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Modeling and Forecasting by the Vector Autoregressive Moving Average Model for Export of Coal and Oil Data (Case Study from Indonesia over the Years 2002-2017)

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ABSTRACT

The vector autoregressive moving average (VARMA) model is one of the statistical analyses frequently used in several studies of multivariate time series data in economy, finance, and business. It is used in numerous studies because of its simplicity. Moreover, the VARMA model can explain the dynamic behavior of the relationship among endogenous and exogenous variables or among endogenous variables. It can also explain the impact of a variable or a set of variables by means of the impulse response function and Granger causality. Furthermore, it can be used to predict and forecast time series data. In this study, we will discuss and develop the best model that describes the relationship between two vectors of time series data export of Coal and data export of Oil in Indonesia over the period 2002-2017. Some models will be applied to the data: VARMA (1,1), VARMA (2,1), VARMA (3,1), and VARMA (4,1). On the basis of the comparison of these models using information criteria AICC, HQC, AIC, and SBC, it was found that the best model is VARMA (2,1) with restriction on some parameters: AR2_1_2 = 0, AR2_2_1 = 0, and MA1_2_1 = 0. The dynamic behavior of the data is studied through Granger causality analysis. The forecasting of the series data is also presented for the next 12 months.

Keywords: Vector Autoregressive Moving Average Model, Information Criteria, Granger Causality, Forecasting
JEL Classifications: C53, Q4, Q47

1. INTRODUCTION

Financial, business, and economic data are very often collected in equally spaced time intervals such as days, weeks, months, or years. In a number of cases, such time series data may be available on several related variables. There are some reasons for analyzing and modeling such time series jointly: (1) To understand the dynamic relationship among variables and (2) to improve the accuracy of forecast and knowledge of the dynamic structure so as to produce good forecast (Tiao, 2001; Pena and Tiao, 2001). The analysis of multiple time series has been developed by Tiao and Box (1981); since then, the development of the theory has been extensively discussed in the literature (Lutkepohl, 2005; Reinsel, 1993). Multivariate time series are of great interest in a variety of fields such as financial, economic, stock market, and earth science, e.g., meteorology (Reinsel, 1993). In multivariate time series analysis, not only the properties of the individual series but also the possible cross relationship among the time series data are discussed. The application of the vector autoregressive (VAR) model has been extensively discussed by Malik et al. (2017), Sharma et al. (2018), and Warsono et al. (2019).

In this study, we discuss and develop the best model that describes the relationship between two vectors of data export of Coal and data export of Oil in Indonesia over the period 2002–2017. On the basis of this objective, the VAR moving average (VARMA) model was developed to explain the relationship between the data export of Coal and Oil in Indonesia over the period 2002–2017.

Methods to find the best model, estimates of parameters, model checking, and forecasting of vector time series are also discussed.

2. STATISTICAL MODEL

The VARMA model is commonly used to forecast multivariate time series data and provides a simple framework to study the dynamic relationships among variables (Koreisha and Pukkila, 2004). The VARMA model is an extension of the ARMA model in univariate time series (Lutkepohl, 2005; Wei, 1990) and is used with the condition that the data have to be stationary over time (Lutkepohl, 2005). The VARMA (p,q) model is a combination of the VAR (p) model and the vector moving average (q) (VMA (q)) model. An m-dimensional time series datum Γ_t is a VARMA (p,q) process if

$$\Gamma_t = \delta + \sum_{i=1}^{p} \Phi_i \Gamma_{t-i} + u_t - \sum_{j=i}^{q} \theta_j u_{t-j} \tag{1}$$

where δ is a constant m×1 vector of means, and $\delta^T = (\delta_1, \delta_2, \delta_m)$, $u_t^T = (u_{1t}, u_{2t}, \ldots, u_{mt})$ are vectors of random noise that are independently, identically, and normally distributed with mean zero and covariance matrix $\Sigma_u = E(u_t u_t^T)$, defined as follows:

$$\Sigma_u = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \cdots & \sigma_{1m} \\ \sigma_{21} & \sigma_{22} & \cdots & \sigma_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ \sigma_{m1} & \sigma_{m2} & \cdots & \sigma_{mm} \end{bmatrix}, \varphi_i = \begin{bmatrix} \varphi_{i,11} & \varphi_{i,12} & \cdots & \varphi_{i,1m} \\ \varphi_{i,21} & \varphi_{i,22} & \cdots & \varphi_{i,2m} \\ \cdots & \cdots & \cdots & \cdots \\ \varphi_{i,m1} & \varphi_{i,m2} & \cdots & \varphi_{i,mm} \end{bmatrix}, \text{and}$$

