Indonesia Private Company Stock Price Forecasting Based on Discrete Time Logistic Differential Model

Andree Sulistio Chandra, Viska Noviantri, Irene Anindaputri Iswanto

Abstract—**Stock investments have long been popular because of their high profit potential, so stock price predictions are always interesting to discuss. This paper applies a discrete logistic model to fit and forecast stock price movements completed by Mean Average Percentage Error (MAPE) calculation. In this model, the logistic parameter is described as a function of time. The logistic parameter is constantly updated based on the stock price database. Furthermore, this model is implemented numerically in Python to construct a Graphic User Interface (GUI) so that stock price prediction can be done quickly. The stock price's historical data for Indonesia's five biggest private companies during the Covid-19 pandemic is applied here to see how accurate this model represents stock price fluctuation in uncertain conditions because of a pandemic. The results show that the fit and forecast have the MAPE average value of 6.158% and 4.736%, respectively, which means that the discrete model can describe the stock price fluctuation in 30 days with high accuracy eventhough in the pandemic era. Investors can use these model analysis results to predict the stock price movement in the future to gain optimum return.**

Index Terms—**stock price, dynamic logistic model, fit and forecast, and desktop application.**

I. INTRODUCTION

INVESTOR can choose any product the financial market provides, such as stocks, bonds, mutual funds, derivatives, and currencies. Each product has different risks and benefits according to the type of investor. Of the many investment products, stock investments have been consistently popular because of their potential for high returns. Furthermore, the stock exchange index is also one of the barometers that shows a country's economic health level [1].

Stock indices attract considerable attention in the financial sector, so stock price modeling has become one of the main topics often discussed. Much research has been conducted to analyze stock price fluctuations using different approaches to gain optimal returns. Generally, there are three categories in predicting stock price methods: machine learning, fundamental analysis, and technical analysis [2]. Various machine learning methods [3], [4], [5], have recently made stock price prediction more accessible and efficient since technological development has risen quickly. A literature review by Mintarya et al. [6] shows that neural networks are the most used model in machine learning to predict stock price fluctuation.

Unlike the machine learning method, fundamental and technical analysis have long been used by investors to predict stock prices. In fundamental analysis, the qualitative method approaches the stock price prediction for long time periods based on external factors. Economic trends become one of these external factors, which can change due to various circumstances such as pandemics, politics, etc. Other factors are the financial performance [7], market sentiment [8], etc. In technical analysis, stock price prediction is derived from historical data on the stock price market. It can be done by many methods, including statistical and mathematical formulas, to represent stock price patterns graphically so the stock price fluctuation can be analyzed further.

Several studies show that the combination between fundamental and technical analysis can investigate the stock price fluctuation better [9], [10], [11]. Picasso et al. [12] develop new strategies in stock trading by combining fundamental (mathematical indicators) and technical (news article sentiments) analysis. Their approach shows that high frequency in trading simulation can raise the annual return up to 80%. The stock price fluctuation is also affected by trading volume. The relationship between them has been examined by using three compartments in the system of nonlinear differential equations [13]. A modified differential equation by time series applied for the Bulgarian stock exchange and completed by risk aversion analysis [14]. The stock price prediction related to stock growth rate, volatility, stock return rate, and interest rate has been modeled by the Schrodinger equation that is solved numerically by the Runge Kutta Method [15]. Viska et al. applied a mathematical approach by using a logistic differential equation to capture the stock price fluctuation during the Covid-19 pandemic for Indonesia Banking Stock Price [16] and Indonesia Stock Exchange [17]. These studies take a constant value for logistic parameters.

This study will develop the previous research [16] and [17] by modifying the logistic model into a discrete model and updating the logistic parameters each time, which means that the logistic parameter is a function over time. Furthermore, the discrete model was implemented in Python programming language to construct a Graphically User Interface (GUI). The GUI can help the user to predict (by fit and forecast process) the stock price fluctuation easily by uploading some historical data. It is also completed by MAPE results for each process so the user can see the accuracy of the prediction. The closing price data for Indonesia's five biggest private

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companies during the Covid-19 pandemic is applied here. For further analysis, the research was completed using some statistical parameters, such as median, standard deviation, and high accuracy percentage based on MAPE value. In the end, the effect of the pandemic on private companies can be drawn from these data.

II. Discrete Time Logistic Model in Stock Price

Stock prices change significantly daily, so it can be described as a function of time, $S(t)$. The rate of change in stock price $\left(\frac{dS(t)}{dt}\right)$ follows the logistic equation introduced by mathematician Verhulst, which is proportional to the current value of stock price but limited to their carrying capacity:

$$\frac{dS(t)}{dt} = \beta(t)\left(1 - \frac{1}{K}S(t)\right)S(t), \tag{1}$$

where K is carrying capacity and $\beta(t)$ is the stock price's intrinsic growth rate (the growth rate without any limiting factors). In equation (1), the intrinsic growth rate β changes by time t since the stock price changes significantly daily. This differentiates it from the general logistic equation, which has the intrinsic growth rate as a constant value.

The logistic differential equation (1) rewrite as

$$\frac{dS(t)}{dt} = \beta(t)S(t) + \alpha(t)S^2(t), \tag{2}$$

where

$$\alpha(t) = -\frac{\beta(t)}{K}.$$

Applying the forward difference scheme to approximate the rate of change in stock price, then the discrete-time model for the governing equation (2) can be derived:

$$\frac{S_{n+1} - S_n}{\Delta t} = \beta_n S_n + \alpha_n S_n^2, \tag{3}$$

where $n = 0, 1, 2, ...$ Furthermore, S_n represents the stock price at discrete time t_n, α_n and β_n is a logistic parameter at discrete time t_n.

Since the logistic parameters α_n and β_n change over time, these parameters can be derived as long as the first three initial stock prices are given (S_0, S_1, S_2). Assume that $\alpha_0 = \alpha_1 = \alpha_2 = \alpha$ and $\beta_0 = \beta_1 = \beta_2 = \beta$, then based on equation (3) it can be obtained

$$S_1 - S_0 = \alpha S_0^2 + \beta S_0, \tag{4}$$

$$S_2 - S_1 = \alpha S_1^2 + \beta S_1. \tag{5}$$

Solve (4) and (5) simultaneously, then the logistic parameters for $n = 0, 1, 2$ can be derived. For $n \geq 3$, the logistic parameter follow the pattern of α_2 and β_2 as follows:

$$\alpha_n = \begin{cases} \frac{S_1^2 - S_0 S_2}{S_0^2 S_1 - S_1^2}, n = 0, 1, 2 \\ \frac{S_{n-1}^2 - S_{n-2} S_n}{S_{n-2}^2 S_{n-1} - S_{n-1}^2}, n \geq 3 \end{cases} \tag{6}$$

$$\beta_n = \begin{cases} \frac{S_0^2(S_2 - S_1) - S_1^3 + S_0 S_1^2}{S_0^2 S_1 - S_1^2}, n = 0, 1, 2 \\ \frac{S_{n-2}^2(S_n - S_{n-1}) - S_{n-1}^3 + S_{n-2} S_{n-1}^2}{S_{n-2}^2 S_{n-1} - S_{n-1}^2}, n \geq 3 \end{cases} \tag{7}$$

