Journal of Actuarial, Finance and Risk Management (JAFRM)
Vol. 1(1), June, 2022.

ARIMA Model in Predicting Jakarta Composite Index

Shafa Luthfia Sari Haerani[1,] Edwin Setiawan Nugraha[2*]

[1,2] Study Program of Actuarial Science, School of Business, President University, 17550, Indonesia
**Corresponding author: edwin.nugraha@president.ac.id*

Abstract— This study discusses stock price modeling using ARIMA model. We apply to model to the Jakarta Composite Index (JCI) as it represents all stock performances listed in Indonesia Stock Exchange. In this study, we propose several ARIMA models based on the daily from June 10th, 2019 until December 6th, 2019. The parameters among the models are estimated by using RStudio. We chose the best model by considering its AIC and RMSE. The best model that is ARIMA (21, 1, 2) with 99% confidence interval. This model is then used to predict the next 15 days (December 09, 2019 to January 02, 2020).

Keywords— ARIMA; Forecasting; Jakarta Composite Index; Time Series Analysis.

I. INTRODUCTION

The JCI (Jakarta Composite Index), also known as IHSG (Indeks Harga Saham Gabungan), is an Indonesia composite stock price index that measures the stock price performance of all listed companies that are traded on the IDX (Indonesia Stock Exchange) (Chandra & Purnomo, 2012). Although the IHSG is an average value of all shares in Indonesia, the points displayed are not just to know the extent of the highest or lowest level, but there are many effects and benefits to this country's economy. By knowing the movement trend, investors will know what the current market conditions are. If the valuation results are implemented in the form of investments, it will impact on the significant turnover of funds in our economy. There are some roles of JCI (Kompasiana, 2017). Firstly JCI can be used as a market indicator. Since it uses the prices of almost all shares on the IDX in its calculations, the JCI is the most important indicator of stock market performance. If we want to see the stock market condition today, we only have to look at the JCI figures' movement. If JCI tends to move up, meaning that stock prices in IDX are increasing. Conversely, if the JCI tends to fall, it means that stock prices on the IDX are declining. Secondly, JCI can be used as an indicator of the level of profit. For example, we can calculate the profit of investing in the stock market on average. The last is JCI can be used as a benchmark of portfolio performance. We can compare our mutual funds or stock portfolios' performance with the JCI. Sirucek (2012) expressed that macroeconomic variables such as economic growth, inflation rate, interest rates, exchange rates, and money supply are considered the dominant factors influencing stock price movements (Febriana et al, 2018). Therefore it constantly fluctuates, which raises the uncertainty about obtaining future returns on investment, reflecting the risks investors will face. Investors are also worried about making decisions between selling or holding shares in the stock market. Making the appropriate and wise decisions in investing is required by an investor to avoid losses. Therefore, a prediction needs to be done so that the risk of loss on the determined decision can be minimized. Scientific predictions about the future will be much more meaningful than predictions based on intuition alone (Sadeq, 2008).

In predicting stock prices, accurate and reliable data analysis is critical. Two analyses that are often used in investment strategies are fundamental and technical analysis. Fundamental analysis tends to focus on analyzing the intrinsic value of shares to measure the performance of a company. Meanwhile, technical analysis focuses on mapping historical price and volume data patterns. By knowing the pattern of stock price movements based on observations of past stock prices, it is expected to be able to predict future stock movement patterns (Hendrawan, 2012). One approach that can be used in predicting future JCI movement is the ARIMA method. The ARIMA model is widely used in periodic series forecasting, and many studies state that the ARIMA model is very good at forecasting the subsequent few periods (Kamruzzaman, 2003, in Rusyida & Pratama, 2020). ARIMA model combines p-th order autoregressive (AR) and q-th moving average (MA) models along with d-th order difference, which is often written simply as ARIMA (p, d, q). The AR model depends on previous values (lag in the past), while MA model depends on the previous error values (lag of error in the past). The AR model and the MA model are combined to produce the ARMA model. The ARIMA model that has gone through the integration process (the process in which non-stationary variables are differencing into stationary variables) is called the ARIMA model.

