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Comparing the Accuracy of Markov Switching – AR and Prophet Models in Predicting the Blue Bird Stock Prices

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ABSTRACT

One form of investment asset that is in high demand for profit is stocks. However, stock prices fluctuate, so a mathematical model is needed to model the movement and calculate stock price predictions. Stock price movements often form several groups (states) of change, so the Markov Switching Autoregressive (MS-AR) model can be used to model and calculate stock price predictions. In addition, stock price movements often contain trend and seasonal patterns, so the Prophet model can be used to model movements and calculate stock price predictions. In this study, the Prophet model is modified by generating random numbers that spread normally with parameter values obtained from the error value of the Prophet base model. This study aims to compare the performance of the MS-AR model with the Prophet model in predicting BIRD stock prices. This research is a quantitative study with secondary data in the form of BIRD stock closing price data for the period 11 February 2023 to 11 February 2024. In this study, two models, MS-AR and Prophet, were built separately. In the MS-AR model, it is necessary to pay attention to the assumptions of the data used, namely normal distribution and stationary. In the Prophet model, there are no special assumptions like those of the MS-AR model, but the Prophet model is good for data containing trends and seasonal patterns. The results of this study show that among the MS-AR models, the MS(2)-AR(3) model is the best model. In addition, the results show that the modified Prophet model performs better than the basic Prophet model. The goodness of model performance is measured by the Mean Absolute Percentage Error (MAPE) metric, with MAPE values for each model being 5.54% for MS(2)-AR(3), 3.38% for the Prophet base model, and 2.88% for Prophet modification. Based on the MAPE value, the Prophet (modified) model is able to predict the closing price of shares better than the MS(2)-AR(3) and Prophet (basic) models. The results of this study can be used by investors as a measuring tool in reading and determining stock price predictions.

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A. INTRODUCTION

The rapid advancements in technology have precipitated numerous alterations, profoundly impacting human activities and necessities. The financial and investment sector, once characterized by its sluggish pace due to its conventional, non-digital nature, has undergone a substantial transformation with the advent of financial technology (Fintech), a consequence of technological progress. Technology can help efficiently promote the capital market as a place to buy and sell shares (He et al., 2025). One of the financial assets investors demand significantly is stocks (Patriya, 2020). However, there are two challenges that stock investors must face, namely determining the type of shares and the time to buy shares (Agung et al., 2025).

Shares of a company have a value that is influenced by internal factors originating from related companies and external factors related to the economic conditions of associated countries (Sukartaatmadja et al., 2023). One factor affecting stock prices is the amount of demand and supply for a stock (Rahmadewi & Abundanti, 2018). Stock prices can increase or decrease over time which indicates that stock prices fluctuate. The ability to see stock price movements is an important thing that an investor needs to have (Almira & Wiagustini, 2020). Therefore, a method is needed that can be used to predict future stock prices.

Currently, many mathematical models have been developed to predict stock prices. Prediction is the process of estimating future needs (Geni et al., 2019). Calculating the predicted value is very important in the decision-making process in trading (Cappello et al., 2025). However, it is not uncommon for stock prices to have non-linear and non-stationary patterns, making it quite challenging to predict stock prices (Myint & Khaing, 2025). The predictive value of stock prices can be calculated using historical data of previous stock prices (Ashraf et al., 2025).

Stock price data classified as time series often form several dynamic state changes as a transition in stock price movements. Markov Regime Switching (MS) is a model that applies the Hidden Markov Model (HMM), which can define stock price movements in different states that are not observed (Yamamoto, 2015). However, using Markov switching models in predicting a value sometimes has not provided significant results (Lu et al., 2024). Furthermore, the strength of the model can be increased by combining other models that can reduce the weakness of the previous model (Kolambe & Arora, 2025). Markov Switching Autoregressive (MS-AR) is an example of combining two models that can be used to model movements and calculate stock price predictions. The MS-AR model performs better than the Autoregressive model (Lim et al., 2025).

Many mathematical models fail to recognize the complexity of stock prices that contain trends, seasonal patterns, and high fluctuations (Kolambe & Arora, 2025). The Prophet model is a model that contains three important components, namely trends, seasonality, and holidays (Shaju & Narayan, 2023). Furthermore, the Prophet model can handle data with outliers (Sanjaya et al., 2023). In addition, the ease of the Prophet model in modelling and predicting stock prices is one of the advantages of the Prophet model (Primawati & Trinoto, 2024). Based on this, the Prophet model can be used to model movements and calculate stock price predictions well.