The fit process is applied here to see the accuracy of the analytical solution results in a short period. The analytical value of stock price S_n for each $n \geq 3$ can be calculated using (3) with actual stock price S_{n-1}, S_{n-2} and S_{n-3}. These analytical values will be compared to the actual values for each time n by calculating MAPE values. If the MAPE values meet the accuracy criteria by Lewi, then the study continues to predict the stock price fluctuation in the future by using the forecast process. Different from the fit process, the analytical value of stock price S_n for each $n \geq 3$ in the forecasting process is evaluated from analytical stock price value S_{n-1}, S_{n-2} and S_{n-3}.

TABLE I
The Computer Configuration

Component	Context
CPU	Intel(R) Xeon(R) CPU E3-1230 v3
RAM	16 GB
Operating System	Windows 10
Data Processing	Python 3.9.1
Data Processing	Pandas 1.3.4
Data Processing	NumPy 1.20.0
Data Visualization	Matplotlib 3.3.4

III. Numerical Results

A. Desktop Application

The discrete model (3) with (6) and (7) was implemented in Python and completed by Graphical User Interface (GUI) development to facilitate the fit and forecasting process. Table I lists all of the computer configurations in GUI development. This GUI helps users do simulations based on actual stock price datasets from many websites in CSV file format. After uploading the CSV file and running the GUI, the GUI layout will be shown in Figure 1. In addition, the help page is also given in this GUI as in Figure 2. Under this page, users can follow the instructions for using this GUI.

Figure 1 consists of five parts, named parts A, B, C, D, and E. Part A shows the information about the file we uploaded, including the file name, data size, and fit interval period. This part is located in the top left corner of GUI window. The fit result completed by MAPE value is shown in part B, where the orange curve represents the actual data and the blue curve represents fit (analytical) results. Part C relates to the forecast process, where the user can choose the start date and duration for the forecast (See Figure 4 for the details). The forecast result is shown in Part D, where the blue and orange curves represent the forecast (analytical) and actual data values, respectively.

The feature buttons (Figure 5) on the picture for fit and forecast results page are designed to make it easier for users to analyze graphic results. The basic features of the toolbar provided are resetting the original view, returning to the previous view, continuing to the next view, panning, zooming, configuring subplots, and saving the image, as shown in Figure. Moreover, this result can be downloaded as a CSV or PDF file through Part E (Figure 6).

As part of the application evaluation with users, researchers interviewed several relevant individuals representing potential application users. They are stock activists and/or observers, researchers, and investors. The interview was conducted using five measurable human factor metrics as the interview framework: time to learn, performance speed, rate of errors, retention over time, and subjective satisfaction. The interview results show that this GUI is user-friendly and can help users observe stock market fluctuations.

