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THE APPLICATION OF STANDARD GENERALIZED AUTOREGRESSIVE CONDITIONAL HETEROSCEDASTICITY (SGARCH) MODEL IN FORECASTING THE STOCK PRICE OF BARITO PACIFIC

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ABSTRACT

Stock potentially yields higher returns than other investments, but is riskier due to volatile prices. To minimize the risk of loss, investors can forecast the stock price to help in deciding whether to buy, sell, or hold the stock. Several methods are available for forecasting the stock price such as ARIMA, ARCH, and SGARCH. ARIMA model works best for series with a constant variance of error. However, almost all stock price series have a non-constant variance of error, known as heteroscedasticity, as such ARIMA isn't suited for modeling the stock price. In contrast, the SGARCH model can handle series with heteroscedasticity. This makes it better suited for modeling stock prices as they have similar characteristics. PT Barito Pacific (BRPT) is a publicly traded firm that works mainly in petrochemical and geothermal energy. BRPT's net profit increased in 2023 by 243% and the demand for geothermal energy is expected to increase due to the government's renewable energy transition project. Therefore, this study forecasts the BRPT's stock price using the SGARCH model with R Studio. The stock price used ranges from October 1st, 2018 to August 16th, 2023 gotten from the Yahoo Finance Website. Based on the least AIC, this study found that ARMA(6,2)-SGARCH(1,1) is the best model for forecasting the stock price. This model gives a very accurate prediction of the stock price from April 1st, 2023 – April 19th, 2023 with a mean absolute error of 78.11, root mean square error of 89.51, and mean absolute percentage error of 9.81%.

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1. INTRODUCTION

Stock investment is the practice of purchasing assets that grow in value over time and offer returns either in terms of profit or growth on capital [1]. However, the fact that stock prices are subject to fluctuate at any time or are volatile should be understood while investing in equities. The high volatility raises the possibility that an investor could face capital loss risk or issuers liquidity risk. To minimize the risk, investors can forecast the future stock price [2]. Forecasting has the advantage of assisting investors in making more educated decisions regarding purchasing, keeping, or selling stocks. However, it is critical to recognize the accuracy limitations of predicting the stock price. Stock markets are driven by a variety of variables, such as economic events, geopolitical issues, and market behavior, all of which can be challenging to forecast precisely.

The forecasting can be done by modeling it with multivariate, nonlinear, or linear time series models. ARIMA (Integrated Autoregressive Moving Average) is a common example of a linear model which assumes for all observation that the error mean and variance is constant over time, this is referred to as homoscedasticity assumption [3]. Meanwhile, stock price data typically tends to have clustered volatility and a non-constant variance of error, which is called heteroscedasticity. Engle (1982) then proposed a non-linear time series model called autoregressive conditional heteroscedasticity (ARCH) model that works best with heteroscedastic series [4]. This model was then generalized by Bollerslev and Taylor (1986) to the GARCH model, also called SGARCH, because the ARCH model isn't competent in dealing with burst data or data with sudden jumps or falls. The advantage of the SGARCH model is it is better suited for modeling stock price data as it mostly has a non-constant variance of error and bursty part. An example of the series is the BRPT's stock price graph which has varying trends and a sudden jump around 2020 since the pandemic of COVID-19. This kind of data trend is more suitable to be modeled with the SGARCH model. Nevertheless, in the real world. Looking at the advantages of the SGARCH model and conformity to the data type, this study decides to utilize the SGARCH model.

Picking reliable stock issuers with good fundamental conditions that are promising long-term financial growth prospects is a must to minimize the risk of loss. One company that allegedly will have favorable prospects is PT Barito Pacific because of its high-demand business sectors in geothermal and increasing financial performance. Started in 1979, Barito Pacific, coded by BRPT in IDX, is a publicly traded firm that works mainly in the petrochemical and geothermal energy industries through its subsidiary, Star Energy Geothermal [5]. The performance of BRPT's net profit rose sharply by 243.40% throughout June 2023 [6]. Thus, it can be said that BRPT has fewer business competitors, and its financial trend is going up.

Moreover, the Indonesian government is currently running the renewable energy transition to fulfill Indonesia's commitment to overcome the threat of greenhouse gas emissions in 2022 [7]. Considering that, BRPT will surely be advantageous as it will increase the demand for its geothermal energy sector. Hence, this study used Barito Pacific stock price as the main data. However, the unresolved geopolitical situation and the high-interest rate regime are still a challenge for BRPT.

Several foregoing related researches have been conducted on forecasting data utilizing the time series model. First, the tea production forecasting with MAPE value of 29.9% [8]. Hence, it has proved that ARIMA tends to be ineffective and less accurate in forecasting the stock price. Second, the stock price forecasting of PT. Adaro Energy Tbk. This paper managed to produce forecast results that have a low MAPE value of 2.16% [9]. Third, the stock price forecasting of Ping An China Insurance applies the GARCH model. This study managed to produce a small average relative error of 1.29% [10].

Considering the good accuracy of GARCH and the weaknesses of ARIMA in the previous studies, therefore, this research intends to evaluate the performance of the SGARCH model, a model developed from ARIMA, in forecasting the stock price of BRPT. The performance will be measured based on the statistical measurement of error value: RMSE, MAE, and MAPE to show an adequate measurement of accuracy. Furthermore, a method for predicting the stock price of BRPT can be recommended to the investors so they can make wise decisions in their investments.