$$\theta_j = \begin{bmatrix} \theta_{j,11} & \theta_{j,12} & \cdots & \theta_{j,1m} \\ \theta_{j,21} & \theta_{j,22} & \cdots & \theta_{j,2m} \\ \cdots & \cdots & \cdots & \cdots \\ \theta_{j,m1} & \theta_{j,m2} & \cdots & \theta_{j,mm} \end{bmatrix}$$

where $i = 1,2,\ldots, p$; $j = 1,2,\ldots, q$.

Model (1) can also be written in a simpler form using the backshift operator B as follows:

$$\Phi(B)\Gamma_t = \delta + \Theta(B)u_t \tag{2}$$

where $\Phi(B) = I_k - \sum_{i=1}^{p} \varphi_i B^i$ and $\Theta(B) = I_k - \sum_{i=1}^{q} \theta_i B^i$, $B^i\Gamma_t = \Gamma_{t-1}$, $B^i u_t = u_{t-1}$, and u_t is vector innovation.

Some properties of the VARMA (p,q) model with p>0 and q>0 are discussed. The model is assumed to be identifiable and innovation u_t has mean zero and covariance matrix Σ_u, which is positive definite; see Graybill (1969) for the definition of a positive-definite matrix. We shall assume that the zeros of the determinant polynomials $|\Phi(B)|$ and $|\Theta(B)|$ are on or outside the unit circle. The series $\{\Gamma_t\}$ will be stationary if the zeros of $|\Phi(B)|$ are on or outside the unit circle and will be invertible when those of $|\Theta(B)|$ are on or outside the unit circle (Tiao, 2001; Tsay, 2005; Reinsel, 1993). To find the best model, we estimated some candidate models (VARMA (1,1), VARMA (2,1), VARMA (3,1), and VARMA (4,1)) using some information criteria (AICC, HQC, AIC, and SBC). The selected best model and estimation of the parameters of the selected model were reviewed. If some parameters are not significant in the selected model, then they will be restricted to zero (Tsay, 2005; Milhoj, 2016) so that the final best model is simpler. The optimal l-step-ahead forecast of Γ_{t+l} for model (1) is as follows (SAS/ETS 13.2, 2014; Lutkepohl, 2005):

$$\hat{\Gamma}_{t+\ell|t} = \hat{\delta} + \sum_{i=1}^{p} \hat{\varphi}_i \Gamma_{t+\ell-i|t} - \sum_{j=1}^{q} \hat{\theta}_j \;{}_{t+\ell-j|t} \tag{3}$$

3. DATA ANALYSIS

The data used in this study are the data export of Coal and Oil from Indonesia from January 2002 to December 2017. The data are from the Central Bureau of Statistics (BPS) Indonesia (BPS (a) 2017, and BPS (b), 2017). The plot of the data is given in Figure 1.

The figure shows that for the export of Oil from Indonesia, the trend increases from 2002 to 2017. From January 2002 to December 2010, the trend increase with volatility is relatively small. However, from 2011 to 2017, the fluctuation of the export is high, which indicates that the volatility of the export is high. From the end of 2012 to 2017, the trend increases. However, from 2010 to the end of 2012, the trend decreases. For the export of Coal from Indonesia, the trend increases from 2002 to 2012 but decreases from the end of 2012 to the end of 2016, and then increases again in 2017. Figure 1 also shows that the data are nonstationary, and this is in line with the augmented Dicky–Fuller test given in Table 1.

Now, we look at the ACF and PACF of data of Coal and Oil given in (Figure 2a and b). From the sample ACF of data of Coal and Oil in (Figure 2a and b), the tails cut off very slowly. This indicates that the time series data of Coal and Oil are not stationary. That is, the means or the variances of time series data of Coal and Oil are not constant over time.

