FORECASTING STOCK PRICES ON THE LQ45 INDEX USING THE VARIMAX METHOD

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Abstract: Forecasting using the Autoregressive Integrated Moving Average (ARIMA) method is not appropriate to predict more than one stock price because this method is only able to model one dependent variable. Therefore, to expect more than one stock prices, the ARIMA method expansion can be used, namely the Vector Autoregressive Integrated Moving Average (VARIMA) method. Furthermore, this research will discuss forecasting stock prices on the LQ45 index using the Vector Autoregressive Integrated Moving Average with Exogenous Variable (VARIMAX) method. Then, after the initial model formation process, the best model is the VARIMAX (0,1,2) model. Finally, the results of this study using the VARIMAX (0,1,2) model obtained the predictive value of the prices and the error values of stocks on the LQ45 index.

1.   INTRODUCTION

The stock exchange is an institution that brings together buyers and sellers in the sense that investors buy or sell securities such as stocks, bonds, or other financial instruments from public companies (Majumder and Hossain, 2019). The stock exchange is not only the focus of investors in running their business, but the stock exchange is also a valuable place for students to study and research. Predicting stock prices is considered one of the most challenging tasks to achieve in financial forecasting due to the complex nature of the stock market (Ye, 2017). There are two analysis methods for stock trading, namely fundamental and technical analysis. Fundamental analysis focuses on company data, such as financial reports, Earnings per Share (EPS), Return on Assets (ROA), Price-Earnings Ratio (P / E Ratio), Return on Equity (ROE), price and book value (P / BV). On the other hand, technical analysis uses past data from stock, including the opening price, high, low, and closing price, and stock volume, to predict future stock price movements (Wichaidit and Kittitornkun, 2015).

Data on stock price movements in the past (history price) can be said as time-series data. One of the time series methods that can be used to predict stock price movements is the Autoregressive Integrated Moving Average (ARIMA) method. However, the ARIMA method is less precise to expect more than one stock price movement because this method is a univariate method that can only model one dependent variable, not more than that. Therefore, to predict more than one stock price movement, you can use the ARIMA expansion method, namely the Vector Autoregressive Integrated Moving Average

(VARIMA) method. Compared to the ARIMA method, the VARIMA method is much more time-efficient and accurate in predicting stock price movements because the amount of data used is more than the ARIMA method. Even the VARIMA method is not only used to predict future stock price movements but this method can also be used to see the relationship between variables (correlation).

Various previous studies have discussed VARIMA multivariate time series modeling, including Warsono, et al. (2019), which tested forecasting and modeling of coal and oil export data using the VARIMA method, which produced the best multivariate time series model, namely VARIMA (2,0,1). Then, Pratama and Saputro (2018) have analyzed and proven the general equation of the VARIMA multivariate time series method by adding exogenous variables to the model so that the multivariate time series method changes to a Vector Autoregressive Moving Average with Exogenous Variable (VARIMAX). Next, Mauludiyanto, et al. (2009), who has tested VARIMA modeling with the effect of outlier detection on rainfall data in Surabaya, produced the best model, namely VARIMA (7,1,0) and the relationship between rainfall variables at locations A, B, and C. Trimono, et al. (2020) have tested farmer exchange rate in central java province using Vector Integrated Moving Average, which results obtained show that by using the VIMA(2.1) model, the FER prediction was very accurate, with MAPE values were 1.91% (rice & palawija sector), 2.44% (horticulture sector), and 2.18% (fisheries sector).

Therefore, from various previous studies and background problems that have been described, this research will discuss forecasting stock prices on the LQ45 index (Liquid 45), namely shares of PT. United Tractors Tbk (UNTR), PT. Gudang Garam Tbk (GGRM), and PT. Unilever Indonesia Tbk (UNVR) using the Vector Autoregressive Moving Average with Exogenous Variable (VARIMAX) method.