2. RESEARCH METHODS

The research approach of this paper is the quantitative and descriptive approach. It uses statistical and hypothesis testing in the analysis process of the time series data which contain numerical data. The descriptive approach is one kind of research that intends to explain the subject of study's characteristics using specific descriptions and measurements. Therefore, the author decided to use the quantitative and descriptive approach as it is more suitable. The explanation of the methodologies and succinct presentation of the fundamental concepts used in this research are described below.

2.1 Stock

An investment that represents ownership in a part of the entity that issued it is a stock, sometimes called equity. The stock price is one example of time series data in the financial field [11]. A stock return is the rise or fall in the price of a stock investment over time, which can be expressed as a percentage change or as a price change [12]. Let R_t denotes the simple return at time t, r_t denotes the log return at time t, p_t denotes the random variable which denotes the stock price at time t, and p_{t-1} denotes the previous stock price. There are two types of formulas to calculate return from stock price, simple returns and continuously compounded returns or log returns. The simple returns can be calculated using **Equation (1)**.

$$R_t = \frac{p_t - p_{t-1}}{p_{t-1}} \tag{1}$$

The log returns can be calculated using **Equation (2)**.

$$r_t = \ln\left|\frac{p_t}{p_{t-1}}\right| = \ln|p_t| - \ln|p_{t-1}| \tag{2}$$

The log return is also called log difference [3]. To get the future stock price p_{t+h} based on the log return r_t where h is the future price horizon, the following formula can be applied [13].

$$p_{t+h} = p_t e^{(r_{t+1}+r_{t+2}+\cdots+r_{t+h})} \tag{3}$$

2.2 Time Series

Time series is known as the observations conducted in chronological order over time [14]. Time series data can be viewed as a discrete-time and continuous space stochastic process. In this case, the time represents the trading day which is discrete and the space is the continuous stock price. The random variable is assumed to be identically independently distributed (i.i.d.).

2.3 ARIMA

Time series $\{Y_t\}$ in which the d-th difference $W_t = \nabla^d Y_t$ is an ARMA process that experiences stationarity is the ARIMA model. $\{Y_t\}$ is a process of ARIMA (p, d, q), if $\{W_t\}$ follows an ARMA (p, q) model. A process of mixed autoregressive moving average with p and q order, abbreviated to ARMA (p, q) is written as

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots - \theta_q e_{t-q} \tag{4}$$

where p denotes the order of AR, q denotes the order of MA, ϕ_p denotes constant or the parameter of AR, e_t denotes the error term at time t, and θ_q denotes constants or the parameter of MA. Luckily, $d = 1$ or at most 2 are typically taken for reasons of practicality. For instance, with $W_t = \Delta Y_t = Y_t - Y_{t-1}$, will generate the equation of ARIMA $(p, 1, q)$ as [15].

$$W_t = \underbrace{\phi_1 W_{t-1} + \phi_2 W_{t-2} + \cdots \phi_p W_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots - \theta_q e_{t-q}}_{ARMA\text{ process}} \tag{5}$$

2.4 ARCH

Heteroscedasticity is the term used when the variance of the error term ($Var(\varepsilon_t)$) is not constant or changing over time [3]. Look at the general equation form of the ARCH(q) model. The conditional mean model is written as

$$Y_t = \varphi(t, Y_{t-1}, Y_{t-2}, \varepsilon_{t-1}, \varepsilon_{t-2}, \dots) + \varepsilon_t \tag{6}$$

The error term is written as

$$\varepsilon_t = \sigma_t z_t \tag{7}$$

and the conditional volatility or variance is written as

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \cdots + \alpha_q \varepsilon_{t-q}^2 \tag{8}$$

Based on **Equation (6)**, the basic idea of the ARMA process, that is the conditional mean. In that equation, Y_t represents a stationary stochastic process where the mean and variance are constant and $\varphi(t, Y_{t-1}, \varepsilon_{t-1}, Y_{t-2}, \dots)$ represents a general function that depends on the historical component. **Equation (7)** describes the equation of the non-constant error or innovation term where σ_t denotes the conditional standard deviation and $z_t \sim NIID(0,1)$. ε_t is also $\varepsilon_t \sim NIID(0, \sigma_t^2)$, but the variance varies depending on t. In **Equation (8)**, q denotes the order of ARCH, α_0 represents omega ω, $\alpha_1, \alpha_2, \dots, \alpha_q$ represents the parameter of ARCH (q), and $\varepsilon_{t-1}^2, \varepsilon_{t-2}^2, \dots, \varepsilon_{t-q}^2$ represents the previous squared error term. Since this equation is variance, the value can't be zero, hence α_0 and $\alpha_1, \alpha_2, \dots, \alpha_q$ must satisfy $\alpha_0 > 0$ and $\alpha_1, \alpha_2, \dots, \alpha_q \geq 0$ [4].