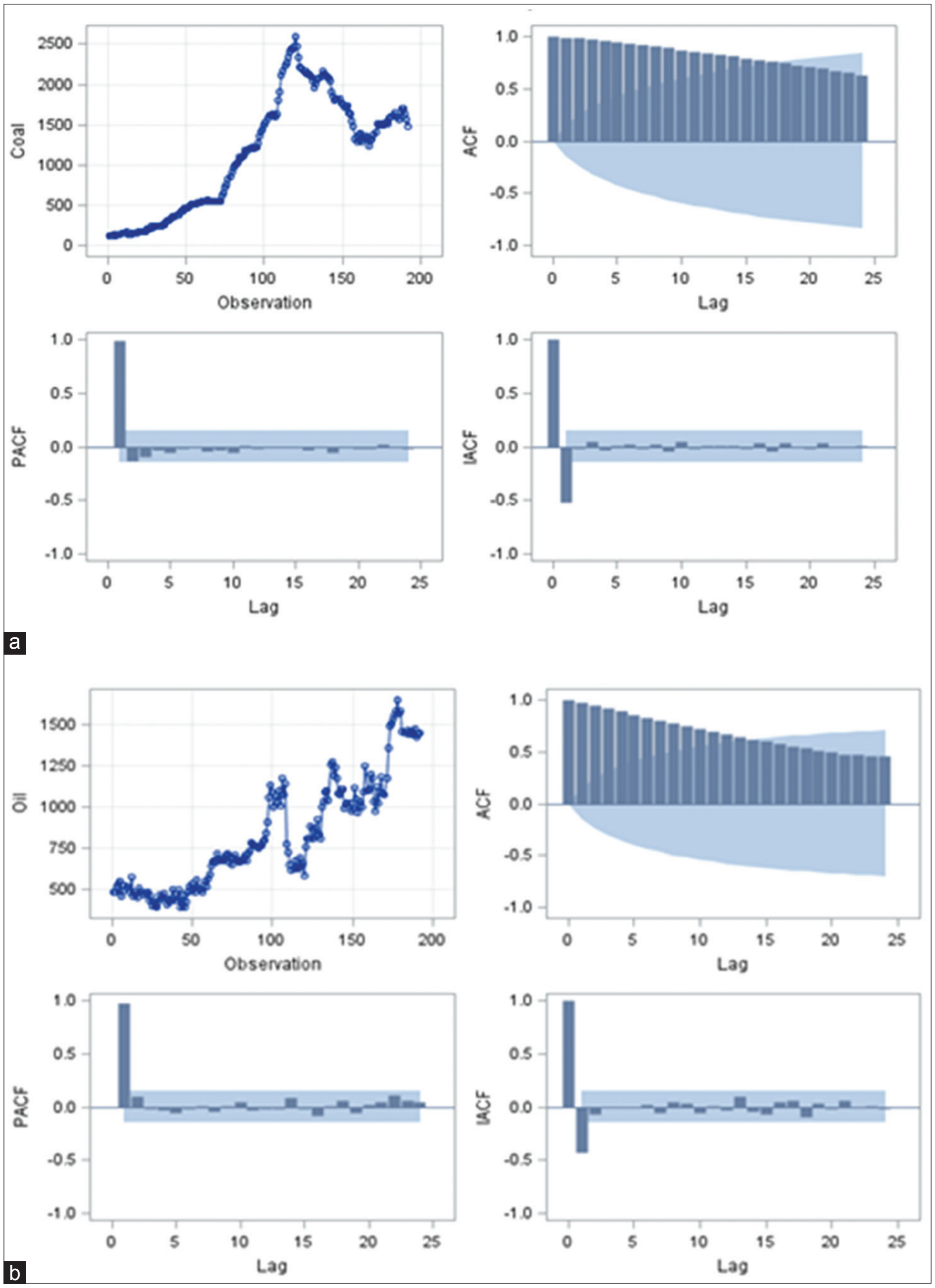
To make the data stationary, differencing needs to be conducted, and the results of differencing with d = 1 are given in Table 2. The assumption of stationarity is attained, and modeling of VARMA can be carried out.