Several studies related to predicting, specifically for time series data, have been done a lot, including Djoni Hatidja, using ARIMA to predict PT Telkom Tbk stock price from January 2010 to March 2011, the result is ARIMA 3,1,3 model was the best. Then, Bambang Hendrawan, to predict the IHSG for companies that are members of Kompas 100 from January 2006 to November 2007, the ARIMA model (2,1,2) was the best result. Paiaman Pardede, predicted the JCI from January 2, 2015, to December 1, 2015, the result is ARIMA model (2,1,2) was the best. Another study was conducted by Sadeq (2008) regarding the JCI prediction analysis, the ARIMA model (1,1,1) was the best result with an average absolute error percentage of 4.14%. Based on the description above, the researcher wants to apply the ARIMA model as an analytical tool to predict how the JCI will move in the future as a guideline for market players, such as investors, economists, and the government.

II. METHODOLOGY

The time series method is a statistical technique of analyzing time-series data to obtain numeric or graphic data output and characteristics related to the data. It can be collected yearly, monthly, weekly, daily, and hourly. Amongst the other two approaches (Smoothing method and Trend Projection method using Regression) (Sobri. 2015), this research uses Box-Jenkins (ARIMA) as the methodology in modeling time-series. Autoregressive Integrated Moving Average (ARIMA) Model is an ARMA model that has to difference as many as d to remove trend and seasonality. ARIMA model is suitable for time-series observations in which the data variables are correlated (dependent), so this model ignores the independent variables as a whole (Tusyakdiah, 2020). The components of the ARIMA model are:

- Autoregressive (AR) Model
  AR model tries to forecast a series based on merely the past values of the series (lags). AR model with p order is denoted by AR (p). The general form of the AR (p) model is (Cryer & Chan, 2008):
  $$X^t = \phi_t X_{t-1} + \cdots + \phi_1 X_{t-p} + \epsilon_t \qquad (2.1)$$

- Moving Average (MA) Model
  MA is a model that solely depends on the previous error values (lag of error in the past). MA model with order q is denoted by MA (q). the general form of the MA (q) model is (Hyndman & Athanasopoulos, 2018):
  $$X^t = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q} \qquad (2.2)$$

- Autoregressive Moving Average (ARMA) Model
  ARMA model is a combination of the AR and MA models. The general form of the ARMA model (p, q) is defined as (Cryer & Chan, 2008):
  $$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \cdots + \phi_p X_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q} \qquad (2.3)$$

  Where:

X_t	: variable value at time t
$X_{t-1}, X_{t-2}, \dots, X_{t-p}$	: past values of time series concerned at time $t, t-1, \dots, t-p$
ϕ_t	: regression coefficients, t:1,2,3,…,p
θ_t	: regression coefficients t:1,2,3,…,p
ε_t	: error value at time t
$\varepsilon_t, \varepsilon_{t-1}, \varepsilon_{t-2}, \dots, \varepsilon_{t-q}$	: the value of the error at $t, t-1. t-2, \dots, t-q$
p	: AR order
q	: MA order

The flowchart below will represent the several steps involved in the ARIMA model analysis.

A. *Data Preparation*

Provide the collected data that will be forecasted using ARIMA model.

B. *Check Stationary*

Before forecasting ARIMA model, it is necessary to ensure that the data is stationary, meaning its mean and variance are time-independent. If the data is non-stationary, it is necessary to modify it to produce stationary data. One method that is commonly used is the differencing method. Differencing is calculating the change or difference in observed values. The Augmented Dickey-Fuller (ADF) test and the Autocorrelation Function (ACF) plot were conducted using the R programming language. If the the p-value is less than 0.05 and the ACF graph dies down slowly the data is already stationary, and conversely. We keep taking differences until we get a stationary output.

C. *Model Identification (finding p, d, q)*

It involves identifying the three components of p, d, q, which specify the ARIMA model. The appropriate ARIMA model can be determined by observing the Autocorrelation function (ACF) and Partial Autocorrelation Function (PACF) plot after differencing. Table 1 below will help us to choose the suitable candidate model.

TABLE 1
ARIMA MODEL IDENTIFICATION USING ACF AND PACF

Model	ACF	PACF
AR (p)	Tails off	Cuts off after lag p
MA (q)	Cuts off after lag q	Tails off
ARMA (p, q)	Tails off	Tails off
ARIMA (p, d, q)	Tails off with differencing	Tails off with differencing

Source: Munawaroh, 2010

D. *Parameter Estimation*

Once the model has been identified, the next step is to estimate the parameter in the model. There are three standard methods used to estimate the parameters:

1) Method of Moments

An estimation procedure involves equating and simplifying the sample moments with appropriate theoretical moments to generate the unspecified parameters.