2.5 GARCH

The conditional variance is specified in the ARCH model as a linear combination of the variances of previous samples, whereas the GARCH model includes the previous conditional variances in the specification. The conditional mean and error term equation of GARCH is the same as the ARCH one explained in **Equation (6)** and **Equation (7)**. The difference is in the conditional variance equation. The general formula of GARCH (p, q) conditional variance is

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \cdots + \alpha_q \varepsilon_{t-q}^2 + \beta_1 \sigma_{t-1}^2 + \beta_2 \sigma_{t-2}^2 + \cdots + \beta_p \sigma_{t-p}^2 \tag{9}$$

where p lags of the conditional variance and q lags of the squared error are used to parameterize the present conditional variance, $\alpha_1, \alpha_2, \dots, \alpha_q$ represents the parameter of the previous squared error term, and $\beta_1, \beta_2, \dots, \beta_q$ represents the parameter for the previous conditional variance. The coefficients of the equation should follow the conditions $\alpha_0 > 0$, $\alpha_i \geq 0$, and $\beta_j \geq 0$ [4].

2.6 Forecasting

Consider an observed time series $x_1, x_2, \dots, x_t$, thereby the goal is to project future data x_{t+h}, where h represents the forecasting horizon (h stands for horizon). Usually, $\hat{x}_t(h)$ represents the forecast of x_{t+h} given at time t for h steps in the future [14]. The discrepancy between an actual value and its forecast is called a prediction "error". One way to write it is as

$$e_{t+h} = x_{t+h} - \hat{x}_t(h) \tag{10}$$

where the training data is given by $\{x_1, \dots, x_t\}$ and the test data is given by $\{x_{t+1}, x_{t+2}, \dots, x_{t+h}\}$. The forecast accuracy may be estimated by finding the prediction errors in various ways as follows [16].

2.6.1 Mean Absolute Error (MAE)

MAE uses the scale-dependent measures for calculating the error based on the absolute, with the formula

$$MAE = \frac{1}{h}\sum_{i=1}^{h}|e_{t+i}| \tag{11}$$

where h denotes the number of test data and i denotes the forecast data point [16].

2.6.2 Root Mean Squared Error (RMSE)

RMSE also uses the scale-dependent measures for calculating the error, but based on the squared, with the formula

$$RMSE = \sqrt{\frac{1}{h}\sum_{i=1}^{h}(e_{t+i})^2} \tag{12}$$

where h denotes the number of test data and i denotes the forecast data point [16].

2.6.3 Mean Absolute Percentage Error (MAPE)

MAPE has formula

$$MAPE = \frac{1}{h}\sum_{i=1}^{h}\left|\frac{e_{t+i}}{x_{t+i}}\right| \times 100\% \tag{13}$$

where h denotes the number of test data and i denotes the forecast data point [16]. MAPE values can be interpreted into four categories, namely: $< 10\%$ = very accurate, $10 - 20\%$ = good, $20 - 50\%$ = reasonable, and $> 50\%$ = inaccurate [17].

2.7 Data Source

In this research, the author utilized the secondary data type which is large easily accessible data obtained by visiting the internet website, Yahoo Finance. The data is the daily stock closing price of BRPT from the period of October 1st, 2018 until August 16th, 2023 with a total of 1068 data.

2.8 Data Analysis Design

The data analysis is done using the R Studio software and Microsoft Office Excel. Figure 1 is the quantitative and descriptive procedures used to achieve the study's goals, that is evaluating the SGARCH method's performance for forecasting the price of BRPT stock.

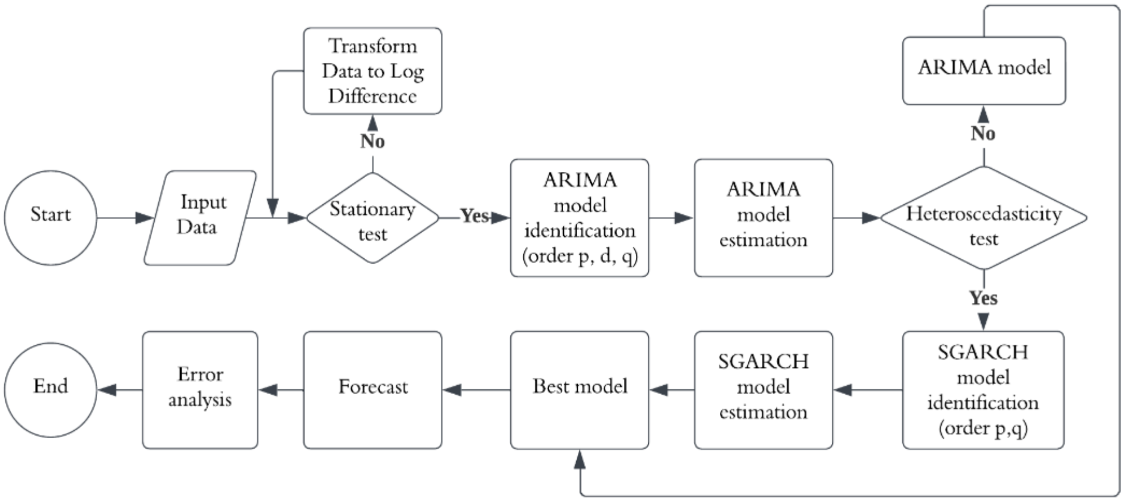


Figure 1. Flowchart of forecasting using the SGARCH model

3. RESULTS AND DISCUSSION

3.1 Import Data

This research uses the historical stock price data of PT. Barito Pacific Tbk. with the stock code BRPT.JK from October 1st, 2018 until August 16th, 2023. The data was collected from the Yahoo Finance Website with a total of 1205 trading days. However, because the market is closed on weekends and public holidays, 576 out of 1781 days, or 32% of the data, contain no value. To preserve the definition of a time series, which is a collection of data ordered sequentially in time, the missing value is estimated using the cubic spline interpolation method with the help of R Studio software. Table 1 shows 8 first and 6 last data after and before interpolation.