Figure 1: Plot of data export of coal and oil from Indonesia from January 2002 to December 2017

Table 1: Augmented Dicky–Fuller unit root tests

Data	Type	Lag	Rho	Pr<Rho	Tau	Pr<Tau	F-test	Pr>F
Coal	Zero mean	3	0.1491	0.7169	0.17	0.7346	-	-
	Single mean	3	−2.1558	0.7584	−1.38	0.5942	1.53	0.6812
	Trend	3	−1.8119	0.9740	−0.67	0.9736	0.95	0.9735
Oil	Zero mean	3	0.7345	0.8613	0.80	0.8843	-	-
	Single mean	3	−1.6886	0.8136	−0.67	0.8511	0.86	0.8521
	Trend	3	−22.4281	0.0368	−3.23	0.0824	5.44	0.0972

Figure 2: (a and b) Plots of trend, autocorrelation function, partial autocorrelation function, and inverse autocorrelation function for data export of coal and oil



3.1. VARMA (p,q) Modeling

To find the best model that fits the data, some VARMA (p,q) models (i.e., VARMA (1,1), VARMA (2,1), VARMA (3,1), and VARMA (4,1)) for prediction and forecasting were applied to the data. The selection of the best model was conducted using some information criteria (AICC, HQC, AIC, and SBC). The minimum values of these criteria indicate the best model.

From Table 3, we conclude the following: on the basis of the minimum values of HQC and SBC, the best model is VARMA

Table 2: Augmented Dicky–Fuller unit root tests

Variable	Type	Rho	Pr<Rho	Tau	Pr<Tau
Coal	Zero mean	−72.68	<0.0001	−5.88	<0.0001
	Single mean	−75.68	0.0013	−5.95	<0.0001
	Trend	−78.02	0.0006	−6.07	<0.0001
Oil	Zero mean	−214.74	0.0001	−10.31	<0.0001
	Single mean	−219.13	0.0001	−10.39	<0.0001
	Trend	−220.36	0.0001	−10.39	<0.0001

Table 3: Criteria AICC, HQC, AIC, and SBC for VARMA (1,1), VARMA (2,1), VARMA (3,1), and VARMA (4,1)

Criteria	Model			
	VARMA (1,1)	VARMA (2,1)	VARMA (3,1)	VARMA (4,1)
AICC	15.969	15.954	15.990	16.039
HQC	16.036	16.046	16.106	16.179
AIC	15.967	15.949	15.980	16.025
SBC	16.138	16.189	16.290	16.405

VARMA: Vector autoregressive moving average, ACF: Autocorrelation function, IACF: Inverse autocorrelation function, PACF: Partial autocorrelation function plot, HQC: Hannan-Quinn criterion, SBC: Schwarz-Bayesian criteria, AICC: Akaike information criterion

Table 4: Schematic representation of parameter estimates of VARMA (1,1) and VARMA (2,1)

Model	Variable/lag	C	AR1	AR2	MA1
VARMA (1,1)	Coal	•	+•		•+
	Oil	•	•−		•−
VARMA (2,1)	Coal	•	−•	+•	−+
	Oil	•	•−	••	•−

+ is>2td error, − is < −2 std error, •is between, VARMA: Vector autoregressive moving average

(1,1); on the basis of the minimum values of AICC and AIC, the best model is VARMA (2,1). Therefore, there are two candidates for the best model. To choose the best model, we check the schematic representation of the parameter estimates of VARMA (1,1) and VARMA (2,1) given in the Table 4. Schematic representation of parameter estimates of VARMA (1,1) and VARMA (2,1).

Table 4 shows that in VARMA (1,1), four parameters are of significance, and in VARMA (2,1), six parameters are of significance. In this case, VARMA (2,1) is chosen as the best model to discuss the characteristics of data and for forecasting data. VARMA (2,1) is represented as follows:

$$\Gamma_t = \delta+\Phi_1\Gamma_{t-1}+\Phi_2\Gamma_{t-2}-\Psi_1\varepsilon_{t-1}+\varepsilon_t \quad (4)$$

where

$$\Gamma_t = \begin{bmatrix} Coal_t \\ Oil_t \end{bmatrix},\ \Gamma_{t-1} = \begin{bmatrix} Coal_{t-1} \\ Oil_{t-1} \end{bmatrix},\ \Gamma_{t-2} = \begin{bmatrix} Coal_{t-2} \\ Oil_{t-2} \end{bmatrix},$$

Φ_1, Φ_2 and Ψ_1 are 2 × 2 matrix parameters for AR1, AR2, and MA1, respectively. ε_t is vector white noise. The estimate model VARMA (2,1) is as follows:

From Table 5, some parameters of the model AR2_1_2, AR2_2_1, and MA1_2_1 are not significantly different from zero. Therefore, we can improve the model by restricting those parameters that are not significant, as suggested by Tsay (2005) and Milhoj (2016). We restrict the parameters AR2_1_2 = 0, AR2_2_1 = 0, and MA1_2_1 = 0, and we conduct the test statistics for these restrictions. From the testing of restricted parameters equal to zero, we obtained the results as given in Table 6.