2. LITERATURE REVIEW

2.1. Autoregressive Integrated Moving Average (ARIMA)

Several time series methods can be used for forecasting, including Autoregressive (AR), Moving Average (MA), and a combination of Autoregressive Moving Average (ARMA). In AR modeling, the general equation is $\zeta_t = \mu + \varphi_1 \zeta_{t-1} + \varphi_2 \zeta_{t-2} + \cdots + \varphi_p \zeta_{t-p} + \varepsilon_t$ (Das, 2019). Then, the general equation of the MA model is $\zeta_t = \mu + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q}$ (Idrees, et al., 2019). In ARMA modeling, the general equation is $\varphi(B)\zeta_t = \mu + \theta(B)\varepsilon_t$ (Adebiyi, et al., 2014). Usually, the shape of the data on the variable varies so that the information is not stationary concerning the average. So that the data can be stationary concerning the standard, then the differentiation process can be carried out on the data. The differentiation process changes the ARMA method into an Autoregressive Integrated Moving Average (ARIMA). The following is the general equation of the ARIMA model (Du, 2018):

$$(1 - B)^d \varphi(B)\zeta_t = \mu + \theta(B)\varepsilon_t \tag{1}$$

with,

$$\varphi(B) = 1 - \sum_{i=1}^{p} \varphi_i B^i; \theta(B) = 1 - \sum_{j=i}^{q} \theta_j B^j$$

where,

ζ_t is the value of the variable in period t.

φ is an autoregressive parameter.

θ is a moving average parameter.

μ is a constant in the model.

$(1 - B)^d$ is differentiation process in the data.

2.2. Vector Autoregressive Integrated Moving Average (VARIMA)

The VARIMA method is developing the ARIMA method, which can model more than one-time series variable or be said to be a multivariate time series model. Previously, it should be noted that the general equation for the VARMA model is $\Phi(B)Z_t = M + \Theta(B)E_t$ (Zadrozny and Chen, 2019).

Like the ARIMA method, the VARIMA method has also gone through a differentiation process so that the general equation for the VARIMA model is obtained as follows (Warsono, et al., 2019):

$$(I - B)^d \Phi(B)Z_t = M + \Theta(B)E_t \tag{2}$$

with,

$$\Phi_i = \begin{bmatrix} \varphi_{i,11} & \varphi_{i,12} & \cdots & \varphi_{i,1m} \\ \varphi_{i,21} & \varphi_{i,22} & \cdots & \varphi_{i,2m} \\ \vdots & \vdots & \ddots & \vdots \\ \varphi_{i,m1} & \varphi_{i,m2} & \cdots & \varphi_{i,mm} \end{bmatrix} i = 1, 2, \dots, p$$

$$\Theta_j = \begin{bmatrix} \theta_{j,11} & \theta_{j,12} & \cdots & \theta_{j,1m} \\ \theta_{j,21} & \theta_{j,22} & \cdots & \theta_{j,2m} \\ \vdots & \vdots & \ddots & \vdots \\ \theta_{j,m1} & \theta_{j,m2} & \cdots & \theta_{j,mm} \end{bmatrix} j = 1, 2, \dots, q$$

$$M^T = (\mu_1, \mu_2, \cdots \mu_m)$$

$$E_t^T = (\varepsilon_{1t}, \varepsilon_{2t}, \cdots, \varepsilon_{mt})$$

$\Phi(B)$ and $\Theta(B)$ are autoregressive polynomial matrices and moving averages of order p and q, each of which is m x m and is a non-singular matrix. M is a constant vector of size m x 1, and Et is a white noise vector of size m x 1, independent, identical, and normally distributed with zero means.

It is assumed that Zt is nonstationary so that it can be reduced by a series of vector series applying the differencing operator $D(B)$, where

$$D(B) = \begin{bmatrix} (I - B)^{d_1} & 0 & 0 & 0 \\ 0 & (I - B)^{d_2} & 0 & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & 0 & (I - B)^{d_n} \end{bmatrix}$$

and $(d_1, d_2, \dots, d_n)$ are non-negative integers. Thus, the general equation for the VARIMA model can be simplified as follows (Wei, 2006):