Table 1. BRPT's Stock Price Data Imputation

No	Date	Close Price After	Close Price Before
1	2018-10-01	363.470	363.470
2	2018-10-02	347.537	347.537
3	2018-10-03	339.570	339.570
4	2018-10-04	322.642	322.642
5	2018-10-05	323.637	323.637
6	2018-10-06	321.223	#N/A
7	2018-10-07	317.150	#N/A
8	2018-10-08	323.637	323.637
⋮	⋮	⋮	⋮
1776	2023-08-11	855.000	855.000
1777	2023-08-12	899.263	#N/A
1778	2023-08-13	905.458	#N/A
1779	2023-08-14	910.000	910.000
1780	2023-08-15	930.000	930.000
1781	2023-08-16	915.000	915.000

After the data imputation, the total data becomes 1781 which then is split into around 92% training data and 8% testing data, with the details given in Table 2. 1643 days will be used for data training, while the rest 138 days is for the testing data which will be used for the comparison between actual and forecasted data. The training data is utilized to forecast the April 1st, 2023 – August 16th, 2023 stock price.

Table 2. BRPT's Stock Price Data Split

Data	Period	Amount	Ratio
Training data	01-10-2018 - 31-03-2023	1643	92%
Testing Data	01-04-2023 - 16-08-2023	138	8%
Total	02-01-2019 - 16-08-2023	1781	100%

3.2 Data Pre-Analysis

The visualization of the training data is presented in Figure 2 with the help of R Studio software. The plot shows a wide variation band of the data trend, meaning that it's very volatile. The bursty pattern happens in this graph around 2020 due to the economic recession during the pandemic of COVID-19.

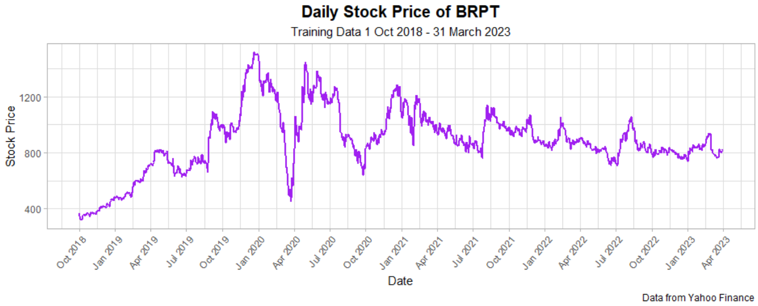


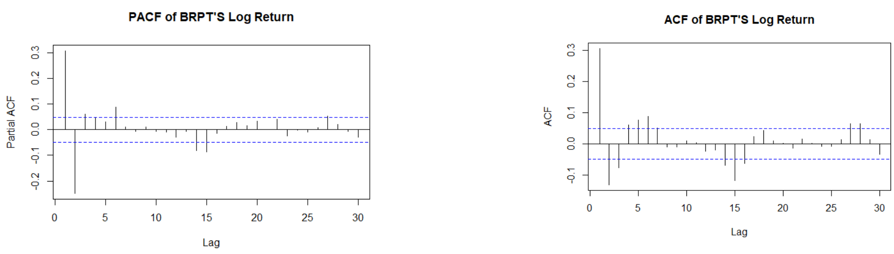
Figure 2. BRPT's daily stock price training data plot

3.3 Stationary Test

To check the stationarity of stock price training data, a statistical test called the Augmented Dickey-Fuller Test is performed with the help of R Studio software. The test output resulted in p-value of 0.06175, meaning that it's greater than the 5% significant level. Thus, the alternative hypothesis (H_1) is rejected, implying the data is not stationary. To make it stationary, the data is transformed into log difference (also called log return). The ADF test is performed again for the log difference series to check the stationarity. The test result shows that the p-value is 0.01, meaning that it's less than 5%. Thus, the null hypothesis is rejected and it is concluded that the log difference series is stationary.

3.4 ARIMA Model Identification

In the stationary test, the stock price data needs a one-time log difference to get the steady state condition, as such, the order $\boldsymbol{d}$ for ARIMA $(\boldsymbol{p}, \boldsymbol{d}, \boldsymbol{q})$, that is 1. the order $\boldsymbol{p}$ and $\boldsymbol{q}$ is identified using the PACF and ACF plot with the help of R Studio Software. Figure 3 displays the PACF and ACF plots. In the PACF plot, the significant spikes under lag 10 from the strongest to weakest correlation are at lag 1, 2, 6, and 3. The significant spikes in the ACF plot are quite similar, which is at lag 1, 2, 6, 3, 5, and 4. Hence, for the creation of the best ARIMA model candidate combinations, the maximum lag $\boldsymbol{p} = \boldsymbol{6}, \boldsymbol{d} = \boldsymbol{1}$, and $\boldsymbol{q} = \boldsymbol{6}$.



(a) **(b)**

Figure 3. PACF and ACF plot of log difference, (a) PACF plot, (b) ACF plot

3.5 ARIMA Model Estimation

The AIC values of the ARIMA (6,1,6) model combination are visualized in Figure 4 with R Studio Software. Based on the lowest AIC value among 49 models, the best model is ARIMA (2,1,5), the one with a blue asterisk in the figure.