Table 6 shows that all the tests are not significantly different from zero. By using these restriction parameters, the final model and the estimation of parameters are presented in Table 7.

The VARMA (2,1) model with restriction AR2_1_2 = 0, AR2_2_1 = 0, and MA1_2_1 = 0 shows that all the parameters are significant, except for the parameter constants. The VARMA (2,1) model with restriction is

$$\Gamma_t = \begin{bmatrix} 4.3746 \\ 5.7036 \end{bmatrix} + \begin{bmatrix} -0.3299 & 0.2472 \\ -0.1714 & -1.1807 \end{bmatrix}\Gamma_{t-1} + \begin{bmatrix} 0.4938 & 0.0000 \\ 0.0000 & -0.1976 \end{bmatrix}$$
$$T_{t-2} - \begin{bmatrix} -0.8284 & 0.2751 \\ 0.0000 & -0.9980 \end{bmatrix}\varepsilon_{t-1} + \varepsilon_t \quad (5)$$

and the covariance of innovation is,

$$\Sigma_t = \begin{bmatrix} 1703.32 & -669.62 \\ -669.62 & 4539.77 \end{bmatrix}$$

The VARMA (2,1) model with restriction can also be written as two univariate regression models:

$$Coal_t = 4.3746-0.3299\,Coal_{t-1}+0.2472\,Oil_{t-1}+0.4938\,Coal_{t-2}+0.8284\,\varepsilon_{1t-1}-\varepsilon_{1t} \quad (6)$$

$$Oil_t = 5.7036-0.1714\,Coal_{t-1}-1.1807\,Oil_{t-1}-0.1976\,Oil_{t-2}+0.9980\,\varepsilon_{2t-1}-\varepsilon_{2t} \quad (7)$$

The statistical test of the parameters in model (5) is given in Table 7, and models (6) and (7) are given in Table 8. On the basis of the statistical test, model (6) is very significant with the statistical test F = 15.30, and the P < 0.0001. The degree of determination of R-square is 0.3352. On the basis of the statistical test, model (7) is very significant with the statistical test F = 3.01, and the P = 0.0079. The degree of determination of R-square is 0.0903. Model (6) also explains that the export of Oil at lag 1 (t-1) has a positive effect on the export of Coal; the export of Coal at lag 1 (*t*-1) has a negative effect on the export of Coal, and the export of Coal at lag 2 (*t*-2) has a positive effect on the export of Coal.

Table 5: Model parameter estimates

Equation	Parameter	Estimate	Standard error	t-value	Pr>|t|	Variable
Coal	CONST1	6.95695	5.87137	1.18	0.2375	1
	AR1_1_1	−0.31645	0.1081	−2.93	0.0038	Coal (t-1)
	AR1_1_2	0.14442	0.09532	1.52	0.1314	Oil (t-1)
	AR2_1_1	0.43243	0.07895	5.48	0.0001	Coal (t-2)
	AR2_1_2	−0.07719	0.05277	−1.46	0.1452	Oil (t-2)
	MA1_1_1	−0.79453	0.10537	−7.54	0.0001	e1 (t-1)
	MA1_1_2	0.22456	0.08598	2.61	0.0097	e2 (t-1)
Oil	CONST2	9.72216	10.114	0.96	0.3377	1
	AR1_2_1	−0.17714	0.13769	−1.29	0.1999	Coal (t-1)
	AR1_2_2	−1.14426	0.10035	−11.40	0.0001	Oil (t-1)
	AR2_2_1	0.06579	0.11978	0.55	0.5835	Coal (t-2)
	AR2_2_2	−0.13139	0.07874	−1.67	0.0969	Oil (t-2)
	MA1_2_1	−0.03194	0.07222	−0.44	0.6588	e1 (t-1)
	MA1_2_2	−1.03147	0.07255	−14.22	0.0001	e2 (t-1)