2) Least Square Estimation

An estimation procedure that determines the best fitting line to the observation data by minimizing the sum of residuals between the estimator and actual data.

3) Maximum Likelihood Estimation

An estimation procedure defines the joint probability density of the examined data to find the parameters that maximize the likelihood function.

E. *Diagnostic Test (Residual Analysis)*

After the parameter model is estimated, the next step will be performing the diagnostic test. It is needed to know how well the model fits the data. If the model is correctly specified, the computed data (fitted value) should have similar properties to the original data. The model specification is changed when the model fits poorly. One of the tests done is by observing whether the estimated model's residual is white noise or not, which is independent, identically distributed normal variables with zero means and common variances. There are 2 tests to check the adequacy of the model’s residual analysis (Azriati, Hoyyi & Mukid, 2014):

1) Normality Test

It is important to verify whether the data distribute normally, the Shapiro-Wilk test was performed. The normality probability plot residual will follow the normal curve line if the residuals are normally distributed.

2) White Noise Process

The ARIMA model assumes that the residual produced are serially uncorrelated sequences. Ljung-Box test was carried out with the following hypothesis, H_0 (the residuals have white noise, there is no correlation between the residuals). In contrast, H_1 (the residuals have no white noise, there is a correlation between the residuals).

F. *Forecasting*

The last step is to use the decent model to generate the prediction values. Sadeq (2012) stated that the ARIMA model's characteristics time series is more suitable for short-term forecasting.

III. ANALYSIS AND RESULTS

All paragraphs have a justified format, i.e., both left-justified and right-justified. The first sentence in the paragraphs must be indented.

A. *Data Preparation*

This study is based on secondary daily closed price data for JCI (Jakarta Composite Index) collected from yahoo finance covering the period from June 10, 2019 to December 6, 2019 with a total number of 130 observations. R program was used for computation and graphical plotting of data. Figure 1 shows the raw data of JCI.