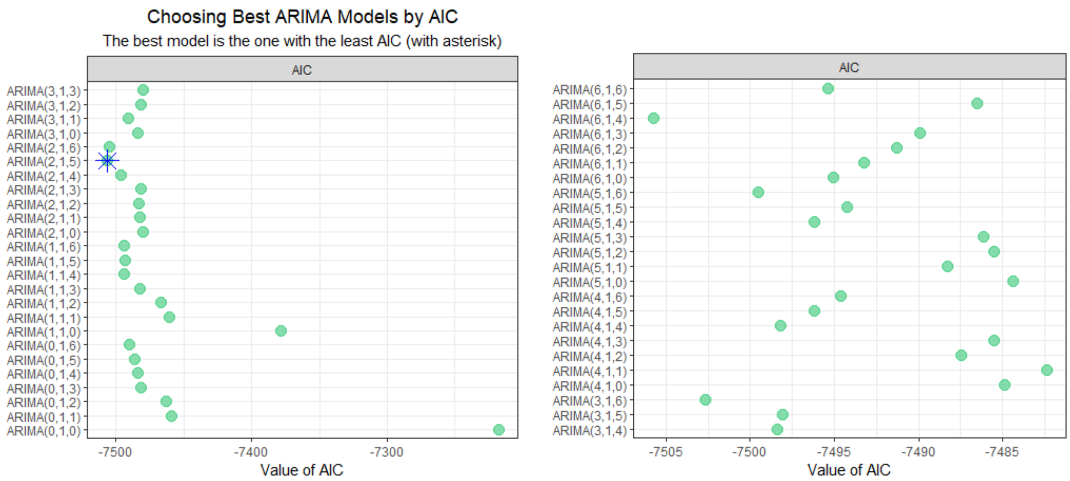


Figure 4. AIC value of ARIMA (6,1,6) model combination

Then, the independence and distribution of ARIMA (2,1,5) are checked using the Ljung-Box Test and Jarque Bera Test. With R Studio Software, the tests are automatically calculated and generate a Ljung-Box Test p-value of 0.9987 and Jarque Bera Test p-value of 2.2e-16. Since the p-value of the Ljung-Box Test is greater than 5%, the null hypothesis fails to be rejected and it can be concluded that all model residuals meet the ideal expectation that they are independently distributed and are white noise series. Meanwhile, the JB Test p-value is less than 5%, thus the null hypothesis that the residuals follow the normal distribution is rejected and concludes that the residuals are not normally distributed. The parameters of the best model are estimated with the help of R Studio Software so that the ARIMA (2,1,5) model equation is written as

$$\begin{aligned} W_t = {} & 1.831\, W_{t-1} - 0.901\, W_{t-2} + e_t + 1.451 e_{t-1} - 0.081 e_{t-2} - 0.464 e_{t-3} \\ & - 0.155\, e_{t-4} + 0.161 e_{t-5} \end{aligned} \tag{14}$$

where $W_t = Y_t - Y_{t-1}$.

3.6 Heteroscedasticity Test

To decide whether the ARIMA or GARCH model will be used for forecasting, the heteroscedasticity of the best ARIMA model's residuals is examined using the LM Test in R Studio Software. The test results in p-values 0, meaning that they are not passing the 5% significant level, as such the null hypothesis that the ARCH effect doesn't exist is rejected. Hence, it can be concluded that the squared residuals of ARIMA (2,1,5) are autocorrelated and the residuals are heteroscedastic.

3.7 SGARCH Model Identification

Three components can be modified from the GARCH model specification, such as the mean model, variance model, and the type of distribution. In this research, the mean model that is used is the ARMA model, the variance model is SGARCH, and the types of distributions are normal distribution and skew-student distribution. Based on the previous section, the max order of the ARMA model that is used is (6,6). for the SGARCH is (2,2) because the author needs to check the theory from Brooks (2019) that seldom is any higher-order GARCH model than GARCH(1,1) estimated or even considered in scholarly economic research.

3.8 SGARCH Model Estimation

This study looks for the least AIC value from the component combination with a max lag of ARMA is (6,6) and SGARCH is (2,2). The comparison of each model based on its AIC value is presented in **Figure 5** and **Figure 6**. Among 392 models, a model with the least AIC value marked by the blue asterisk is the best model combination, ARMA (6,2)-SGARCH (1,1) with the skew-student distribution.

Next, the residual diagnostic of the best model is carried out by checking the distribution and heteroscedasticity. The skew-student Q-Q plot in Figure 7 shows that most of the dots are approaching the straight line, implying the skew-student distribution fits the distribution of the ARMA(6,2)-SGARCH(1,1) model's residuals.