$$D(B)\Phi(B)Z_t = M + \Theta(B)E_t \tag{3}$$

2.3. Vector Autoregressive Integrated Moving Average with Exogenous Variable (VARIMAX)

Method VARIMAX is developing method VARIMA by adding exogenous variables (dummy variables) into the model. This method was formed because it has non-random residuals (white noise) and is not average, so adding some exogenous variables to the model

equation is necessary. Then, the general equation of model A is as follows (Pratama and Saputro, 2018):

$$(I - B)^d \Phi(B) Z_t = M + \Theta(B) E_t + \Psi(B) X_t \tag{4}$$

$\Psi(B)$ is an exogenous variable parameter in the form of a polynomial matrix of size m x r. Xt is an exogenous variable or a dummy variable in a vector measuring m x 1.

2.4. Mean Absolute Error (MAE)

One of the risk calculations that can be used in calculating the magnitude of the error value of a time series model is to use the Mean Absolute Error (MAE). The MAE value is obtained from the average absolute price of two variables, namely in the case of this study the actual stock price and the predictive stock price. The following is the form of the equation formula from the MAE model (Chai and Draxler, 2014):

$$\text{MAE} = \frac{1}{n} \sum_{t=1}^{n} |\zeta_t - \zeta_t'| \tag{5}$$

where,

ζ_t is actual value;

ζ_t' is redictive value;

n is the amount of data.

2.5. Akaike Information Criteria (AIC)

The AIC method is a method that can be used to select the best regression model found by Akaike and Schwarz. The method is based on the maximum likelihood estimation (MLE) method. To calculate the AIC value, the following formula is used (Fathurahman, 2009):

$$AIC = e^{\frac{2k}{n}} \frac{\sum_{i=1}^{n} \hat{\mu}_i^2}{n}$$

where,

k is number of parameters estimated in regression model;

n is number of observations;

e is 2,718;

μ is Residual.

According to the AIC method, the best regression model is the regression model that has the smallest AIC value.

3. METHODOLOGY
3.1. Source of Data

The data used in this study came from the official website of yahoo finance (www.finance.yahoo.com). The amount of data used is 585 data, obtained from the daily closing price of the LQ45 index, namely PT. United Tractors Tbk (UNTR), PT. Gudang Garam Tbk (GGRM), PT. Unilever Indonesia Tbk (UNVR). The period used in this study was 9 months, from January 1, 2019 to September 30, 2019.

3.2. Analytical Procedures

1. Descriptive analysis of daily closing price data on LQ45 index shares.
2. Data stationarity testing. If the data is stationary, then the data can be constructed into a model at a later stage. However, if the data is not stationary, it is necessary to do a differentiation process (if it is not stationary on the mean) or log transformation (if it is not stationary in variance) of the data.
3. Construct data into a VARIMAX model. At this stage the process begins with the identification of the model, then estimates the model parameters, and tests the suitability of the model. If a residual model that is not white noise is obtained, it is necessary to detect and eliminate the presence of outliers and add dummy variables to the model.
4. The application of the VARIMAX model that has been obtained is carried out to obtain the predicted value of the stock price in the future period.
5. Finally, the results of inputting the VARIMAX model will be matched with the actual data in the next period, so that the error value is obtained in the model.

4. RESULTS

4.1. LQ45 Stock Data Descriptive Analysis

The data used in this study are the daily closing price of LQ45 index shares, namely the shares of PT. United Tractors (UNTR), PT. Gudang Garam (GGRM), and PT. Unilever Indonesia (UNVR). Then the results of descriptive statistical analysis of the three stocks are as follows:

Tabel 1. LQ45 Stock Descriptive Statistics Results

Variables	Number of Data	Minimum	Maximum	Means	Standard Deviation
UNTR	195	19975	29000	25541.92	2302.140
GGRM	195	51050	94400	78472.82	8063.863
UNVR	195	41600	50025	46694.23	2216.342

Based on Table 1, it is known that the amount of data used in this study amounted to 195 on each stock variable. Then of the three stocks, GGRM shares had the highest price of 94400 rupiah, while UNTR's stock had the lowest price of 19975 rupiah. Furthermore, for the average or as a measure of data concentration, GGRM shares have the highest value of 78472.82, while UNTR shares have the lowest value of 25541.92. Next for the standard deviation or as the average deviation of the data, GGRM shares still have the highest value of 8063,863, while UNVR shares have the lowest value of 2216.342.