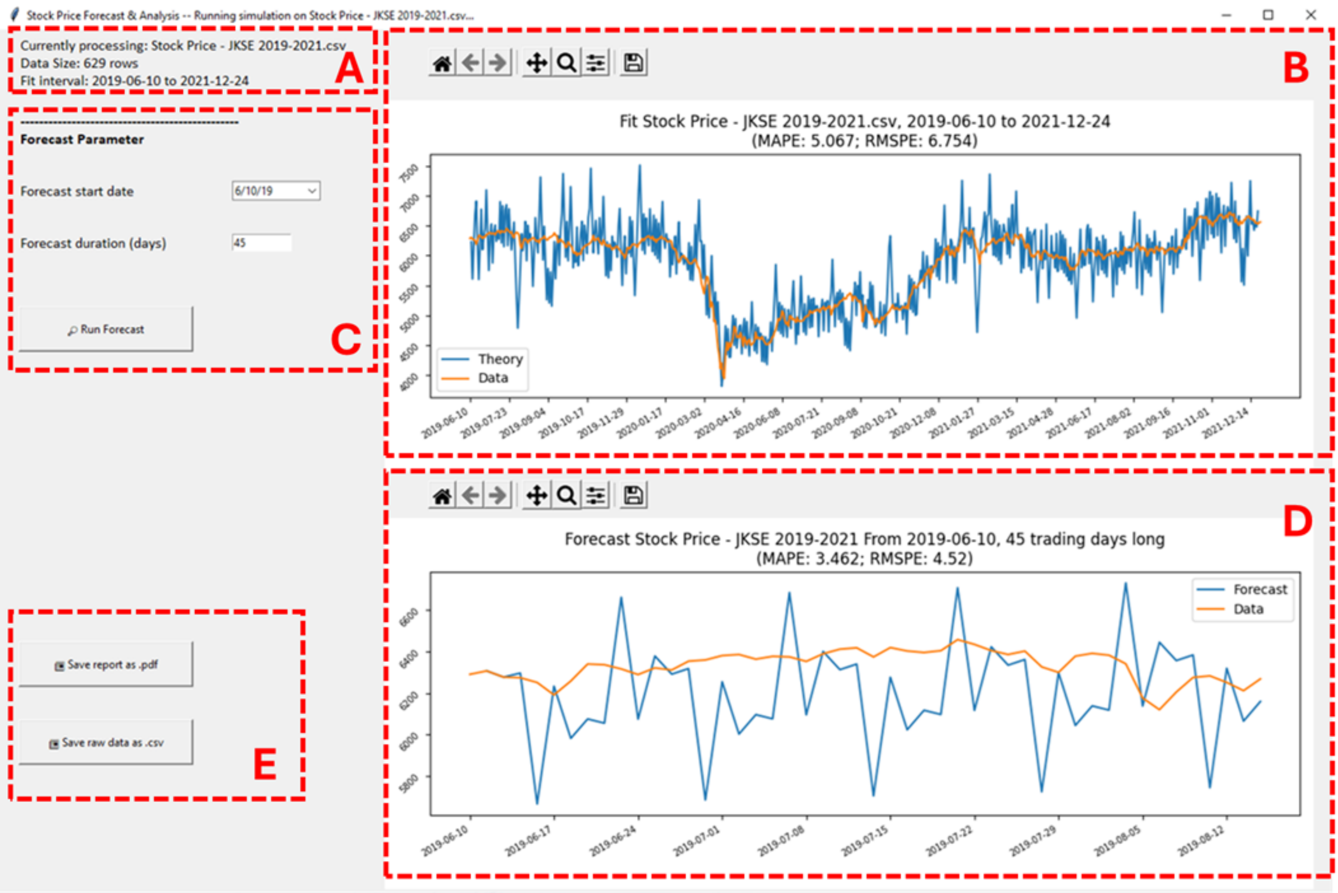

Fig. 1. Graphical User Interface

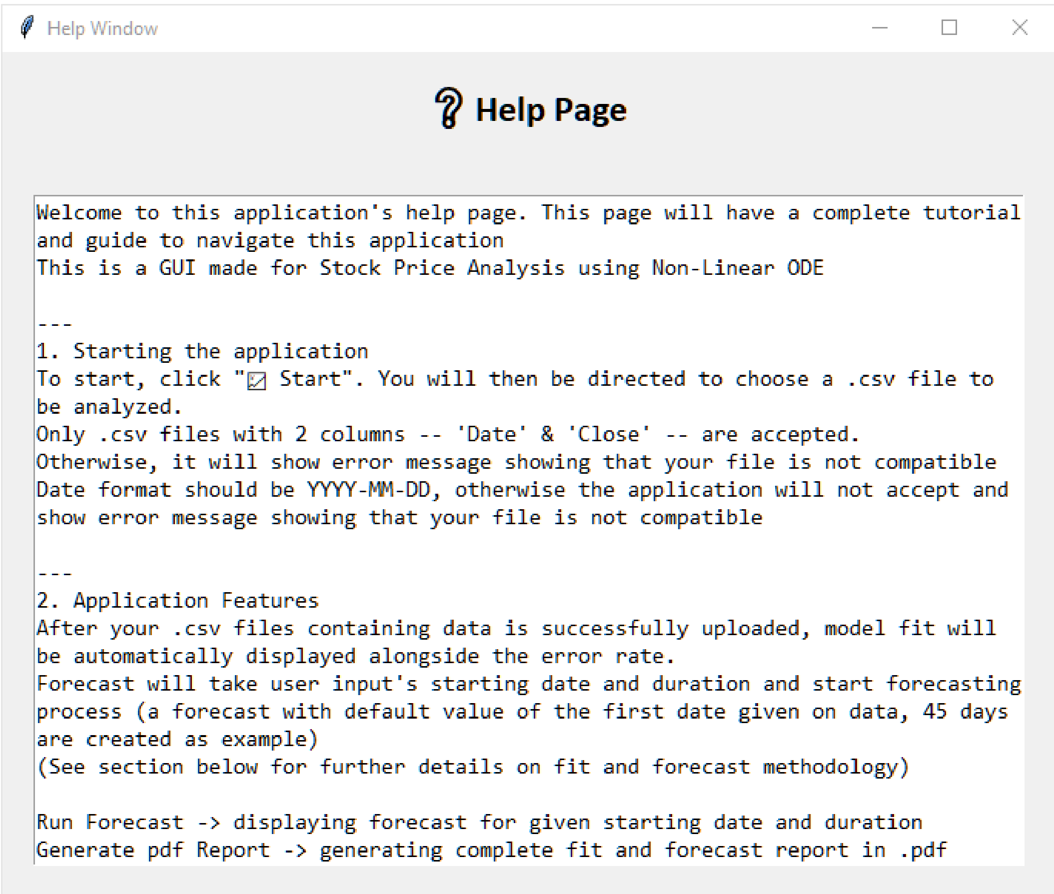

Fig. 2. Help Page

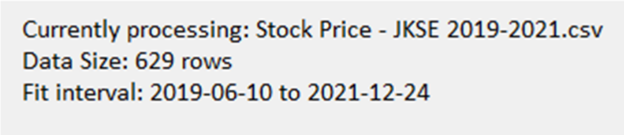

Fig. 3. Part A: Processing Data Information in GUI

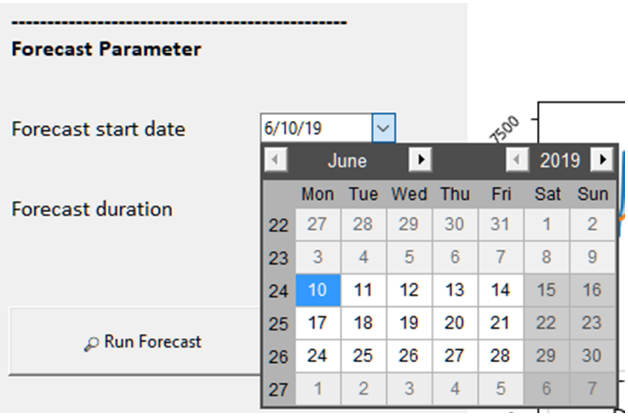

Fig. 4. Part C: Forecast Input in GUI

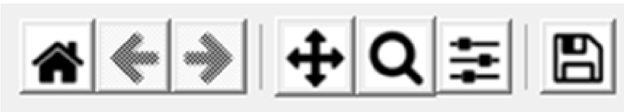

Fig. 5. Part B and D: Fit and Forecast Toolbar

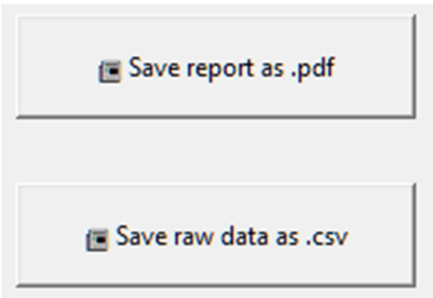

Fig. 6. Part E: Results Download

B. Fit Result

The daily closing price of Indonesia's five biggest private companies apply to do the fit process. There are PT. Bank Central Asia Tbk (BBCA), PT. Hanjaya Mandala Sampoerna Tbk (HMSP), PT. Astra Internasional Tbk (ASII), PT. Gudang Garam Tbk (GGRM), and PT. Unilever Indonesia Tbk (UNVR). The closing stock price dataset is obtained from historical data on *https://finance.yahoo.com*, in periods June 10^{th}, 2019 until October 26^{th}, 2021. This period was chosen to see whether the discrete logistic model can describes the actual stock price dynamic during uncertain conditions due to the Covid-19 pandemic or not. The actual closing price in the first three times (10 - 12 June 2019) can be used to calculate the logistic parameter (6) and (7) for $n = 0, 1, 2$. Then, the fit value S_n for each $n \geq 3$ can be derive from (3), (6), and (7) with the value S_n, S_{n-1}, S_{n-2} are the actual value of closing stock price.

After compiling the GUI for these five companies, the fit stock prices are shown in Figure 7 - 11. In quantity, the fit stock price (blue curve) fluctuates more than the actual stock price (orange curve), but this fluctuation follows the actual stock price pattern. In February - April 2020, when the first Covid-19 was released in Indonesia, actual stock prices for these companies dropped significantly, but the fit results still captured this condition well.