Date	Close	Date	Close	Date	Close	Date	Close
2019-06-10	6289.609863	2019-07-25	6401.365234	2019-09-09	6326.212891	2019-10-23	6257.806152
2019-06-11	6305.992188	2019-07-26	6325.236816	2019-09-10	6336.672852	2019-10-24	6339.646973
2019-06-12	6276.176758	2019-07-29	6299.035156	2019-09-11	6381.954102	2019-10-25	6252.345215
2019-06-13	6273.082031	2019-07-30	6376.996094	2019-09-12	6342.173828	2019-10-28	6265.383789
2019-06-14	6250.265137	2019-07-31	6390.504883	2019-09-13	6334.842773	2019-10-29	6281.138184
2019-06-17	6190.524902	2019-08-01	6381.541992	2019-09-16	6219.435059	2019-10-30	6295.747070
2019-06-18	6257.330078	2019-08-02	6340.180176	2019-09-17	6236.689941	2019-10-31	6228.316895
2019-06-19	6339.262207	2019-08-05	6175.703125	2019-09-18	6276.632813	2019-11-01	6207.190918
2019-06-20	6335.698242	2019-08-06	6119.471191	2019-09-19	6244.470215	2019-11-04	6180.344238
2019-06-21	6315.436035	2019-08-07	6204.194824	2019-09-20	6231.473145	2019-11-05	6264.151855
2019-06-24	6288.464844	2019-08-08	6274.670898	2019-09-23	6206.199219	2019-11-06	6217.544922
2019-06-25	6320.444824	2019-08-09	6282.131836	2019-09-24	6137.607910	2019-11-07	6165.624023
2019-06-26	6310.488770	2019-08-12	6250.595215	2019-09-25	6146.403809	2019-11-08	6177.985840
2019-06-27	6352.709961	2019-08-13	6210.961914	2019-09-26	6230.333984	2019-11-11	6148.740234
2019-06-28	6358.628906	2019-08-14	6267.334961	2019-09-27	6196.889160	2019-11-12	6180.992188
2019-07-01	6379.687988	2019-08-15	6257.585938	2019-09-30	6169.102051	2019-11-13	6142.500977
2019-07-02	6384.897949	2019-08-16	6286.657227	2019-10-01	6138.250000	2019-11-14	6098.950195
2019-07-03	6362.622070	2019-08-19	6296.714844	2019-10-02	6055.424805	2019-11-15	6128.345215
2019-07-04	6375.966797	2019-08-20	6295.737793	2019-10-03	6038.528809	2019-11-18	6122.625000
2019-07-05	6373.477051	2019-08-21	6252.966797	2019-10-04	6061.251953	2019-11-19	6152.089844
2019-07-08	6351.827148	2019-08-22	6239.245117	2019-10-07	6000.582031	2019-11-20	6155.108887
2019-07-09	6388.323242	2019-08-23	6255.597168	2019-10-08	6039.601074	2019-11-21	6117.363770
2019-07-10	6410.683105	2019-08-26	6214.509766	2019-10-09	6029.160156	2019-11-22	6100.242188
2019-07-11	6417.065918	2019-08-27	6278.170898	2019-10-10	6023.641113	2019-11-25	6070.762207
2019-07-12	6373.345215	2019-08-28	6281.645996	2019-10-11	6105.799805	2019-11-26	6026.187988
2019-07-15	6418.233887	2019-08-29	6289.119141	2019-10-14	6126.876953	2019-11-27	6023.039063
2019-07-16	6401.879883	2019-08-30	6328.470215	2019-10-15	6158.166016	2019-11-28	5953.060059
2019-07-17	6394.608887	2019-09-02	6290.545898	2019-10-16	6169.591797	2019-11-29	6011.830078
2019-07-18	6403.293945	2019-09-03	6261.589844	2019-10-17	6181.014160	2019-12-02	6130.055176
2019-07-19	6456.539063	2019-09-04	6269.664063	2019-10-18	6191.946777	2019-12-03	6133.895996
2019-07-22	6433.546875	2019-09-05	6306.803223	2019-10-21	6198.986816	2019-12-04	6112.878906
2019-07-23	6403.810059	2019-09-06	6308.950195	2019-10-22	6225.497070	2019-12-05	6152.117188
2019-07-24	6384.986816					2019-12-06	6186.868164

Figure1. Raw data of JCI
(Source: yahoo finance, 2020)

B. Plotting the Data

Figure 2 and Figure 3 below depict the original time series plot and decomposing plot. It can be observed in Figure 2, the pattern of JCI ranging from June 10, 2019, until December 6, 2019, has fluctuated. Whereas, the decompose plot describes that the trend is decreasing over time. Table 2 displays the descriptive statistics of the data.

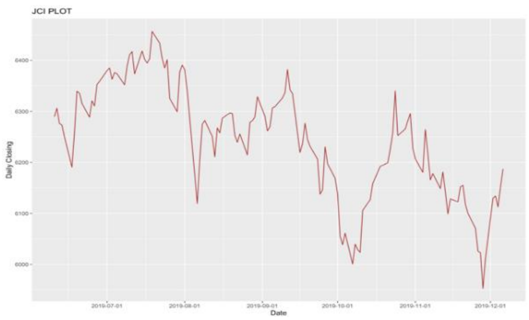

Figure 2. Daily Closing price of JCI data pattern
(Source: Processed data, 2020)

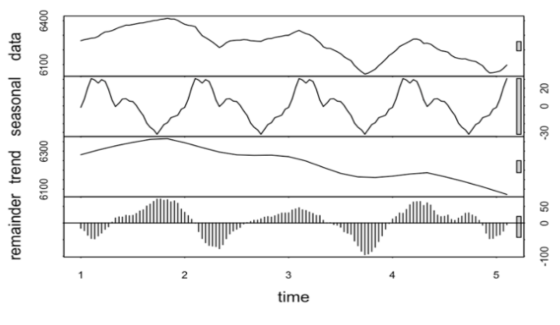

Figure 3. Decomposing plot of JCI stock prices
(Source: Processed data, 2020)

TABLE 2

DESCRIPTIVE STATISTICS OF JCI STOCK PRICES

	Min.	**1st Qu.**	**Median**	**Mean**	**3rd Qu.**	**Max.**
Date	2019-06-10	2019-07-24	2019-09-07	2019-09-07	2019-10-22	2019-12-06
Close	5953	6166	6257	6243	6328	6457

Source: Processed data, 2020

C. Check Stationary

Before forecasting the ARIMA model, it is necessary to ensure that the data is stationary, meaning its mean and variance are constant over time.