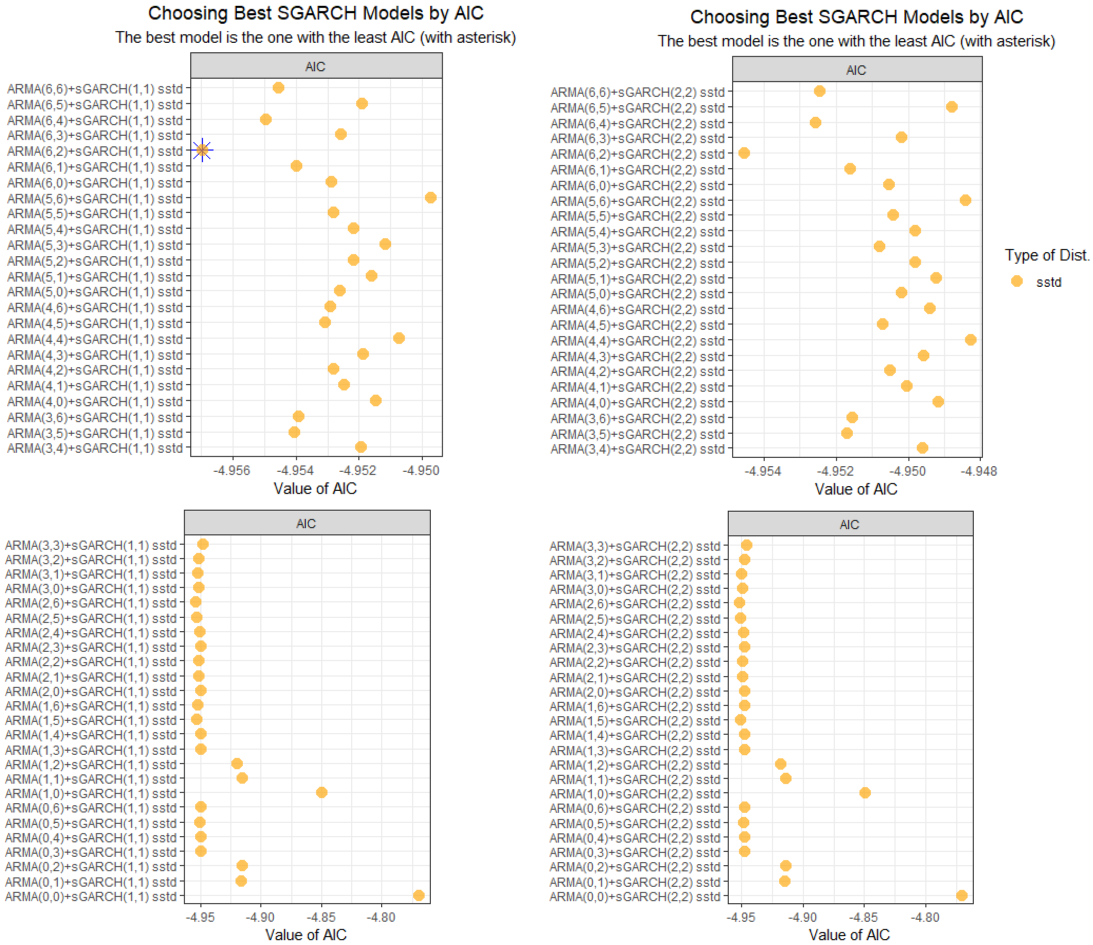


Figure 5. AIC value of SGARCH Model Combination with Skew-Student Distribution

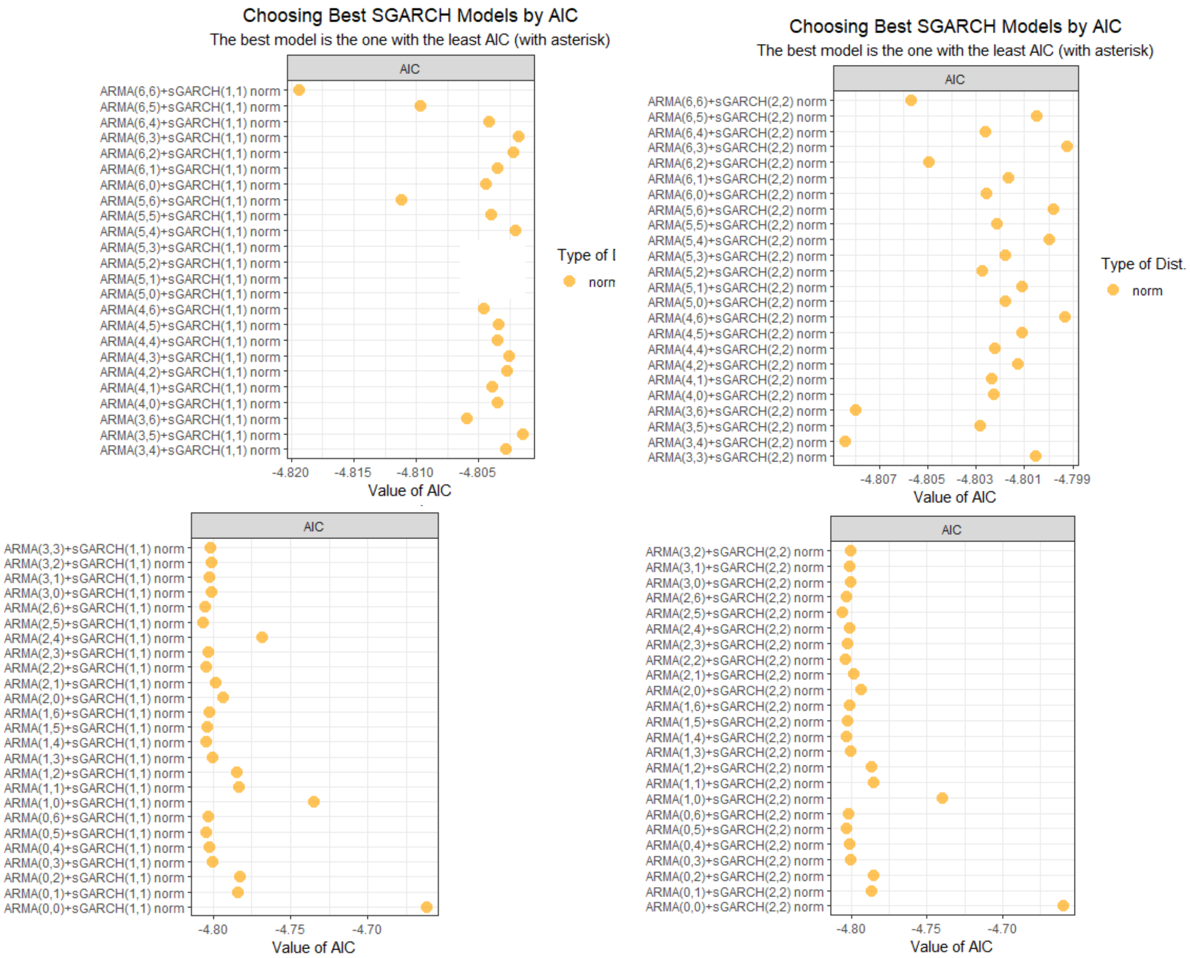


Figure 6. AIC value of SGARCH model combination with Normal Distribution

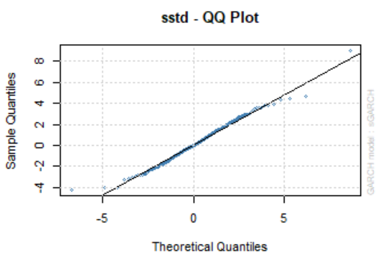


Figure 7. Skew-Student Q-Q plot of ARMA(6,2)-SGARCH (1,1)

The heteroscedasticity of the best model residuals is checked to ensure that there was no ARCH effect component on the residuals. Using the LM Test, the p-values at lag 3, 5, and 7 are 0.4382, 0.2306, and 0.1381 respectively, indicating all the p-values greater than 5% significant level. Thus, the null hypothesis is rejected and it can be inferred that the residuals are homoscedastic.

To construct the equation of the best model, ARMA(6,2)-SGARCH(1,1) with skew-student distribution, the parameter is estimated with the help of R Studio Software. The result of the estimation is shown in Table 3.

Table 3. Parameter Estimation of ARMA(6,2)-SGARCH(1,1) With Skew-Student Distribution

Parameter	Estimate	Parameter	Estimate
AR1	1.906441	MA1	-1.419213
AR2	-1.656368	MA2	0.652058
AR3	0.797284	α_0	0.000242
AR4	-0.235169	α_1	0.991621
AR5	-0.003012	β_1	0.007379
AR6	0.030089		

Thus, the equation of the conditional mean Y_t of ARMA (6,2) with skew-student distribution is written as

$$\begin{aligned} Y_t &= 1.906\, Y_{t-1} - 1.656\, Y_{t-2} + 0.797\, Y_{t-3} - 0.235\, Y_{t-4} - 0.003\, Y_{t-5} \\ &\quad -0.003\, Y_{t-6} + \varepsilon_t + 1.419\, \varepsilon_{t-1} - 0.652\, \varepsilon_{t-2} \end{aligned} \tag{15}$$

and the conditional volatility σ_t^2 of SGARCH(1,1) is written as