TABLE II
MAPE AND ACCURACY CRITERIA FOR FIT STOCK PRICE

Company	MAPE Average	Accuracy
BBCA	5.796	High
HMSP	6.158	High
ASII	5.669	High
GGRM	5.518	High
UNVR	5.919	High

Fit accuracy will be analyzed by calculating Mean Absolute Percentage Error (MAPE) each time, then compared to Lewis Criteria. The order of companies starting from the smallest to the biggest MAPE values are GGRM, ASII, BBCA, UNVR, and HMSP. Overall, the MAPE average for all companies is less than 10%, as in Tabel II, which means that the fit results using the logistic model are highly accurate even in uncertain conditions because of Covid-19.

C. Forecast Result

Since the MAPE values for fit results are less than 10%, we use the logistic discrete model (3) to predict (forecast) the stock price. As in the fit process, the actual closing price in the first three times was used to calculate the logistic parameter (6) and (7) for n = 0, 1, 2 as in Table III. All values in this table become the initial value for the numerical steps (3), (6), and (7) to derive the forecast value S_n.

Previous research [16] shows that the forecast results will be better for smaller periods. Since the first Covid-19 case in China was released in December 2019, this research will forecast stock prices during that period. For these reasons, we choose a forecast duration of 30 days and a forecast start date of 4 November 2019 as an input in Figure 4. As a result, the forecast stock price for all companies is shown in Figure 12 - 16. Overall, the magnitude of forecast results (blue curve) is greater than the actual stock price (orange curve) as in the fit results. The MAPE values for the forecasting results are less than 10% as seen in Table IV, which means the logistic model can predict the stock price for 30 days. BBCA has the smallest MAPE value, and GGRM has the largest MAPE. However, UNVR has the smallest MAPE standard deviation, which means that the MAPE values have low variation and are close to the MAPE average. In other words, UNVR became the company with the most stability during this observation period. In addition, the UNVR stock price forecast gives the most accuracy up to 97.5%. In other words, UNVR became the company with the most stability during this observation period. These results also show that the MAPE value in the fit and forecasting process may differ; a bigger MAPE in fit results does not lead to a bigger MAPE in forecast results.

More forecast simulations were conducted here by setting 30-day trading days on different starting days. Figure 17 and 18 shows the dynamic MAPE value as a function of the forecast starting day. The green, blue, black, yellow, and red curves describe the MAPE value for BBCA, HMSP,