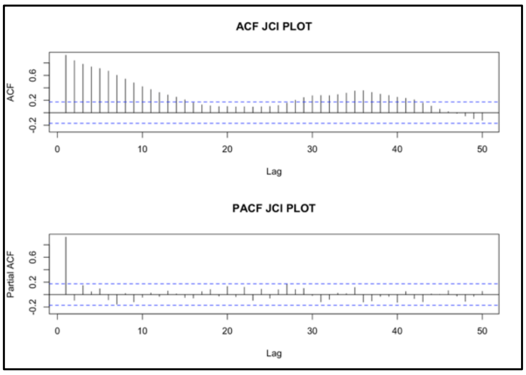

Figure 4. The correlogram of JCI stock price before differencing
(Source: Processed data, 2020)

```
Augmented Dickey-Fuller Test

data:  jkse_daily19$clean_Close
Dickey-Fuller = -3.2418, Lag order = 5, p-value = 0.08405
alternative hypothesis: stationary
```

Figure 5. Result of ADF test before differencing
(Source: Processed data, 2020)

Figure 4 is the correlogram of the JCI time series. The ACF plot dies down from the graph slowly, which means it is not stationary in mean value. Moreover, Figure 5 shows the ADF test with the p-value exceeds 5% does not reject the unit-root null hypothesis. In this case, the first difference is made to obtain the stationarity of the data. After the first difference, the JCI series becomes stationary, as shown in Figure 6 and Figure 7, with the alteration of the ADF test p-value to be less than 5% rejecting the null hypothesis.

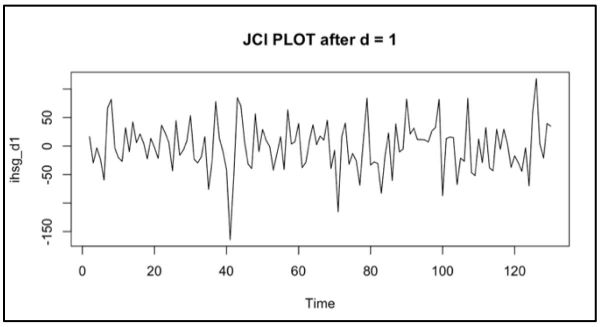

Figure 6. Time series plot after differencing
(Source: Processed data, 2020)

```
Augmented Dickey-Fuller Test

data:  ihsg_d1
Dickey-Fuller = -4.1479, Lag order = 5, p-value = 0.01
alternative hypothesis: stationary
```

Figure 7. Result of ADF test after differencing
(Source: Processed data, 2020)

D. Model Identification (finding p, d, q) in ARIMA Model

Once the data is stationary, the first step is identifying the candidate of the ARIMA model. By observing the ACF and PACF plot after differencing, the appropriate ARIMA model can be determined. According to Figure 8, the ACF plot cut off at lag 2 and PACF plot cut off at lag 2. Then it can be identified that the AR (p) model was AR (2), MA (q) was MA (2), and d was 1 because only the first difference is carried out. Therefore there were 8 candidate models, which consisted of (0,1,1), (0,1,2), (1,1,0), (1,1,1), (1,1,2), (2,1,0), (2,1,1), and (2,1,2).

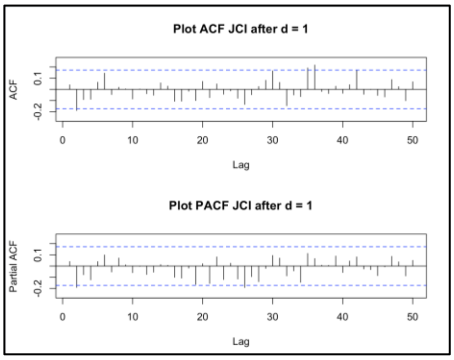

Figure 8. The correlogram of JCI stock price after differencing
(Source: Processed data, 2020)

E. Model Fitting

In this study we begin with proposing eight different ARIMA models to select the best model as in Table 3. The model (2,1,2) was chosen as it has the least AIC and RMSE values.