A substantial body of research has been dedicated to stock price predictions. For instance, Hery et al. (2024) utilized the Prophet model to forecast Grab's stock price. Additionally, research conducted by Kömm & Küsters (2015) is related to using Markov Switching. The present study employs a zero-inflated price prediction model, integrating the Markov Switching model with autoregressive and heteroscedastic time series data. Additionally, research conducted by Yamamoto et al. (2015) focuses on the modelling of time series data using ARIMA and Markov switching models, particularly in the context of state transitions in cellular networks.

This research aims to predict the closing price of BIRD shares utilizing the Markov Switching Autoregressive (MS-AR) and Prophet Models. A comparison of the MS-AR and Prophet models' accuracy will be conducted, with the comparison determined by the Mean

Absolute Percentage Error (MAPE) value. A distinguishing feature of this research is the employment of the Prophet model, which differs from previous studies. In this study, the Prophet model is modified by adding a random number that spreads normally with parameters obtained from the Prophet base model error value. This is done to improve model performance accuracy and adjust the stochastic nature of stock price movements.

B. METHODS

The present study investigates the performance of two models in predicting stock prices, with the objective of assisting investors in determining the most effective model for interpreting stock price movements, particularly in the context of PT Blue Bird Tbk (BIRD) shares. The models employed in this study are the Markov Switching Autoregressive (MS-AR) and Prophet Models. The models employed in this study are the Markov Switching Autoregressive (MS-AR) and the Prophet models. The flowchart of this research step, as shown in Figure 1.

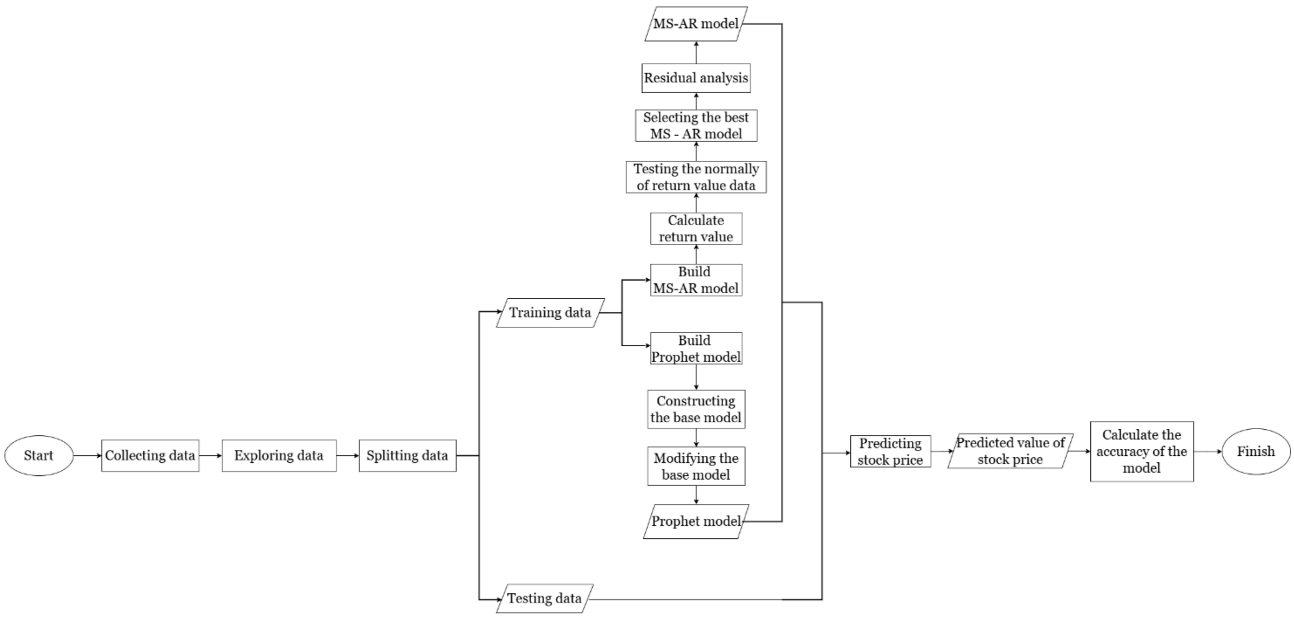

Figure 1. Research flowchart

The research methodology involves the construction of two models, namely MS-AR and Prophet, utilizing training data. Following the successful construction of these models, they were employed to predict BIRD stock prices using testing data. The performance of these models was subsequently determined by measuring the error in prediction using the Mean Absolute Percentage Error (MAPE) metric.