Table 6: Testing of restricted parameters

Parameter	Estimate	Standard error	t-value	P-value	Equation
Restrict1	−22.631	15.899	−1.42	0.156	AR2_1_2=0
Restrict2	3.701	8.531	0.43	0.665	AR2_2_1=0
Restrict3	−12.569	22.093	−0.57	0.57	MA1_2_1=0

Table 7: Model with restriction AR2_1_2=0, AR2_2_1=0, and MA1_2_1=0 and parameter estimates

Equation	Parameter	Estimate	Standard error	t-value	Pr>|t|	Variable
Coal	CONST1	4.3746	5.9932	0.73	0.4663	1
	AR1_1_1	−0.3299	0.0873	−3.78	0.0002	Coal (t-1)
	AR1_1_2	0.2472	0.1049	2.36	0.0195	Oil (t-1)
	AR2_1_1	0.4938	0.0663	7.45	0.0001	Coal (t-2)
	AR2_1_2	0	0	-	-	Oil (t-2)
	MA1_1_1	−0.8284	0.0882	−9.39	0.0001	e1 (t-1)
	MA1_1_2	0.2751	0.1201	2.29	0.0232	e2 (t-1)
Oil	CONST2	5.7036	9.8061	0.58	0.3377	1
	AR1_2_1	−0.1714	0.0704	−2.44	0.0158	Coal (t-1)
	AR1_2_2	−1.1807	0.064	−18.44	0.0001	Oil (t-1)
	AR2_2_1	0	0	-	-	Coal (t-2)
	AR2_2_2	−0.1976	0.0619	−3.19	0.0017	Oil (t-2)
	MA1_2_1	0	0	-	-	e1 (t-1)
	MA1_2_2	−0.9980	0	−9980	<0.0001	e2 (t-1)

Table 8: Univariate diagnostic checks

Model	Variable	R-square	Standard deviation	F-value	p-value
6	Coal	0.3352	41.271	15.3	<0.0001
7	Oil	0.0903	67.377	3.01	0.0079

Table 9: Granger causality Wald test

Test	Group	DF	Chi-square	P-value
Test 1	Group 1 variable: Coal Group 2 variable: Oil	3	11.88	0.0078
Test 2	Group 1 variable: Oil Group 2 variable: Coal	3	3.74	0.2912

Model (7) explains that the export of Coal at lag 1 (t-1) and the export of Oil at lag 1 and lag 2 (t-1 and t-2) have a negative effect on the export of Coal.

Granger causality is used to test two null hypotheses. Test 1 tests the null hypothesis where the export of Coal is influenced only by itself and not by the export of Oil. Test 2 tests the null hypothesis where the export of Oil is influenced only by itself and not by the export of Coal (SAS/ETS 13.2, 2014). From the results of the Granger causality tests, Table 9 demonstrates the following: (1) For Test 1, Chi-square = 11.88 and the P = 0.0078; hence, we reject the null hypothesis. We conclude that the export of Coal is not only influenced by itself but also influenced by the export of Oil. (2) For Test 2, Chi-square = 3.74 and the P = 0.2912; hence, we cannot reject the null hypothesis. We conclude that the export of Oil is influenced only by itself and not by the export of Coal.

The patterns of the distribution of errors for data of Coal and Oil based on model VARMA (2,1) with restriction are given in Figure 3.

From (Figures 3a and 3b), the patterns of the distribution of errors for data of Coal and Oil are very close to normal distribution. If we look