TABLE 3
QUALITY OF THE MODELS ACCORDING TO ITS AIC AND RMSE

	(0,1,1)	**(0,1,2)**	**(1,1,0)**	**(1,1,1)**	**(1,1,2)**	**(2,1,0)**	**(2,1,1)**	**(2,1,2)**
AIC	1340.58	1337.31	1340.71	1341.09	1338.68	1337.92	1338.49	1335.64
RMSE	42.8544	41.8733	42.8760	42.6047	41.8688	42.0763	41.8376	40.3992

Source: Processed data, 2020

However, when the PACF residual plot was detected, there was a lag that exceeds the Bartlet line which is at lag 21 as illustrated in the Figure 9. In order to avoid the poor result in prediction, the AR (p) is converted to AR (21). Table 4 presents the AIC and RMSE value comparison between (2,1,2) and (21,1,2) model. Despite having a greater AIC value, the RMSE shrank from 40.39929 to 38.38026.

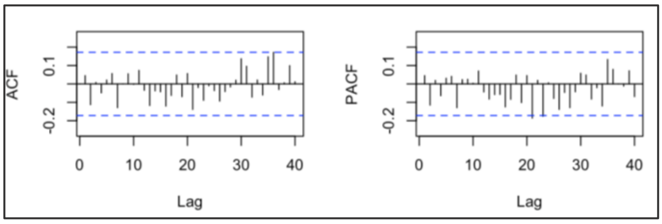

Figure 9. Correlogram of (2,1,2) model's residuals
(Source: Processed data, 2020)

TABLE 4
MODEL ESTIMATION OF (2,1,2) AND (21,1,2) MODEL

	(2,1,2)	**(21,1,2)**
AIC	1335.64	1358.88
RMSE	40.39929	38.38026

Source: Processed data, 2020

Then, the ARIMA model equation is

$$\begin{aligned} Y_t \; = \; & 0.1871Y_{t-1} + 0.2976Y_{t-2} - 0.0644Y_{t-3} + 0.0054Y_{t-4} + 0.0764Y_{t-5} \\ & + 0.1468Y_{t-6} - 0.1016Y_{t-7} + 0.0138Y_{t-8} + 0.0060Y_{t-9} \\ & - 0.0949Y_{t-10} + 0.0201Y_{t-11} - 0.0534Y_{t-12} - 0.0380Y_{t-13} \\ & + 0.0257Y_{t-14} + 0.0273Y_{t-15} - 0.1074Y_{t-16} - 0.1299Y_{t-17} \\ & + 0.0625Y_{t-18} - 0.1255Y_{t-19} + 0.0774Y_{t-20} - 0.0993Y_{t-21} \\ & - 0.1688e_{t-1} - 0.5817e_{t-2} + e_t \end{aligned} \tag{3.1}$$

F. Diagnostic Test (Residual Analysis)

The next stage was to check the normality and the autocorrelation of residuals by employing the Shapiro-Wilk test and Box-Pierce or Ljung-Box test.

1) Normality Test

It is important to verify whether the data distribute normally, the Shapiro-Wilk test was performed. The p-value is more significant than 5% which accepts the null hypothesis that the errors are normally distributed. Figure 10 and Figure 11 indicates the normal Q-Q plot of the residuals and the histogram.

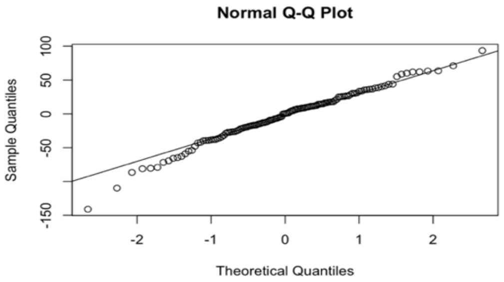

Figure 10. Normal Q-Q plot of (21,1,2) model
(Source: Processed data, 2020)

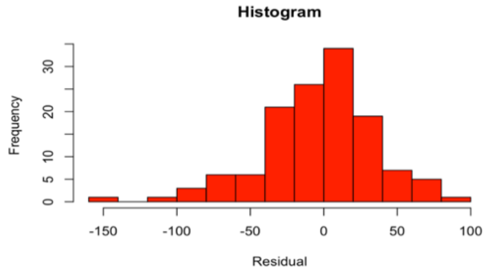

Figure 11. Residual histogram of (21,1,2) model
(Source: Processed data, 2020)