1. Type and Source of Data

The data used in this study is closing stock price data used to predict stock prices. The data is quantitative secondary data collected from the page https://finance.yahoo.com/. Stock closing price data is time series data that depends on time. This is in line with what Privalsky (2023) said that what distinguishes time series data from other data is its relationship with time. A time series is defined as a collection of measured values with a time sequence that can be expressed as follows.

$$Y_{t_1}, Y_{t_2}, \ldots, Y_{t_T}; Y_{t_k} \in \mathbb{R}^n, k = 1,2, \ldots, T, \quad (1)$$

where, $t_1 < t_2 < \cdots < t_T$ (Deistler & Scherrer, 2022). The time sequence used for stock closing prices in this study is daily data. The data time period used in this study is February 11, 2023, to February 11, 2024, with a total of 237 data. Furthermore, the data is divided into training and testing data. Training data is used to build a model with a total of 191 sorted initial period data. After the model is successfully built, it is necessary to test the performance of the model using testing data with a total of 46 sorted end-period data.

2. Analysis Procedures

In this research, two models will be constructed, namely MS-AR and Prophet. These models will be utilized to predict BIRD stock prices. However, the Prophet model will undergo modification by adding a random number that Spreads normally with the error value parameter obtained from the basic Prophet model. The analysis procedure for this research follows the following steps:

a. Data Collection

The data used in this study is the closing price data of BIRD shares for the time period February 11, 2023, to February 11, 2024. The data is collected in Microsoft Excel so that it can be processed to build and test the model.

b. Data Exploration

Data exploration is important to see the characteristics of the data to be used. This is intended to determine the suitability of the data with the model used. Data exploration used in this study includes checking for missing values, checking data stationarity, and checking data normality.

Checking for missing values is necessary so that the model built is not biased. Furthermore, data stationarity checks are important, especially for MS_AR models that require stationary data. Data stationarity checking can be done by performing the Augmented Dickey-Fuller (ADF) statistical test. The ADF test is a modification of the Dickey-Fuller (DF) test by adding an autoregressive component to the DF test model (Cipra, 2020). The accuracy of the ADF test can be influenced by the choice of lag length (Maitra & Politis, 2024). In ARIMA modeling, the value of d can be determined by the ADF test (Karmakar et al., 2024).

Checking data normality is important because good data used to build models is data that spreads normally. A formal test that can be used to check data normality is the Kolmogorov-Smirnov test. The Kolmogorov-Smirnov test can be used to compare an event that is quantitative and separated over time (Luiz & de Lima, 2021). The Kolmogorov-Smirnov test is one of the ten normality tests that shows the result that when the skewness and kurtosis coefficients are equal to or close to zero, the normality test is not affected by the sample size and vice versa (Demir, 2022).

c. Data Splitting

The data that has been collected previously is divided into training and testing data. The data division is done by considering the adequacy of training data to build a good model. In this study, the data was divided into 191 training data, or about 80% which was sufficient to construct the model. Furthermore, the rest of the data is used as testing data to test the performance of the model.

d. MS-AR Model Building

The MS-AR model is constructed through a series of processes. First, the data used in this study for the MS-AR model is return data, so it is necessary to calculate the return value. According to Ruppert & Matteson (2015), the return value can be determined in three forms: net return, gross return, and log return. The return value employed in this study is log return, which can be calculated using the following formula:

$$R_t = \log\left(\frac{Y_t}{Y_{t-1}}\right) \tag{2}$$

where, R_t is the value of log return, Y_t is value of stock price at time t, and Y_{t-1} is value of stock at time $t-1$. The second process in building the MS-AR model is to test the normality of the log return data. Furthermore, the third process is to test the stationarity of the log returns data. The second and third processes have been carried out previously in the data exploration step. The main process in building the MS-AR model is to select the best MS-AR model from several candidate models. The best model selection is based on Akaike's Information Criterion (AIC) value, the Mean Absolute Percentage Error (MAPE) value, and the number of parameters that are significant at the 5% significance level. The AIC value is commonly used to select an ARIMA model from several candidate ARIMA models (Makoni & Ndlovu, 2024). Selection of the best model with AIC value is done based on the smallest AIC value (Singh et al., 2024). Furthermore, the best model based on the MAPE value is the model with the smallest MAPE value. Then, the model with the most significant parameters at the 5% significance level (according to the number of parameters of each model), is the best. However, generally, the best model is the one with all parameters significant to the significance level. The last process in building the MS-AR model before it is used to predict stock prices is residual analysis to see white noise in the residuals of the selected model. Check white noise on residuals to see whether the variance value is constant (Hartanto, 2022). A model is good enough if the residuals contain white noise.

e. Prophet Model Building

The data used to build the Prophet model is the closing price data of BIRD stock directly. The first process in constructing the Prophet base model is to fit the data with the available package. The software used to build the Prophet model in this study is Julia 1.10.4 with the Python programming language. Furthermore, after successfully constructing the base model, the model is modified by adding a random number normally distributed with the distribution parameters obtained from the error value generated from the Prophet base model.