4.2. Data Stationarity Testing

In the data stationarity test for variance, to find out whether the data is stationary to variance, you can go through the Box-Cox transformation where if the Rounded Value is 1, it can be said that the data is stationary to variance. Figure 1 is a test of data stationarity against variance.

It can be seen that in Figure 1, UNTR shares have a UCL (Upper Control Level) of 2,75 and an LCL (Lower Control Level) of -0,05 with a Runded Value of 1, meaning that it can be said that the data on UNTR shares has been stationary to variance. Likewise with GGRM stock, which in this stock has a UCL value of 2,51 and an LCL of 0,31 with a Rounded Value of 1. This means that GGRM stock is stationary to variance. The same is the case with UNVR shares, where the shares have a UCL value of 3,64 and an LCL of -1,76

with a value of Rounded Value of 1. This means that both UNVR, UNTR, and GGRM stocks are stationary to variance.
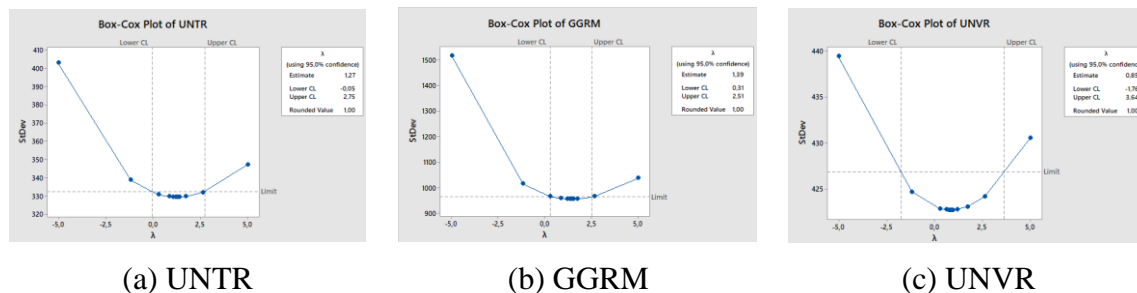

| (a) UNTR | (b) GGRM | (c) UNVR |

Figure 1. Variance Stationarity Test

In the data stationarity test against the average, to find out whether the data is stationary to the average, it can be through the Dickey-Fuller test. If the p-value of all variables is less than 0,05, it can be said that the data has been stationary to the average. Table 2 is the results of the data differencing.

Table 2. Dickey-Fuller Test Result VARIMA Model

Variable	Dickey-Fuller	P-Value
UNTR	-208.20	0.0001
GGRM	-219.63	0.0001
UNVR	-279.99	0.0001

After the process of data differentiation at the level stage, it is clear in Table 2 that the p-value of each variable is less than 0,05. Therefore, it can be concluded that the data has been stationary to the mean and because it has been through a decreasing (differencing), the model has changed from VARMA to VARIMA.

4.3. Constructing the VARIMAX Model

At this stage, the VARIMAX model will be formed or constructed. The process of VARIMAX model formation consists of 3 stages, namely model identification, model parameter estimation, and model suitability testing. The following is the process of forming the VARIMAX model:

VARIMAX Model Identification

The model identification process at this stage is finding the best model based on the smallest AIC value of each model order. Table 3 is the result of the AIC value for each model order:

Table 3. Results of AIC Value VARIMA Model

Lag	MA 0	MA 1	MA 2	MA 3	MA 4	MA 5
AR 0	39.8913	39.7605	**39.7409**	39.7992	39.8632	39.8739
AR 1	39.9511	39.8202	39.8261	39.8614	39.9328	39.9065
AR 2	39.9242	39.8452	39.8345	39.8634	39.9277	39.9134
AR 3	39.9181	39.9084	39.8871	39.9404	39.9911	40.0099
AR 4	39.9511	39.9562	39.9604	40.0035	40.0068	40.0320
AR 5	40.0387	39.9534	39.9881	40.0475	40.0443	40.1506

Table 3 shows that the best model in this study is VARIMAX (0,1,2) because the smallest AIC value is 39.7409. Furthermore, the VARIMAX (0,1,2) model is used to find the estimated parameter values of the three variables.