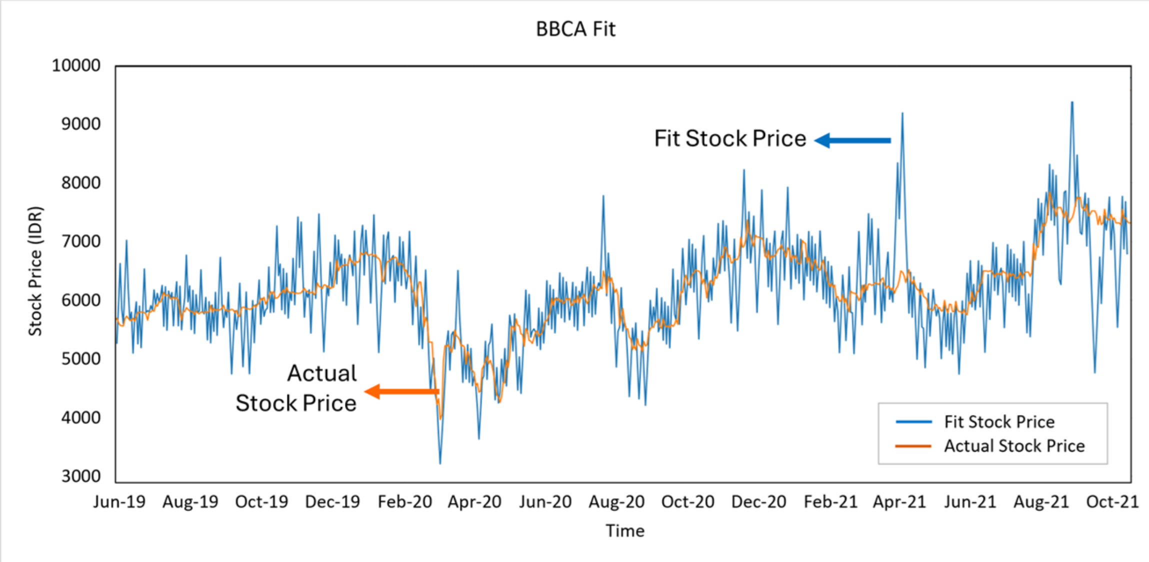

Fig. 7. Fit Stock Price for BBCA

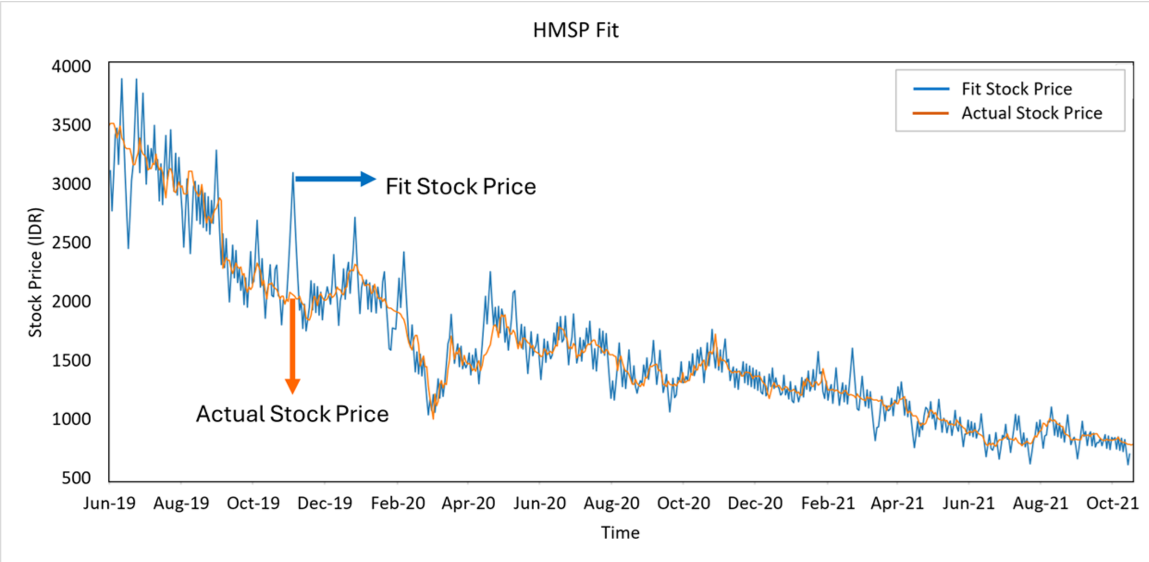

Fig. 8. Fit Stock Price for HMSP

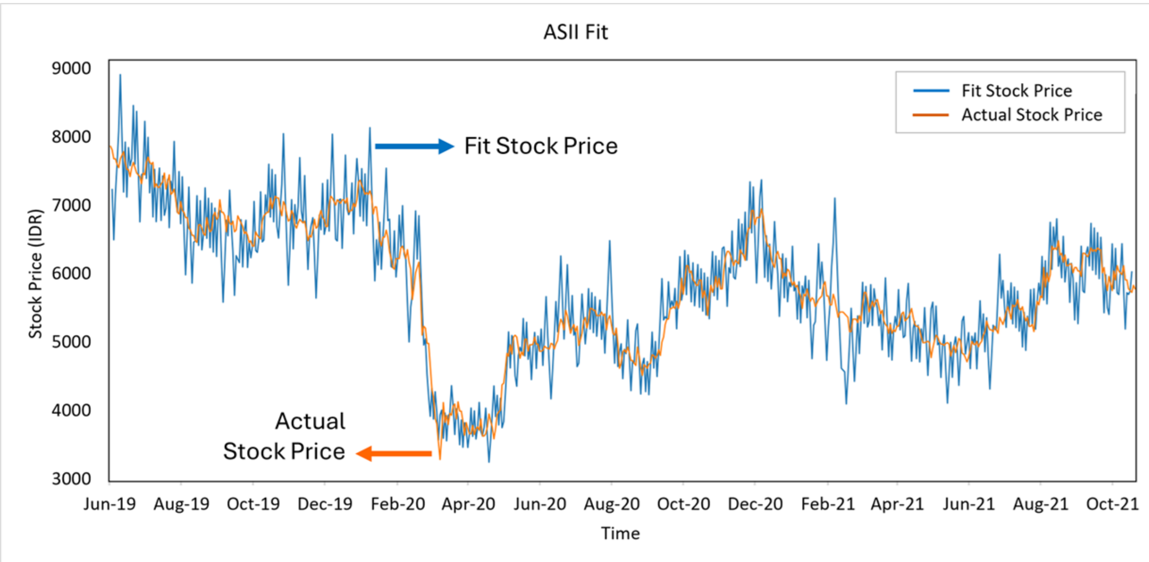

Fig. 9. Fit Stock Price for ASII

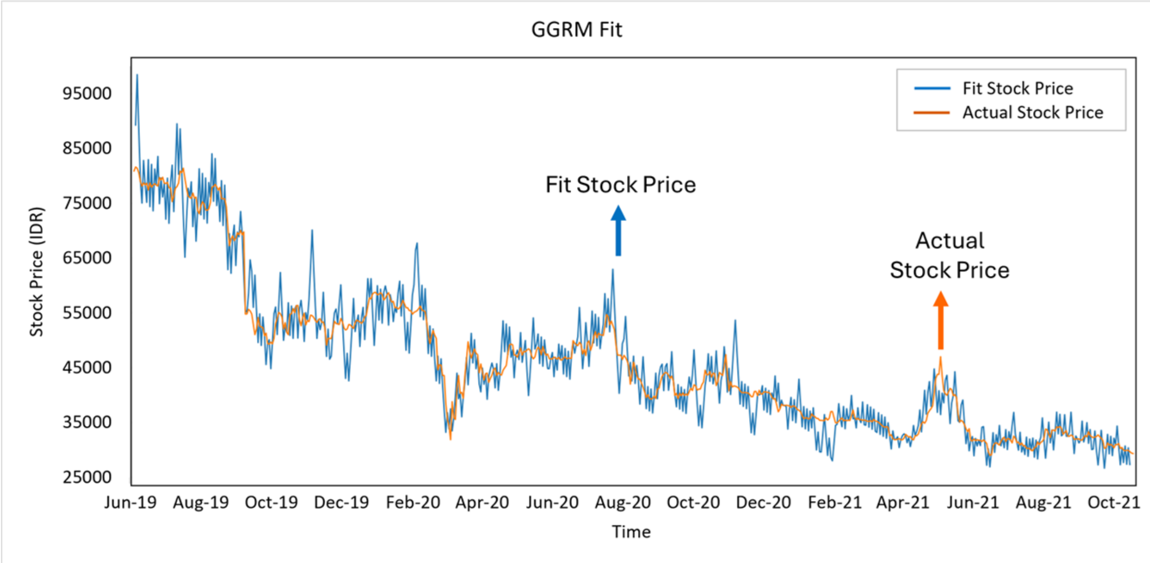

Fig. 10. Fit Stock Price for GGRM

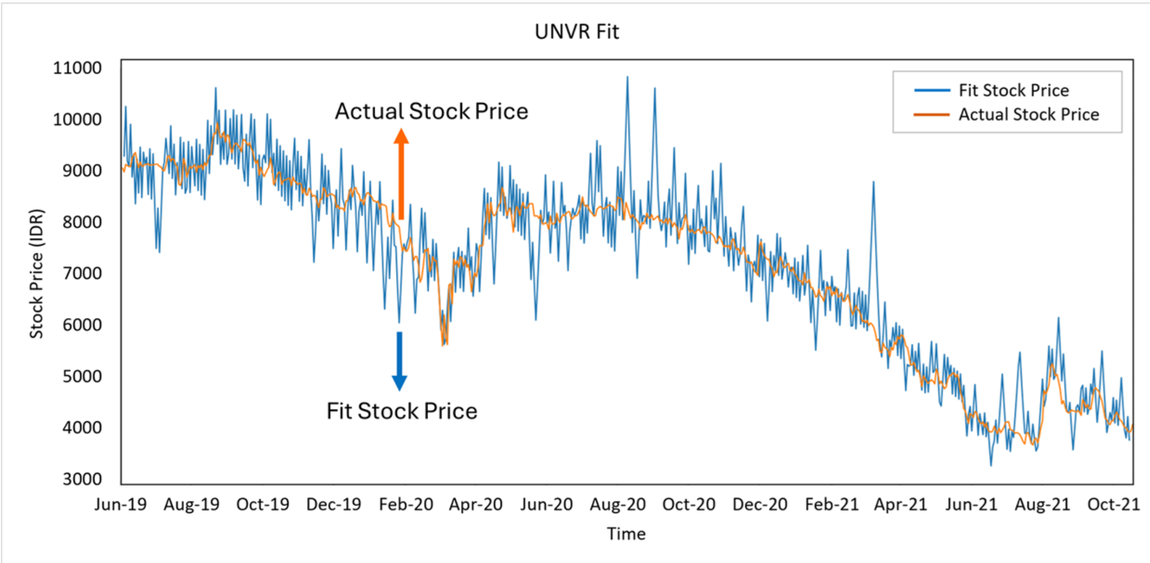

Fig. 11. Fit Stock Price for UNVR

TABLE III
THE INITIAL VALUE FOR DISCRETE-TIME MODEL

	BBCA	HMSP	ASII	GGRM	UNVR
Jun 10, 2019 (S_0)	IDR 5,580.00	IDR 3,360.00	IDR 7,675.00	IDR 79,300.00	IDR 8,930.00
Jun 11, 2019 (S_1)	IDR 5,910.00	IDR 3,380.00	IDR 7,625.00	IDR 80,000.00	IDR 8,860.00
Jun 12, 2019 (S_2)	IDR 5,845.00	IDR 3,380.00	IDR 7,500.00	IDR 79,775.00	IDR 9,000.00
$\alpha_0 = \alpha_1 = \alpha_2$	1.2572 x 10^{-5}	1.7721 x 10^{-6}	1.2873 x 10^{-6}	1.4678 x 10^{-7}	-2.6476 x 10^{-6}
$\beta_0 = \beta_1 = \beta_2$	-0.0736	-0.0060	-0.0099	-0.0117	0.0236

ASII, GGRM, and UNVR, respectively. In addition, Figure 19 shows the MAPE average for all five companies based on Figure 17 and 18. There was a significant change when the forecast started from January to April 2020; the MAPE value increased by more than 10%, except for UNVR. It may be due to uncertain conditions because of Covid-19 as a global pandemic. The model cannot predict the actual stock price well during these periods. However, Figure 19 describes that almost all MAPE averages are less than 10%.

Furthermore, ASII, as an automotive company, reaches MAPE for over 30% in this period. This condition may be due to a decline in annual car wholesales of more than 95 percent in this period. Almost all companies have a high MAPE only for this period, but the MAPE value for GGRM is also more than 15% in September 2019, March and September 2020, and July 2021. Many sources report that GGRM's revenue and net profit declined by at least 25% as a cigarette company due to COVID-19. It may cause the forecast results for GGRM to be less good than those of others. Meanwhile, the MAPE forecasting results for UNVR have the most stable MAPE values.