f. BIRD Stock Price Prediction

The MS-AR model, the Prophet base model, and the modified Prophet model are used to predict BIRD stock prices. Stock price predictions are performed for the number of tests used. Therefore, the stock price prediction in this study was performed for 46 periods into the future.

g. Model Accuracy Calculation

A good model used to predict data is a model with the best level of accuracy. Stock prices move stochastically, so there is uncertainty in making predictions (Liantoni & Agusti, 2020). One of the tools that can be used to measure the accuracy of a model is MAPE. The MAPE metric is scale-independent and the results are easy to understand, which is why MAPE is widely used to measure error rates (Kim & Kim, 2016). The MAPE value is appropriate for the financial sector because the level of profit and loss is generally measured in relative terms (de Myttenaere et al., 2016). According to Babarinde & Madyira (2022), the MAPE value can be determined using the following formula.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{Y_t - \hat{Y}_t}{Y_t}\right| \times 100\% \tag{3}$$

where, $\hat{Y}_t$ is the predicted value of the stock's closing price. Markov-switching is a model with the application of a hidden Markov model (HMM) with an unobserved state (Yamamoto et al., 2015). The Markov-switching model was first introduced by Hamilton and is now widely used in various fields, especially finance. Based on Javier & Héctor (2021), for example, it is assumed that the random variable S_t takes values from the finite set $\{1,2,\dots,m\}$ and the probability of the random variable S_t taking a value j depends on the previous value S_{t-1}. The sequence (S_t) is called an m-state homogeneous Markov chain with stationary transition probability $\{p_{ij}\}_{i,j=1,2,\dots,m}$, where p_{ij} is the probability that state i is followed by state j. For each $i \in \{1,2,\dots,m\}$, the following equation applies,

$$p_{i1} + p_{i2} + \cdots + p_{im} = 1 \tag{4}$$

Based on Inayati et al. (2024), the mathematical formula of the MS-AR(p) model can be written as follows.

$$Y_t^M = c_{S_t} + \sum_{p=1}^{P} \phi_{pS_t} Y_{t-p} + \epsilon_t \tag{5}$$

where Y_t^M is the predicted value of BIRD stock prices with the MS-AR(p) model, c_{S_t} and ϕ_{pS_t} are constants that depend on the state, and $\epsilon_i, i = 1,2,\dots,m$ is a random numbers variable with a variance value that is only affected by the state, i.e. for $S_t = i$ obtained $\epsilon_i \sim \mathcal{N}(0, \sigma_i^2)$. In simple terms, MS-AR modelling as shown in Figure 2.

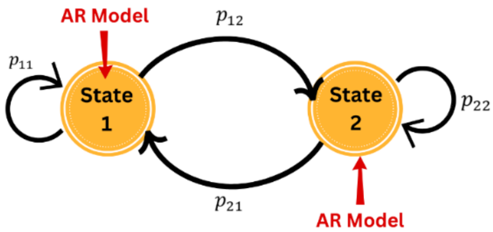

Figure 2. Illustration of MS-AR modelling

Based on Figure 2, each state formed from the Markov Switching model is modelled with an Autoregressive (AR) model. Furthermore, the probability value of moving (transition) from state 1 to state 1 is p_{11}, and from state 1 to state 2 is p_{12}. Then, the value of the transition opportunity from state 2 to state 2 is p_{22}, and from state 2 to state 1 is p_{21}. Determining the number of states can be done by looking at the characteristics of the stock price data or by using traditional clustering methods, such as k-means. K-means is a widely used algorithm for clustering due to its simplicity and effective fine-tuning capabilities (Fränti & Sieranoja, 2019). One way to determine the optimal k value in the k-means algorithm is the elbow method. Another model used in this research is the Prophet. Prophet is a package released by Facebook in 2017. Prophet is suitable for time series data, especially for data that contains trend, seasonal, and holiday patterns. Based on (Taylor & Letham, 2018), the mathematical equation for the Prophet model can be written as follows.

$$Y_t^P = g_t + s_t + h_t + \epsilon_t \tag{6}$$

where Y_t^P is the predicted value of BIRD stock prices with the Prophet model, g_t growth (trend) component, s_t seasonal component, h_t holiday component, and ϵ_t error component. The basic Prophet model in this study was built using the Prophet package available in the Python programming language. The mathematical equations for the basic Prophet model in this study are written as follows.