VARIMAX Model Parameter Estimation

In the parameter estimation process the same as the previous stage. After restricting the model parameters, the results of the parameter estimation of significance are obtained as in Table 4. In Table 4 it is known that the significant model parameter estimation results are the UNTR and GGRM variables with parameters ψ_{111}, ψ_{113}, ψ_{122}, θ_{223}. Furthermore, for the purposes of forming the model, the estimated parameter values are converted into a matrix.

Table 4. VARIMAX (0,1,2) Model Estimation Result

Input Variable	Parameter	Estimation	P-value	Output Variable
UNTR	ψ_{111}	-1938.700	0.0001	$x_{1,t\text{-}1}$
	ψ_{113}	-1185.200	0.0126	$x_{3,t\text{-}1}$
GGRM	ψ_{122}	-14182.200	0.0001	$x_{2,t\text{-}1}$
	θ_{223}	0.560	0.0001	$\varepsilon_{3,t\text{-}2}$
UNVR	-	-	-	-

The following are the matrices of the significant VARIMAX (0,1,2) model parameter estimation values:

$$\hat{\Theta}_2 = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0.560 \\ 0 & 0 & 0 \end{bmatrix}$$

$$\hat{\Psi}_{t-1} = \begin{bmatrix} -1938,7 & 0 & -1185.2 & 0 \\ 0 & -14182.2 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

then from the matrix, the VARIMAX (0,1,2) model equation can be formed as follows:

a. UNTR Shares ($\zeta_{1,t}$)

$$\zeta_{1,t} = -1938.7\, x_{1,t-1} - 1185.2\, x_{3,t-1} + \zeta_{1,t-1} + \varepsilon_{1,t} \tag{7}$$

where $\zeta_{1,t}$ is UNTR share price in period t, $\zeta_{1,t\text{-}1}$ is UNTR share price in period t-1, $x_{1,t\text{-}1}$ is the value of the dummy variable x_1 in period t-1, $x_{3,t\text{-}1}$ is the value of the dummy variable x_3 in period t-1, $\varepsilon_{1,t}$ is the residual value of UNTR shares in the VARIMAX (0,1,2) model period t.

b. GGRM Shares ($\zeta_{2,t}$)

$$\zeta_{2,t} = -14182.2 x_{2,t-1} + \zeta_{2,t-1} + \varepsilon_{2,t} - 0.56\varepsilon_{3,t-2} + 0.56\varepsilon_{3,t-3} \tag{8}$$

where $\zeta_{2,t}$ is GGRM share price in period t, $\zeta_{2,t\text{-}1}$ is GGRM share price in period t-1, $x_{2,t\text{-}1}$ is the value of the dummy variable x_2 in period t-1, $\varepsilon_{2,t}$ is the residual value of GGRM shares in the VARIMAX (0,1,2) model period t, $\varepsilon_{3,t\text{-}2}$ is the residual value of UNVR shares in the VARIMAX (0,1,2) model period t-2, $\varepsilon_{3,t\text{-}3}$ is the residual value of UNVR shares in the VARIMAX (0,1,2) model period t-3.

c. UNVR Shares ($\zeta_{3,t}$)

$$\zeta_{3,t} = \zeta_{3,t-1} + \varepsilon_{3,t} \tag{9}$$

where $\zeta_{3,t}$ is UNVR share price in period t, $\zeta_{3,t\text{-}1}$ is UNVR share price in period t-1, $\varepsilon_{3,t}$ is the residual value of UNVR shares in the VARIMAX (0,1,2) model period t.