2) White Noise Process

White noise assumptions aim to identify the existence of correlation among the residuals generated by ARIMA models. Ljung-Box test was carried out with the following hypothesis, H_0 (the residuals have white noise, there is no correlation between the residuals). In contrast, H_1 (the residuals have no white noise, there is a correlation between the residuals). The results of Ljung-Box tests are provided below:

TABLE 5
LJUNG-BOX TEST OF (21,1,2) MODEL

X^2	df	p-value
0.6673	7	0.9986
1.213	14	1
2,305	21	1
7.2557	28	1

Source: Processed data, 2020

According to Table 5, lag 7, 14, 21, and 28 passed the test. These outputs shows that the p-value indeed exceeds the level of significance (alpha (α) = 5%), so that H_0 is fulfilled.

G. Forecasting

Figure 12 is the graphical illustration of JCI stock price and the price calculated from ARIMA (21,1,2) model and the forecasting result for the 15 days ahead. The red line and blue line represent the real data and the model (21,1,2) respectively, while the light blue in the grey area represents the forecasted plot with a 99% confidence interval.

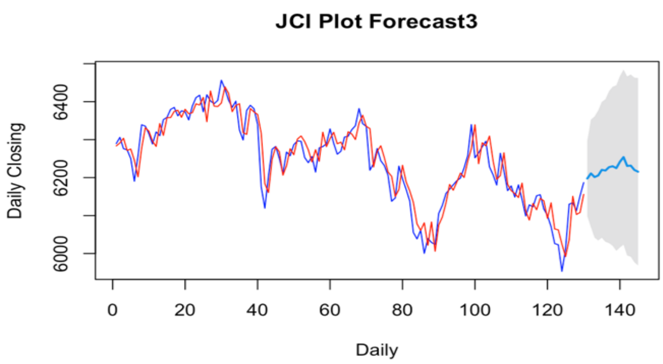

Figure 12. Graph of JCI stock price observed value and fit value & forecast value for the next 15 days
(Source: Processed data, 2020)

It appeared that the forecasting with a 99% confidence interval produced quite good results as the actual data is inside the lower and upper intervals. Moreover, in Table 6, the predicted stock price on December 9, December 16, December 17 in 2019 has a nearly close number to the actual data.

TABLE 6
PREDICTED AND ACTUAL VALUES OF JCI STOCK PRICE FOR THE NEXT 15 DAYS WITH 99% OF CONFIDENCE LEVEL

Period	Predicted values	Actual values	Lower limit 99	Upper limit 99
09/12/2019	***6197.537***	***6193.79***	6098.304	6296.77
10/12/2019	6211.026	6183.50	6069.392	6352.66
11/12/2019	6201.472	6180.10	6042.038	6356.90
12/12/2019	6205.565	6139.40	6034.448	6376.681
13/12/2019	6220.469	6197.32	6041.569	6399.369
16/12/2019	***6218.568***	***6211.59***	6030.979	6406.157
17/12/2019	***6227.557***	***6244.35***	6027.496	6427.618
18/12/2019	6229.852	6287.25	6020.438	6439.266
19/12/2019	6225.018	6249.93	6007.102	6442.935
20/12/2019	6241.546	6284.37	6016.056	6467.035
23/12/2019	6253.989	6305.91	6023.489	6484.489
26/12/2019	6230.764	6319.44	5995.03	6466.498
27/12/2019	6231.544	6329.31	5991.57	6471.518
30/12/2019	6220.111	6299.54	5976.952	6463.271
02/12/2020	6215.499	6283.58	5968.751	6462.247

The italic bold represents the closest results of predicted values to actual values amongst

IV. CONCLUSION

This study demonstrates an extensive process of developing the ARIMA (Autoregressive Integrated Moving Average) model for stock price prediction. The results obtained show that ARIMA (21,1,2) is the appropriate model to forecast the JCI as it fulfills all the residual analysis requirements and has the least RMSE value. This prediction result of JCI for the 15 days ahead could give investors a guide to make profitable investment decisions.

REFERENCES

[1] J.D. Cryer and Chan, K. S. "Model for Stationary Time Series," in *Time series analysis: with applications in R.*, 2nd ed., NY, Springer Science & Business Media, 2008, pp. 66.