$$Y_t^P = g_t + s_t. \tag{7}$$

Based on Equation (7), it can be seen that the Prophet base model does not contain a random component that allows the prediction results to be the same at each iteration. This shows the deterministic nature of the results obtained and is not consistent with the nature of stock prices, which move stochastically. The basic Prophet model is modified in this study by adding random numbers that are normally distributed with the value of the distribution parameter obtained from the error value. This is done so that the prediction results obtained have properties consistent with the nature of stock prices that move stochastically. In addition, random numbers are added to increase the accuracy of modelling the movement and calculating the predicted value of stock prices. The error value (ϵ_t) is obtained by calculating the difference between the actual data value (Y_t) and the prediction result with the basic Prophet model (Y_t^P), which is formulated as follows.

$$\epsilon_t = Y_t - Y_t^P. \tag{8}$$

Furthermore, the error values obtained are used to calculate the normal distribution parameters, namely μ_{error} and σ_{error}, which are formulated as follows.

$$\mu_{error} = \frac{1}{n}\sum_{t=1}^{n} \epsilon_t \tag{9}$$

and,

$$\sigma_{error} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(\epsilon_t - \mu_{error})^2}\,. \tag{10}$$

The values μ_{error} and σ_{error} are used to generate a random number, or in this study, a random error value $(\tilde{\epsilon}_t)$. The generated numbers are normally distributed with previously calculated parameters, so the generated random numbers can be written as $\tilde{\epsilon}_t \sim \mathcal{N}(\mu_{error}, \sigma^2_{error})$. Furthermore, the generated random numbers are entered into the mathematical equations of the basic Prophet model, so that the modified Prophet model is obtained, which is written as follows.

$$Y_t^{PM} = g_t + s_t + \tilde{\epsilon}_t \tag{11}$$

where Y_t^{PM} is the predicted value of BIRD stock prices with the modified Prophet model.

C. RESULT AND DISCUSSION

1. Data Exploration

Data exploration is important at the beginning of the research to see if the characteristics of the data fit the selected model. The first process in data exploration in this study is to check for missing values so that the model built is not biased. Based on the inspection results, there are no missing values in the training data used, so the data is good enough to be used to build the model. The second process of data exploration in this study is to check the stationarity of the data with the ADF test. Based on the ADF test on the training data, the $p-value = 0.476 > 0.05 = \alpha$ is obtained, which means that the training data is not stationary. The MS-AR model requires stationary data, so the BIRD stock closing price data (training) cannot be used directly. One way to overcome this is to calculate the log return value of the training data using Equation (2). Based on the ADF test on the log return data, the $p-value = 1.069e-15 < 0.05 = \alpha$, which means that the log return data is stationary.

The third process of data exploration in this study is to check the normality of the data with the Kolmogorov-Smirnov test. Based on the Kolmogorov-Smirnov test on the training data, the $p-value = 0.108 > 0.05 = \alpha$ is obtained, which means training data is normally distributed. In addition, for the log return data, $p-value = 0.404 > 0.05 = \alpha$ is obtained, which means log return data is normally distributed. Therefore, in this study, the MS-AR model was built by log return data (training), while the Prophet model was built directly by closing stock price data (training).

2. Markov Switching Autoregressive (MS-AR) Model

a. Cluster Analysis

To build the MS-AR model, it is necessary to determine the number of states in the data used. A simple way to determine the number of states in the data is to use traditional clustering methods such as k-means. In the k-means algorithm, the method that can be used to determine the optimal number of k values is the elbow method shown in Figure 3.

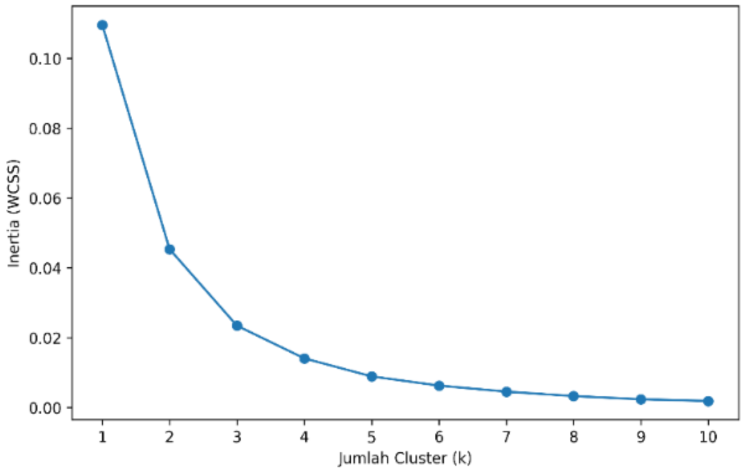

Figure 3. Elbow method to determine the optimal $\boldsymbol{k}$ value

Based on the figure 3, it can be seen that there is a fairly steep decrease in inertia value between cluster point 1 and cluster point 2. This shows that the optimal value of k in this study is two. Therefore, the number of states used in this study is two.

b. MS-AR Model Construction

The number of states in the data used in this study was obtained by the previous elbow method, which is 2 states. Next, it is necessary to determine the value of the autoregressive order, namely the correct order p for the MS-AR model in this study. The determination of the autoregressive order value in this study was done by trial and error by trying various possibilities. Furthermore, the order p is selected based on the small AIC, MAPE values and has parameters that are all or almost all significant at the 5% significance level and obtained order $p = 3$. The MS-AR model in this study is MS(2)-AR(3), based on the number of states and the autoregressive order value. Estimated parameter values for the MS(2)-AR(3) model are determined in each state, namely states 1 and 2. The estimated parameter values for each state are shown in Table 1.