Fit Test VARIMAX Model

a. White Noise Test
    The following are the results of the VARIMAX (0,1,2) model white noise test using the multivariate Ljung-Box method, obtained as follows:

```
Ljung-Box Statistics:
         m      Q(m)      df    p-value
 [1,]   1.00     7.79    9.00     0.56
 [2,]   2.00    16.48   18.00     0.56
 [3,]   3.00    30.01   27.00     0.31
 [4,]   4.00    37.97   36.00     0.38
 [5,]   5.00    43.35   45.00     0.54
 [6,]   6.00    57.74   54.00     0.34
 [7,]   7.00    68.12   63.00     0.31
 [8,]   8.00    76.09   72.00     0.35
 [9,]   9.00    90.03   81.00     0.23
[10,]  10.00    97.74   90.00     0.27
[11,]  11.00   104.21   99.00     0.34
[12,]  12.00   108.16  108.00     0.48
[13,]  13.00   118.83  117.00     0.44
[14,]  14.00   131.33  126.00     0.35
[15,]  15.00   140.69  135.00     0.35
[16,]  16.00   148.19  144.00     0.39
[17,]  17.00   154.09  153.00     0.46
[18,]  18.00   158.95  162.00     0.55
[19,]  19.00   165.90  171.00     0.60
[20,]  20.00   173.60  180.00     0.62
[21,]  21.00   184.82  189.00     0.57
[22,]  22.00   189.00  198.00     0.66
[23,]  23.00   194.64  207.00     0.72
[24,]  24.00   199.88  216.00     0.78
```

Figure 2. White Noise Test Result on Residual VARIMAX (0,1,2)

In Figure 2 it is known that the p-value of each lag is more than 0.05. This indicates that the residual distribution is random or white noise. Then to prove the residual is normal or not, the residual normality test can be carried out at a later stage.