[2] J.D. Cryer and Chan, K.S. "Model for Stationary Time Series," in *Time series analysis: with application in R.*, 2nd ed., NY, Springer Science & Business Media, 2008, pp. 77.

[3] R.J. Hyndman and G. Athanasopoulos, "ARIMA Models," in *Forecasting: Principles and practice.*, 2nd ed., Melbourne, Australia: OTexts, 2018. [Online]. Available: http://otexts.com/fpp2/

[4] K. F. Azriati., A. Hoyyi., and M. A. Mukid. "Verifikasi model arima musiman menggunakan peta kendali moving range (Studi kasus: Kecepatan rata-rata angin di badan meteorologi klimatologi dan geofisika stasiun meteorologi maritime Semarang)," *Jurnal Gaussian*, vol.3, no.4, pp. 701-710, 2014, DOI: https://doi.org/10.14710/j.gauss.v3i4.8081

[5] R. S. Febrina., S. Sumiati., and K. Ratnawati. "Pengaruh variabel makroekonomi dan harga saham asing terhadap indeks harga saham gabungan," *Jurnal Bisnis dan Manajemen*, vol.5, no.1, pp. 118-126, 2018, DOI: https://doi.org/10.26905/jbm.v5i1.2321

[6] B. Hendrawan. "Penerapan model arima dalam memprediksi ihsg," *Jurnal Integrasi*, vol.4, no.2,pp.205-211, 2012, ISSN: 2085-3858

[7] W. Y. Rusyida and V. Y. Pratama. "Prediksi harga saham garuda Indonesia di tengah pandemic covid-19 menggunakan metode arima," *Square: Journal of Mathematics and Mathematics Education*, vol.2, no.1, pp. 73-81, DOI: 10.21580/square.2020.2.1.5626

[8] Andre ASatryo, "Mengenal ihsg lebih jauh," Kompasiana, October 25, 2017. https://www.kompasiana.com/andreasatryo/59f00055ed4ed63703445412/mengenal-ihsg-lebih-jauh

[9] Halimah Tusyakdiah, "Penerapan metode auto regressive integrated moving average (arima) pada peramalan harga bitcoin terhadap rupiah dengan R," Medium. January 15, 2020. https://halimatusyak.medium.com/penerapan-metode-auto-regressive-integrated-moving-average-arima-pada-peramalan-harga-bitcoin-77558605eaf5

[10] Yahoo! Finance, "Jakarta Composite Index (JKSE) from June 10, 2019 to December 6, 2019," Yahoo finance, accesed November 15, 2020. https://finance.yahoo.com/quote/%5EJKSE/history?period1=1559347200&period2=1580428800&interval=1d&filter=history&frequency=1d&includeAdjustedClose=true

[11] J. Chandra and B. R. Purnomo, "Pengaruh nilai tukar USD, inflasi, dan resesi Amerika Serikat terhadap ihsg," [Abstract]. Doctoral dissertation, University of Gadjah Mada, Yogyakarta, 2012.

[12] S. Munawaroh, "Analisis model arima box-jenkins pada data fluktuasi harga emas," Doctoral dissertation, University of Islam Negeri Maulana Malik Ibrahim, Malang, 2010.

[13] A. Sadeq, "Analisis prediksi indeks harga saham gabungan dengan metode arima (Studi pada ihsg di bursa efek Jakarta)," Doctoral dissertation, University of Diponegoro, 2008.

[14] M. Sobri, "Analisis spectral dalam penentual periodisitas tersembunyi dari data prakiraan cuaca di kota Surabaya," dissertation, University of Islam, Bandung, 2015.

[15] N. S. Firdaus, “The implementation of Indonesia economic diplomacy: strengthening economic relations with Kazakhstan, 2015 – 2017, “B.A. thesis, Department of International Relation, University of President, Bekasi, 2019. Accessed January 20, 2020 http://repository.president.ac.id/xmlui/handle/123456789/3104
[16] A.N. Salman, “Contribution to Graph Theory,” Ph.D. dissertation, Department of Applied Mathematics, University of Twente, Netherlands, 2005.
[17] On the potential for machine learning in prediction of insurance policy sales, Department of Mathematics and Computer Science, Eindhoven University of Technology, Netherlands, 2017.