Table 1. Estimation of MS(2)-AR(3) model parameters

State	**AIC**	**MAPE (%)**	**Parameter**	**Coefficient**	**Pr(> |z|)**
1	-859.86	5.82	Constant	-0.0047	0.009*
			AR(1)	-0.2019	0.022*
			AR(2)	-0.2470	0.006*
			AR(3)	-0.0972	0.252
2	-859.86		Constant	0.0169	0.006*
			AR(1)	0.6974	0.000*
			AR(2)	0.6281	0.010*
			AR(3)	-0.3255	0.041*

**parameters are significant at the 5% level*

Based on Table 1, it can be seen that the AIC value is the same in each state. The AIC value given is quite small compared to the AIC value in other autoregressive orders. Furthermore, the MAPE value for the MS(2)-AR(3) model on the training data is 5.82% <10%, which means that the model has seen the movement of the training data very well. In addition, only 1 parameter is insignificant in state 1, while all parameters are significant in state 2. Then, based on Table 1 and Equation (5), the mathematical equation for the MS(2)-AR(3) model can be written as follows:

To state 1:

$$Y_t^M = -0.0047 - 0.2019Y_{t-1} - 0.2470Y_{t-2} - 0.0972Y_{t-3} + \epsilon_t.$$

To state 2:

$$Y_t^M = 0.0169 + 0.6974Y_{t-1} + 62810.2470Y_{t-2} - 0.3255Y_{t-3} + \epsilon_t.$$

with the following transition probability matrix,

$$P = \begin{bmatrix} 0.70720460 & 0.29279540 \\ 0.77431698 & 0.22568302 \end{bmatrix}.$$

The next step in building the MS-AR model is to perform residual analysis. Residual analysis is performed to check the presence of white noise in the residuals. In this study, the white noise test is performed with the Ljung-Box test. The p-value obtained from the Ljung-Box test is $0.999872 > 0.05$, which means that the residuals in the model already contain white noise. Based on this, the MS(2)-AR(3) model can be good enough to predict BIRD stock prices.

c. BIRD Stock Price Prediction

The MS(2)-AR(3) model that has been constructed previously is used to predict the predicted value of the closing price of BIRD shares in the next 46 days. The data used to build the MS(2)-AR(3) model is log return data, so the forecasting results obtained are log return values. Therefore, the log return value needs to be converted into the closing price of the stock using Equation (2). The predicted value of the closing price of BIRD stocks in the next 46 days as shown in Figure 4.

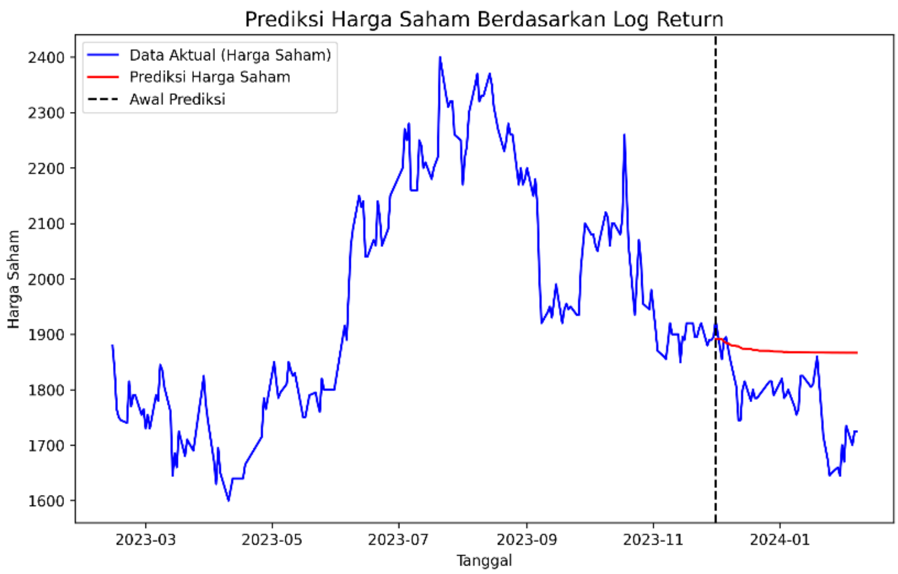

Figure 4. BIRD stock price prediction with MS(2)-AR(3)

Figure 4 shows that the predicted value of the closing price of BIRD stock has decreased insignificantly. The predicted value, represented by the red line, tends to be flat, and some values are overlap with the actual test data at several points. Therefore, the prediction results of the MS(2)-AR(3) model are good enough.