Table 10: Forecasting data export of coal and oil for the next 12 months

Variable	Obs	Time	Forecast	Standard error	95% confidence limits	
Coal	193	Jan-18	1435.32	41.2713	1354.43	1516.21
	194	Feb-18	1423.18	74.7498	1276.68	1569.69
	195	Mar-18	1405.14	105.776	1197.82	1612.45
	196	Apr-18	1414.37	133.962	1151.81	1676.93
	197	May-18	1403.87	158.292	1093.62	1714.12
	198	Jun-18	1419.77	181.434	1064.16	1775.37
	199	Jul-18	1412.01	201.151	1017.76	1806.26
	200	Aug-18	1428.84	220.704	996.271	1861.42
	201	Sep-18	1423.49	237.428	958.14	1888.84
	202	Oct-18	1438.64	254.431	939.968	1937.32
	203	Nov-18	1436.25	269.171	908.687	1963.82
	204	Dec-18	1448.49	284.278	891.316	2005.67
Oil	193	Jan-18	1466.25	67.3779	1334.19	1598.3
	194	Feb-18	1452.16	88.374	1278.95	1625.37
	195	Mar-18	1471.96	105.267	1265.65	1678.28
	196	Apr-18	1460.16	121.305	1222.41	1697.91
	197	May-18	1474.31	134.017	1211.64	1736.97
	198	Jun-18	1467.44	147.056	1179.22	1755.67
	199	Jul-18	1475.73	157.785	1166.48	1784.98
	200	Aug-18	1474.33	168.923	1143.25	1805.42
	201	Sep-18	1477.16	178.459	1127.39	1826.94
	202	Oct-18	1480.72	188.247	1111.76	1849.68
	203	Nov-18	1479.07	196.984	1092.99	1865.15
	204	Dec-18	1486.43	205.753	1083.16	1889.7

Figure 3: (a and b) Distribution of error for data of (a) Coal and (b) Oil

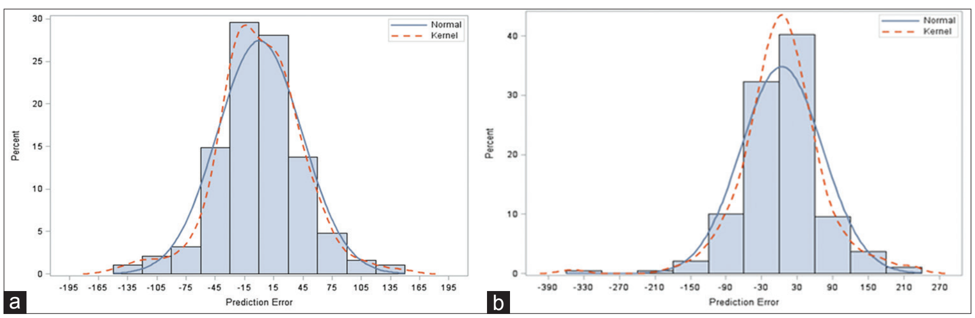
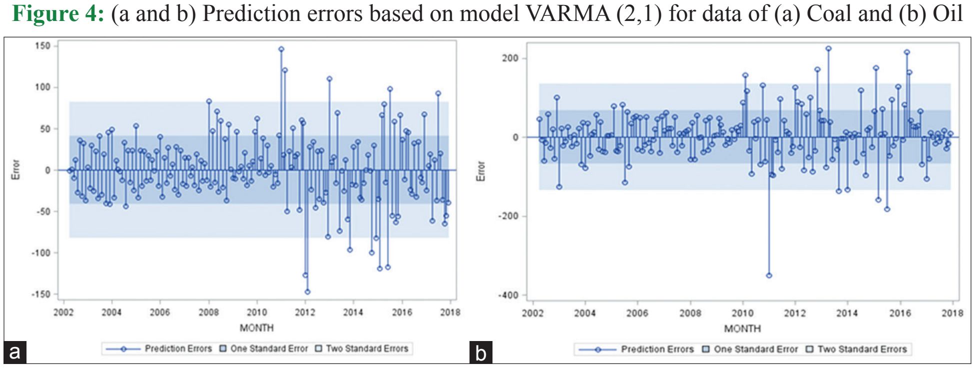


Figure 4: (a and b) Prediction errors based on model VARMA (2,1) for data of (a) Coal and (b) Oil



at the prediction errors for data of Coal and Oil (Figure 4a and b), for the data of Coal, it is clear that the prediction errors from 2002 to 2011 are homogeneous, but from 2012 to 2017 the errors fluctuate and are beyond two standard errors. This indicates that the prices are unstable in this horizon (2012-2017). Figure 1 supports this argument: from 2002 to 2010, the price increases; from 2011 to 2016, the price is unstable and decreases; and from 2016 to 2017, the price increases. Similar to the errors of data for Oil, from 2002 to 2010, (Figure 4b) shows that the prediction errors are homogeneous and within two standard errors; however, from 2011 to 2016, the errors fluctuate and several are beyond two standard errors. This indicates that the Oil price in this horizon (2011-2016) is unstable. Figure 1 also supports this argument: from 2002 to 2010, the price increases slowly; and from 2011 to 2016, the price is unstable.