$$\sigma_t^2 = 2.42 \times 10^{-4} + 0.992\varepsilon_{t-1}^2 + 0.007\sigma_{t-1}^2 \tag{16}$$

3.9 Forecast

After getting ARMA(6,2)-SGARCH(1,1) as the best model, it is used for predicting the stock price series of BRPT. Using the log difference data for the period October 1st, 2018 – March 31st, 2023, the stock price will be simulated from April 1st, 2023 to August 16th, 2023. The simulation works by entering the initial value of the log difference successively into a previous model specification and samples are taken from the distribution of residuals. The log return series is then converted back into a series of stock prices. Through this step, a stock price time series with the same characteristics as the model being studied can be constructed.

With the help of R Studio Software, four simulations of stock price prediction are presented in **Figure 8** where the black line represents actual data, the red line represents simulation 1, the purple line represents simulation 2, the green line represents simulation 3, and the yellow line represents simulation 4.

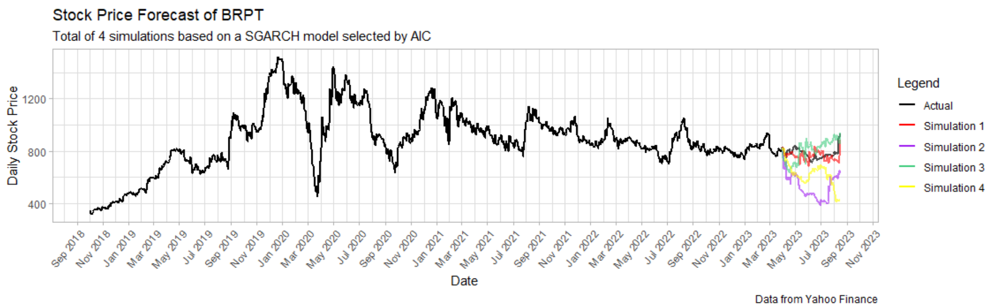


Figure 8. BRPT Stock Price Forecast

The clearer comparison plot between forecasted and actual data can be seen in **Figure 9**. It's seen that simulation 1 can capture the trend of the actual data for most of the forecast period more precisely than the other simulation. Generally speaking, simulation 2, 3, and 4 forecasted prices are closer to the actual value from the period April 1st, 2023 – April 10th, 2023. After that period, the values are going away from the actual value. However, simulation 3 starts capturing the actual value trend again from May 12th, 2023.