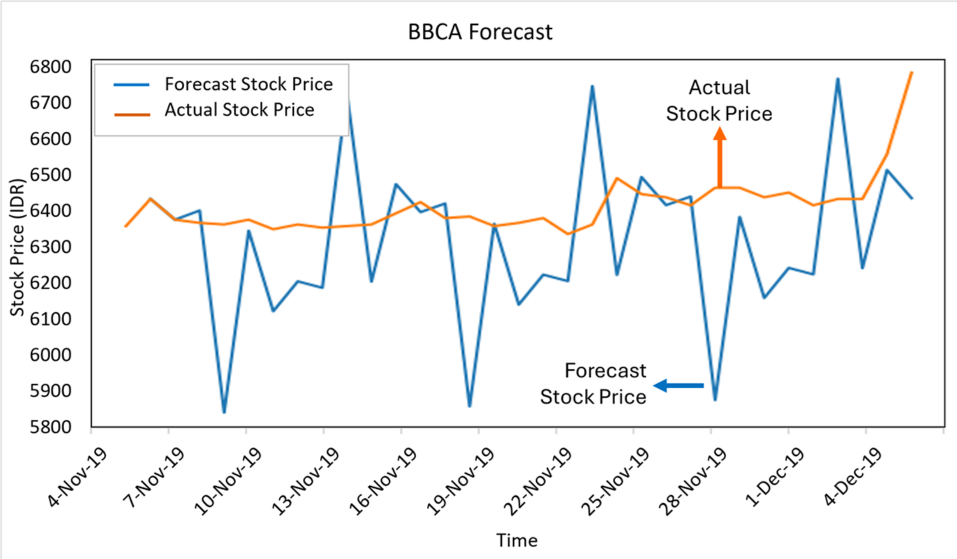

Fig. 12. Forecast Stock Price for BBCA

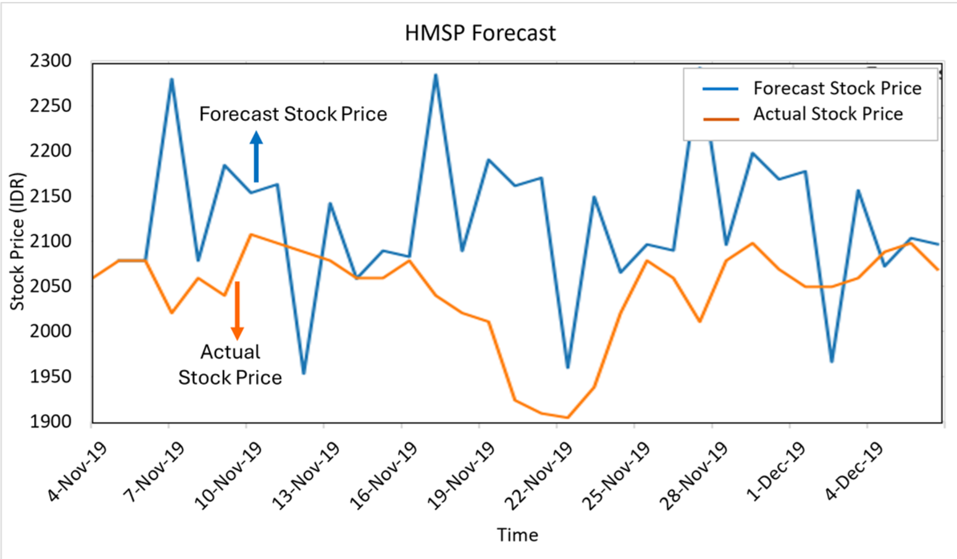

Fig. 13. Forecast Stock Price for HMSP

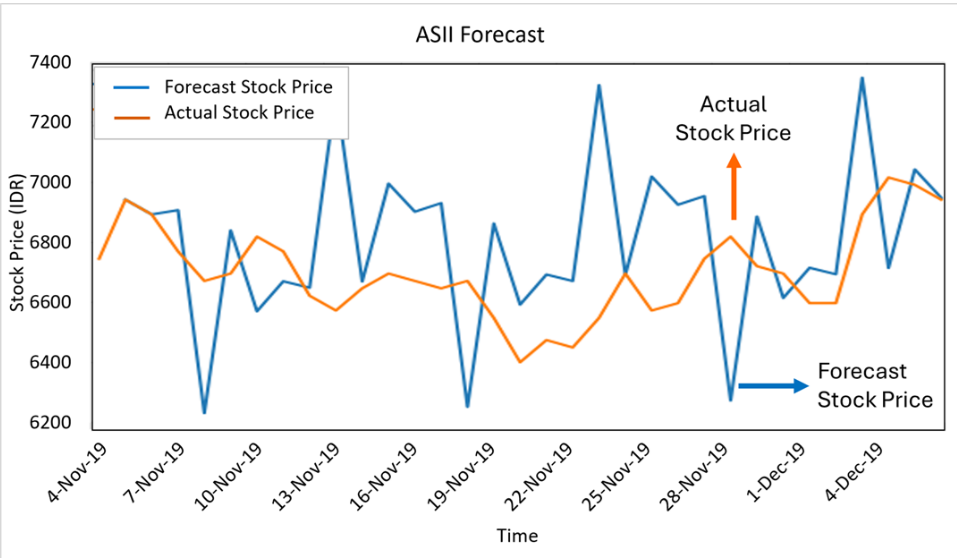

Fig. 14. Forecast Stock Price for ASII

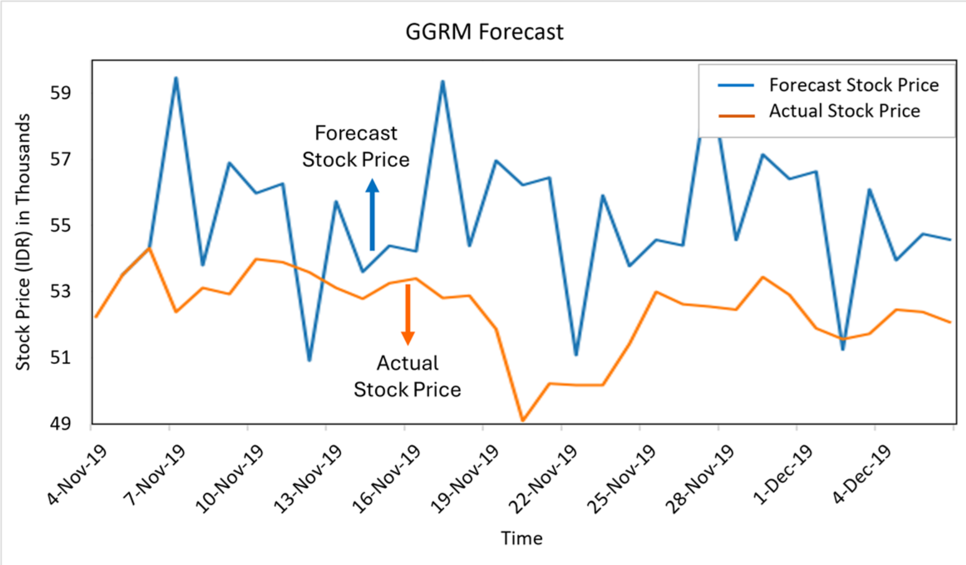

Fig. 15. Forecast Stock Price for GGRM

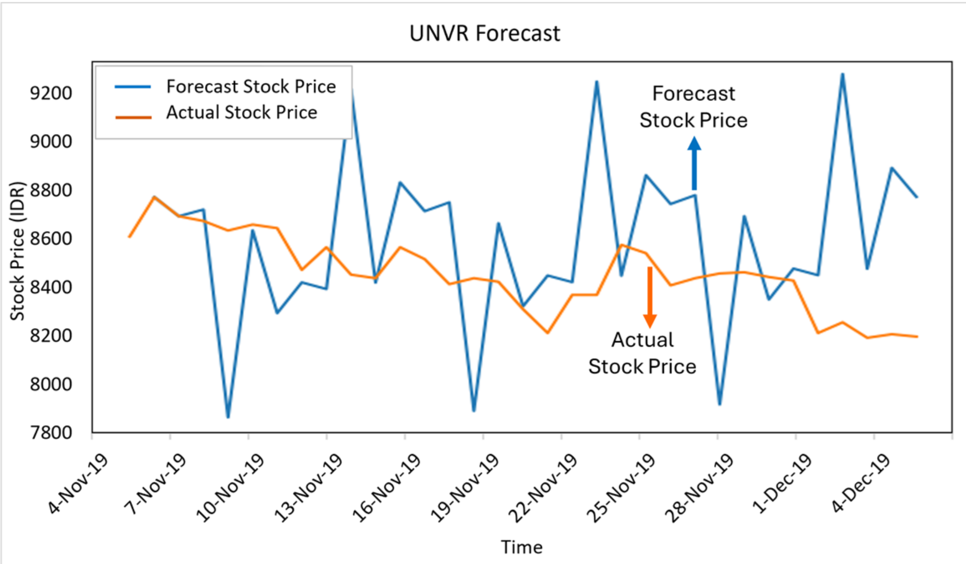

Fig. 16. Forecast Stock Price for UNVR

TABLE IV
MAPE AND ACCURACY CRITERIA FOR FORECAST STOCK PRICE

Company	MAPE Average	MAPE Median	MAPE Standard Deviation	High Accuracy
BBCA	2.713	4.059	2.797	92.5
HMSP	4.736	6.783	3.871	80.0
ASII	3.645	5.287	5.251	87.5
GGRM	5.880	5.405	5.420	77.5
UNVR	3.497	4.733	2.293	97.5

IV. CONCLUSION

A discrete-time differential model has successfully modelled the stock price fit and forecast by updating the logistic parameters over time. Some analytical approach was applied here to complete the numerical scheme before it was implemented in Python. The fit and forecast simulation results show that the model is very accurate since the MAPE values for these processes are less than 10%. Furthermore, based on the forecast simulations of different trading starting days, the MAPE value increased significantly from February to April 2020, which is related to the first Covid-19 case in Indonesia. It means that news sentiment has a significant influence on the stock market.

In addition, GUI development was constructed using the discrete-time logistic model. This GUI has been evaluated through interviews with several relevant users. The interview results show that this GUI is user-friendly and can help users observe stock market fluctuations in the next 30 days as a consideration to gain optimal returns.

