will remain stable between US\$15 and US\$18 billion until mid-2024, while non-oil and gas exports will fluctuate between US\$18 and US\$24 billion with a slight downward trend. The volatility of both variables is expected to increase, indicating greater uncertainty for long-term forecasts.

Table 12. Rolling Window Metric Results

Metric	Variables	Mean	Standard Deviation
MAPE	Import	11.103981	10.688477
MAPE	Export	8.805135	6.851417
MAE	Import	1.766109	1.680255
MAE	Export	1.816345	1.395257
RMSE	Import	1.766109	1.680255
RMSE	Export	1.816345	1.395257

Based on Table 12, the rolling window metric table shows the prediction performance of the VARIMA (2,1,2) model using three accuracy measures, namely MAPE, MAE, and RMSE. The evaluation results show that the model has quite good performance with a difference in performance between import and export predictions. For MAPE, exports have a lower error rate (8.81%) than imports (11.10%), which means the model is more accurate in predicting exports. Meanwhile, the MAE and RMSE values show the opposite pattern where imports have a slightly smaller error (1.77) than exports (1.82). The consistency of the MAE and RMSE values that are almost the same indicates that the error distribution is quite normal without extreme outliers, and the relatively stable standard deviation indicates that the rolling window technique provides consistent evaluation results throughout the test period.

Based on the identification results, this study obtained the optimal VARIMA (2,1,2) model, which means two lags in the AR component, one time differencing, and two lags in the MA component.

CONCLUSIONS AND RECOMMENDATIONS

Based on the research results, it can be concluded that the VARIMA(2,1,2) model is the optimal model for forecasting Indonesia's non-oil and gas exports and imports. The selection of this model is supported by the results of order identification using MACF and MPACF, competitive information criteria, and the stability and significance of parameters after the restriction process. The model produced MAPE values of 11.10% for imports, which is categorized as good, and 8.81% for exports, which is categorized as very good. These results indicate that the model has adequate predictive ability for both variables.

The diagnostic tests also showed that the residuals met the assumptions of white noise and multivariate normality, indicating that the model is suitable for forecasting purposes. The forecast results for the 2022–2024 period show relatively stable fluctuations, with import estimates ranging from USD 14.32 million to USD 18.48 million and export estimates ranging from USD 18.38 million to USD 26.41 million. These findings provide a useful quantitative basis for formulating foreign trade policies, particularly in anticipating the range and fluctuation of projected non-oil and gas exports and imports. The results can support policymakers in planning export targets, adjusting import needs for production inputs, and preparing strategies to respond to possible changes in trade performance. Further research is recommended to extend the observation period and include external variables, such as exchange rates, inflation, commodity prices, and global economic conditions, to improve the accuracy of long-term forecasts.

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