2. Prophet Model

a. Base Model

The Prophet base model is built according to the mathematical equation given by Equation (7). The data used to construct the Prophet base model is the closing price data of BIRD stock (training) directly. The results of predicting the closing price of BIRD stock with the Prophet base model as shown in Figure 5.

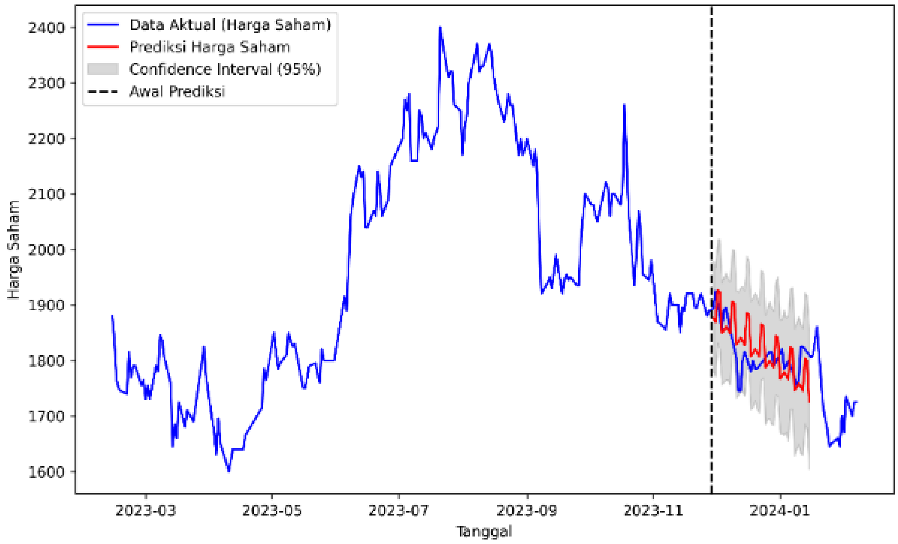

Figure 5. BIRD stock price prediction with Prophet (base)

Based on the figure 5, it can be seen that the prediction results given by the Prophet model follow the trend formed from the actual closing price data on the training data. Based on Figure 5, it can be seen that there is still a difference between the predicted stock prices and the actual data in the testing data. However, the difference is not large enough and the prediction results are still in the confidence interval for predicting the closing price of BIRD shares. Therefore, the prediction results with the Prophet (base) model are good enough and close to the actual value.

b. Modified Model

Based on the mathematical equations in the Prophet base model, it can be seen that there is no random number component. In addition, the prediction results given by the basic Prophet model always give the same results. This shows that the Prophet base model is deterministic, which is not consistent with the nature of stock prices, which are stochastic. The Prophet base model is built according to the mathematical equation given by Equation (7).

The Prophet model modification performed in this study is to add a random number so that the model is stochastic according to Equation (11). The random number is generated by following a normal distribution with parameters obtained from the error value of the Prophet base model. The error value is calculated according to Equation (8). In addition, the error value obtained is used to calculate the normal distribution parameters according to Equations (9) and (10). The normal distribution parameters obtained from the error values are $\mu_{error} = -43.154$, and $\sigma_{error} = 58.385$. Therefore, the random numbers to be generated can be written as $\tilde{\epsilon}_t \sim \mathcal{N}(\mu_{error}, \sigma_{error}^2)$ or $\tilde{\epsilon}_t \sim \mathcal{N}(-43.154, 58.385^2)$.

The random numbers generated with normal distribution or $\tilde{\epsilon}_t \sim \mathcal{N}(-43.154, 58.385^2)$ are added to the mathematical equations of the basic Prophet model and form the modified Prophet model written in Equation (11). The modified Prophet model has a random component, which is consistent with the stochastic nature of stock prices. The results of predicting the closing price of BIRD stock for the next 46 days using the modified Prophet model as shown in Figure 6.