Figure 5: (a and b) Model and forecast for the next 12 months of data export for coal

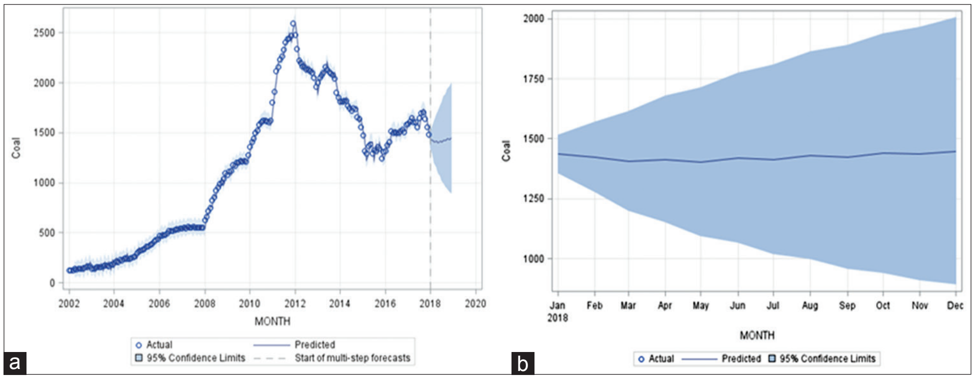
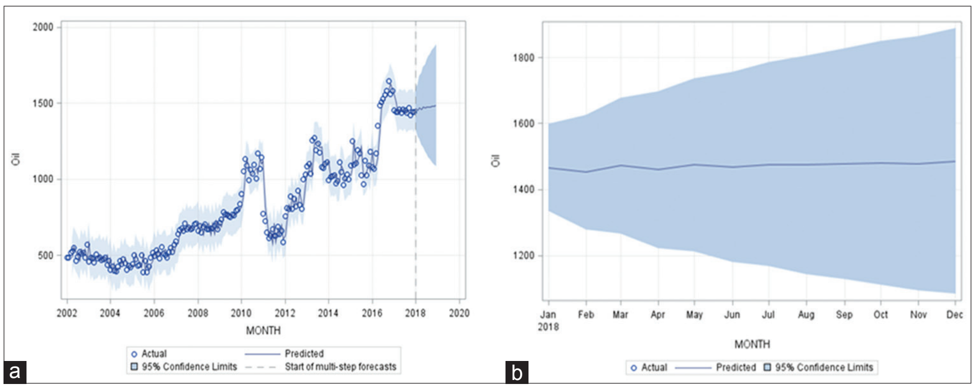


Figure 6: (a and b) Model and forecast for the next 12 months of data export for oil



The graphs of the model for data of Coal (Figure 5a) and for data of Oil (Figure 6a) show that the data and their predictions are close to each other, which indicates that the models fit with the data. Table 10 shows that the forecasts for the data of Coal begin at 1435.317 for the first period and then decrease for the second to the ninth periods. Starting from the tenth period up to the twelfth period, the forecast increases and reaches a value of 1448.491. The forecast for data of Oil begins at 1466.245 for the first period and then fluctuates with the trend increase up to the twelfth period. In the twelfth period, the value 1486.427 is attained. The confidence interval of the prediction increases: it is smaller in the first period and larger over time up to the twelfth period. This indicates that even though the model is sound and fits with the data, if the model is used to forecast for long periods, the prediction becomes unstable. This is demonstrated by the large confidence interval. (Figures 5b and 6b) describe the behavior of the confidence interval over time from the first period up to the twelfth period.

4. CONCLUSION

In this study, the focus is on how to find the best model and use it for forecasting the data export of Coal and Oil of Indonesia over the years 2002-2017. We have developed the best model using the criteria AICC, HQC, AIC, and SBC, which fit the data. The best model is VARMA (2,1), with restriction on some parameters that are non significantly different from zero. The restricted parameters are AR2_1_2 = 0, AR2_2_1 = 0, and MA1_2_1 = 0. All the parameters in the model, AR and MA, are significant, except for the parameter constants. The model shows that the prediction and the real data fit well with each other.

The forecasting results show that the standard error increases over time; the standard error in the first month is relatively small compared with the prediction of the means, but increases over time up to forecasting for the next 12 months. This indicates that the model is sound when forecasting for short periods, but the results are unstable (because of the higher standard error) when forecasting for long periods.

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