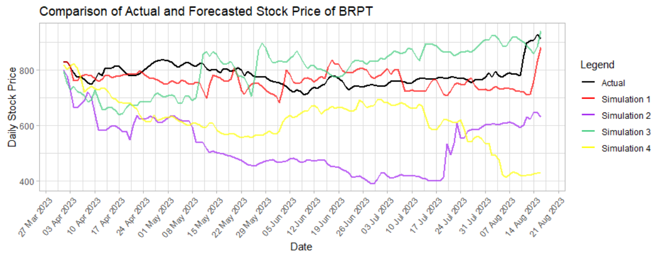


Figure 9. The BRPT Actual and Forecasted Stock Price Comparison

3.10 Error Analysis

To make it more precise, this study calculates the error measurement, such as the MAE, RMSE, and MAPE values. The results of the measurement are presented in **Table 4**. Based on the MAPE value, simulation 1 is indicated as very accurate, simulation 3 is indicated as good, while simulations 2 and 3 are indicated as reasonable. Overall, the mean of all simulation MAE is 137.62, RMSE is 152.86, and MAPE is 17.52% indicating good accuracy.

Table 4. Statistical Error Measurement of Forecasted Stock Price

Simulation	MAE	RMSE	Simulation	MAPE	Accuracy
1	43.55	53.36	1	5.49%	Very Accurate
2	251.76	263.61	2	32.32%	Reasonable
3	89.59	97.75	3	11.50%	Good
4	165.60	196.70	4	20.78%	Reasonable
Mean	137.62	152.86	Mean	17.52%	Good

Based on Table 5, all data in simulation 1 are very accurate to the actual one, so there is no degrading point. In simulation 2, the accuracy starts turning to good at the 6th data point and decreases to reasonable at the 30th data point. By taking the average of each MAPE per data point of all simulations, the overall accuracy turns from very accurate to good at the 20th point.

Table 5. Degrading Start Point of Accuracy Based on MAPE

Simulation	Degrading Start Point			Total of Each Category			
	Good	Reasonable	Inaccurate	Very Accurate	Good	Reasonable	Inaccurate
1	0	0	0	138	0	0	0
2	6	30	0	8	21	109	0
3	15	0	0	14	124	0	0
4	26	135	0	25	109	4	0
Average	20	0	0	19	119	0	0

Table 6 describes the average error measurement of all simulations for the first point to the particular point.

Table 6. All Simulation Average MAE and RMSE for Particular Point

Period	Point	MAE	RMSE	Period	Point	MAPE	Accuracy
01 April 2023	1	20.11	20.11	01 April 2023	1	2.42%	Very Accurate
19 April 2023	19	78.11	89.51	19 April 2023	19	9.81%	Very Accurate
07 May 2023	37	107.03	119.03	07 May 2023	37	13.23%	Good
25 May 2023	55	122.88	136.34	25 May 2023	55	15.23%	Good
12 June 2023	73	126.15	137.93	12 June 2023	73	15.97%	Good
30 June 2023	91	126.24	137.90	30 June 2023	91	16.15%	Good
18 July 2023	109	129.85	140.92	18 July 2023	109	16.69%	Good
05 August 2023	127	131.62	142.67	05 August 2023	127	16.94%	Good
16 August 2023	138	137.62	152.86	16 August 2023	138	17.52%	Good

In conclusion, with the model ARMA(6,2)-SGARCH(1,1) skew-student distribution and 1643 training data, the first 19 forecast data accuracy is indicated very accurate with MAE 78.11, RMSE 89.51, and MAPE 9.81% in the period April 1st, 2023 – April 19th, 2023. In the period April 20th, 2023 – August 16th, 2023 in data point range 20-138, the forecast data accuracy is good. Compared to the previous related research, Medellu (2022), MAPE value of 29.9% using the ARIMA model, this research forecasts more accurate results with MAPE of 9.81%.

4. CONCLUSIONS

In this work, the stock price of BRPT is forecasted for April 1st, 2023 – August 16th, 2023 using the GARCH model with SGARCH as the variance model, ARMA as the mean model, and skew-student as the distribution type. The stock price series is transformed into a log difference for stationarity. Then, $t + h$ log difference is simulated based on the residuals' distribution, skew-student distribution, by entering the log difference initial value sequentially to the best model specification, ARMA (6,2)-SGARCH (1,1).

The forecasted stock price is close enough to the actual value, so it is categorized as very accurate in the period April 1st, 2023 – April 19th, 2023 in the data point range 1-19 with MAE 78.11, RMSE 89.51, and MAPE 9.81%. Then, the accuracy decreases to good in the period April 20th, 2023 – August 16th, 2023 in data point range 20-138 with MAE 137.62, RMSE 152.86, and MAPE 17.52%. Hence, the researcher can conclude the SGARCH method is very accurate in predicting the future stock price for a maximum of 19 data, and the accuracy will decrease for more than 19 data.

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