b. Residual Normality Test

The following are the results of the VARIMAX (0,1,2) model residual normality test using the Kolmogorov-Smirnov test method:

```
            One-sample Kolmogorov-Smirnov test

data:  ds
D = 0.081923, p-value = 0.1499
alternative hypothesis: two-sided
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Figure 3. Kolmogorov-Smirnov Residual Normality Test Results

Based on Figure 3, it is known that the p-value is 0.1499, which is greater than the significance level of 0.05. This means that the residual data in the VARIMAX (0,1,2) model is formally normal. Then for the distribution of residual data it can be seen through the Q-Q plot as follows:
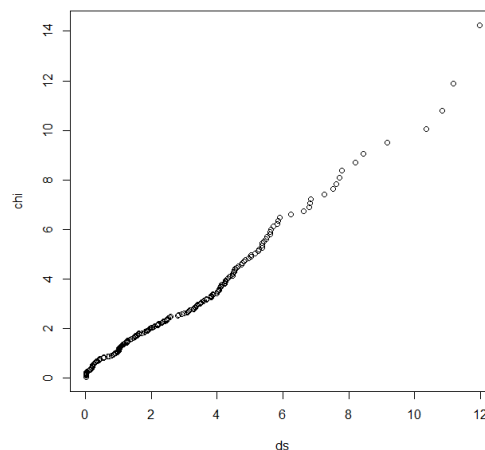

Figure 4. Q-Q Plot of VARIMAX (0,1,2) Model

Based on Figure 4, it is known that the residual movement of the VARIMAX (0,1,2) model has followed the assumption of a normal multivariate distribution, because the residual distribution of the model is pointing upwards and forming a diagonal line on the graph. Therefore, it can be said that the VARIMAX (0,1,2) model can be used for forecasting stock prices on the LQ45 index and knowing the relationship between model variables, because it fulfills the model suitability test assumptions.

4.4. The Application of the VARIMAX (0,1,2) Model

At this stage of applying the VARIMAX model, the model equations that have been obtained will be proven. The results obtained will be the predictive value of the stock price on the LQ45 index. The following is a calculation of the three LQ45 index stocks by predicting stock price movements in the next 1 day or in the 196th period:

a. UNTR Shares ($\zeta_{1,t}$)

$\zeta_{1,t} = -1938,7x_{1,t-1} - 1185,2x_{3,t-1} + \zeta_{1,t-1} + \varepsilon_{1,t}$ known:

$\zeta_{1,196} = -1938,7x_{1,195} - 1185,2x_{3,195} + \zeta_{1,195} + 0$ $x_{1,195} = 0$

$\zeta_{1,196} = -1938,7(0) - 1185,2(0) + 20575 + 0$ $x_{3,195} = 0$

$\zeta_{1,196} = 20575$ $\zeta_{1,195} = 20575$

b. GGRM Shares ($\zeta_{2,t}$)

$\zeta_{2,t} = -14182,2x_{2,t-1} + Z_{2,t-1} + \varepsilon_{2,t} - 0,56\varepsilon_{3,t-2} + 0,56\varepsilon_{3,t-3}$ known:

$\zeta_{2,196} = -14182,2x_{2,195} + Z_{2,195} + 0 - 0,56\varepsilon_{3,194} + 0,56\varepsilon_{3,193}$ $x_{2,195} = 0$

$\zeta_{2,196} = -14182,2(0) + 52375 + 0 - 0,56(0) + 0,56(-500)$ $\zeta_{2,195} = 52375$

$\zeta_{2,196} = 52375 - 280$ $\varepsilon_{3,194} = 0$

$\zeta_{2,196} = 52095$ $\varepsilon_{3,193} = -500.$

c. UNVR Shares ($\zeta_{3,t}$)

$\zeta_{3,t} = \zeta_{3,t-1} + \varepsilon_{3,t}$ known:

$\zeta_{3,196} = \zeta_{3,195} + 0$ $\zeta_{3,195} = 46500$

$\zeta_{3,196} = 46500$

From these calculations, that the forecasting of stock prices in the next 1 day period; for UNTR shares it is 20575 rupiah, for GGRM shares it is 52095 rupiah, and for UNVR shares it is 46500 rupiah.

4.5. VARIMAX (0,1,2) Model Validation

After the model is obtained, the next step is to validate the model. The goal is to find out the amount of error value that occurs in the model. Calculation of the amount of error value can use the Mean Absolute Error (MAE). The following is the calculation result of the error value of the VARIMAX (0,1,2) model for the three LQ45 stocks for the next one day period:

Table 5. Result of VARIMAX (0,1,2) Model Validation

UNTR Shares	GGRM Shares	UNVR Shares
$MAE = \dfrac{1}{n}\sum_{t=1}^{n}\lvert \zeta_{1,t} - \zeta'_{1,t}\rvert$	$MAE = \dfrac{1}{n}\sum_{t=1}^{n}\lvert \zeta_{2,t} - \zeta'_{2,t}\rvert$	$MAE = \dfrac{1}{n}\sum_{t=1}^{n}\lvert \zeta_{3,t} - \zeta'_{3,t}\rvert$
$= \lvert 20550 - 20575 \rvert$	$= \lvert 52275 - 52092 \rvert$	$= \lvert 46200 - 46500 \rvert$
$= \lvert -25 \rvert$	$= \lvert 183 \rvert$	$= 300$
$= 25$	$= 183$	

It can be seen from table 5 that the smallest error value is UNTR stock, which is 25 and the largest error value is UNVR stock, while for GGRM stock the error value is between the two stocks.

5. CONCLUSIONS

Forecasting methods Vector Autoregressive Integrated Moving Average with Exogenous Variable is obtained VARIMAX (0,1,2) with the multivariate equations $\zeta_{1,t} = -1938{,}7x_{1,t-1} - 1185{,}2x_{3,t-1} + \zeta_{1,t-1} + \varepsilon_{1,t}$, $\zeta_{2,t} = -14182{,}2x_{2,t-1} + Z_{2,t-1} + \varepsilon_{2,t} - 0{,}56\varepsilon_{3,t-2} + 0{,}56\varepsilon_{3,t-3}$, $\zeta_{3,t} = \zeta_{3,t-1} + \varepsilon_{3,t}$. Then forecasting stock prices in the next period using VARIMAX method is obtained the share price of UNTR is 20575 rupiah with an error of 25, the share price of GGRM is 52095 rupiah with an error of 183, the share price of UNVR is 46500 rupiah with an error of 300. This shows that although stock prices can fluctuate based on time in response to the company's circumstances and company external factors, the stock price movements can be predicted using the VARMA method.

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