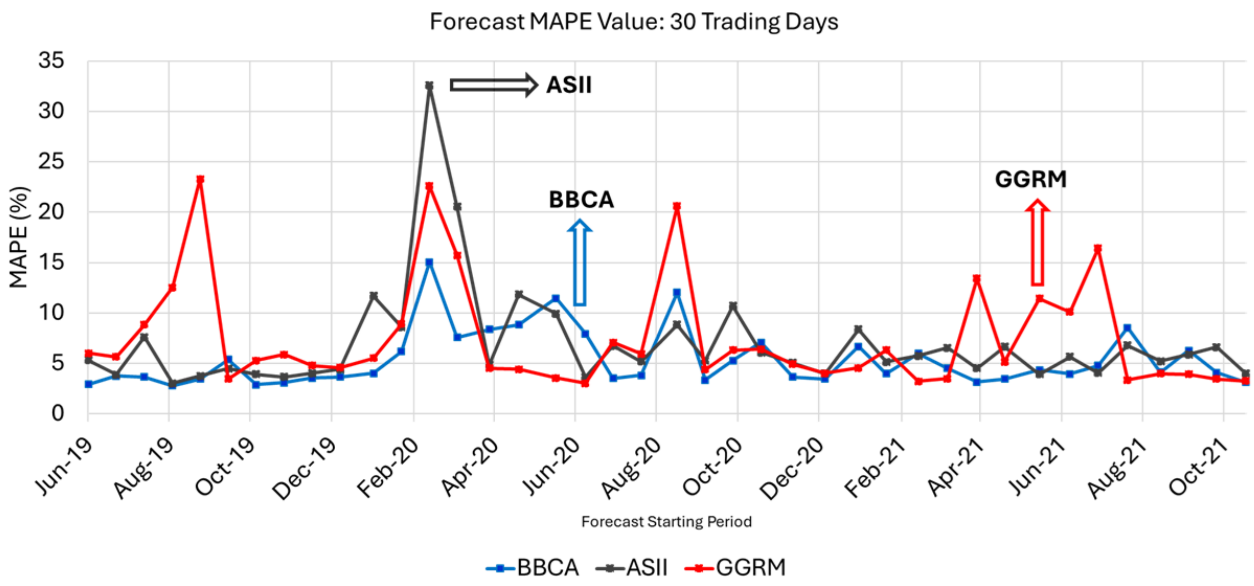

Fig. 17. The Forecast MAPE Value for 30 Trading Days in Different Starting Days: BBCA. ASII, and GGRM

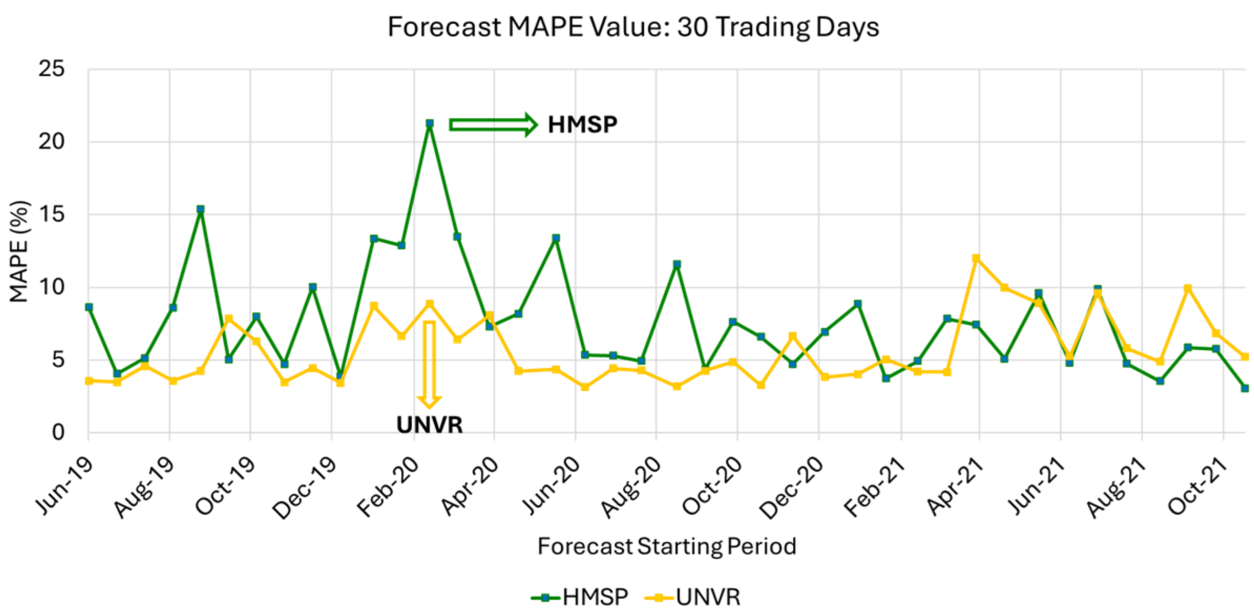

Fig. 18. The Forecast MAPE Value for 30 Trading Days in Different Starting Days: HMSP and UNVR

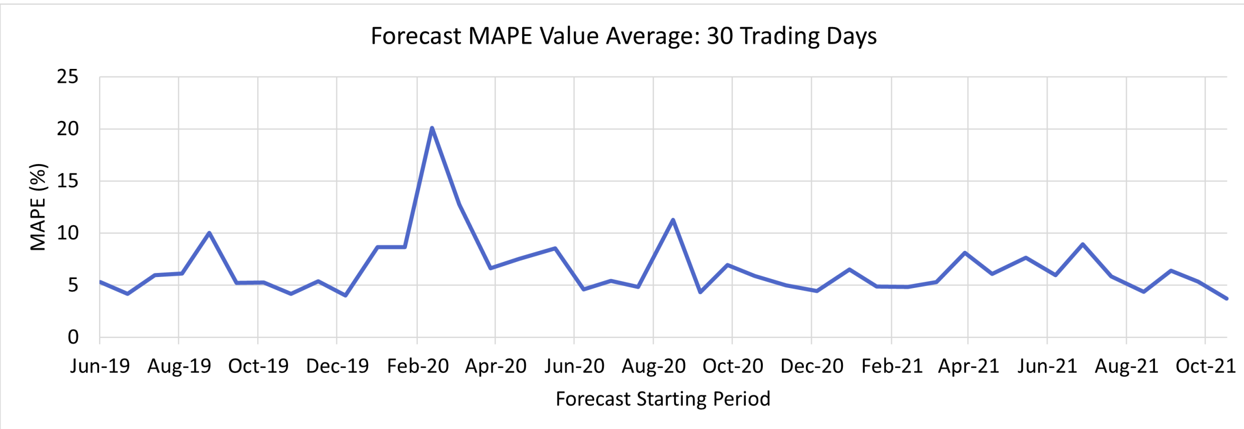

Fig. 19. The Forecast MAPE Value Average for 30 Trading Days in Different Starting Days

Data Availability Statement

The authors confirm that the data supporting the findings of this study are available in the article. The result of the finding data is accessible via GitHub at https://github.com/viska-noviantri/Stock-Price-Logistic-MAPE/tree/main, and may be downloaded free of charge.

Credit Authorship Contribution Statement

Andree Sulistio Chandra: Methodology, Investigation, Software, Data Curation. **Viska Noviantri**: Writing – original draft, review, and editing, Methodology, Investigation, Formal analysis, Conceptualization, Validation, Supervision. **Irene Anindaputri Iswanto**: Software, Visualization, Supervision.

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