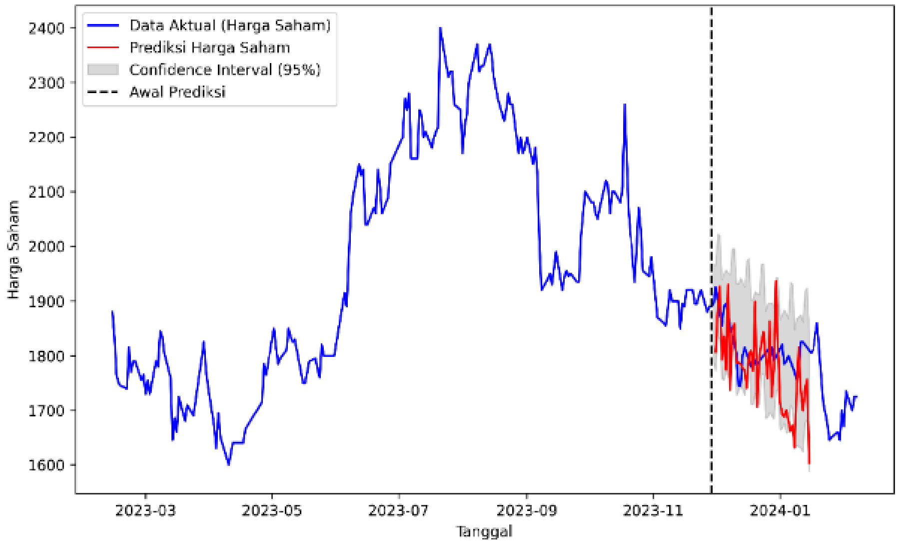

Figure 6. BIRD stock price prediction with Prophet (modified)

From the above figure, it can be seen that the prediction results with the modified Prophet model have a downward trend. The difference between the actual data (test) and the prediction results with the modified Prophet model tends not to be too large. In addition, when compared with the prediction results obtained with the base Prophet model, the prediction results obtained with the modified Prophet model provide results that are more in line with the characteristics of stock prices that move stochastically due to the influence of factors that affect stock price movements.

c. Model Accuracy

In this study, the calculation of the model accuracy level is performed using the MAPE metric. The calculation of the MAPE value is done according to equation (3). The accuracy levels of the MS(2)-AR(3), Prophet (base), and Prophet (modified) models are shown in Table 2.

Table 2. Model accuracy with MAPE metric

Model	MAPE (%)	Description
MS(2) −AR(3)	5.54	Very well
Prophet (base)	3.38	Very well
Prophet (modified)	2.88	Very well

Table 2 shows that the MAPE value provided by these models is <10%, which means that the model predicted the closing price of BIRD stock very well. However, among these models, the Prophet (modified) model has the lowest MAPE value. Therefore, the best model among these models for the BIRD closing stock price data used in this study is the Prophet (modified) model. The goodness of the MS-AR model in predicting out sample or testing data is in accordance with research conducted by Zhang et al. (2020), which says that the model with Markov Switching is able to predict well compared to those Markov Switching. However, modelling stock prices using only the Markov Switching model sometimes gives suboptimal results, so the Markov Switching model needs to be combined with other models for optimal results (Lu et al., 2024).

Furthermore, research with the Prophet model has been conducted by Wang & Vo (2025), who compared the Prophet model with ARIMAX. The results showed that the Prophet model was not better than ARIMAX in predicting stock prices in the Vietnam stock price index. Then, other research related to prediction using the Prophet model was conducted by Chang et al. (2024), which concluded that Prophet is not better than the Long Short-Term Memory (LSTM) and Extreme Gradient Boosting (XGBoost) models in predicting the stock prices of Apple, Amazon, Google, and Microsoft. The shortcomings of the Prophet model can be due to data that is unsuitable for the Prophet model or the need for modifications to the model. This distinguishes these studies from this study, which modified the Prophet model and obtained an excellent model in predicting the closing price of BIRD stock.

D. CONCLUSION AND SUGGESTIONS

The stock price of PT Blue Bird (BIRD) can be predicted very well using the Markov Switching (MS-AR) and Prophet models. The Prophet model can be modified by adding random numbers that are normally distributed with the distribution parameters obtained from the error value. The MAPE value obtained for the MS(2)-AR(3) model is 5.54%, the Prophet (base) model is 3.38%, and the Prophet (modified) model is 2.88%. Based on the MAPE value obtained, the Prophet (modified) model is the best model for predicting the closing price of BIRD stock compared to the MS(2)-AR(3) and Prophet (base) models. The models that have been built, especially the Prophet (modified) model, are simple and do not require many assumptions to be met in modelling and predicting BIRD stock prices.

Future research may use other models such as the MSAR-TVP model or a combination of the MS-AR model with Prophet. In addition, in this study, random numbers were generated according to a normal distribution with parameters obtained from the error values of the Prophet model. In future research, the random numbers can be generated with other distributions such as standard normal, uniform, or other distributions depending on the data used.

REFERENCES

Agung, I. W. P., Arifin, T., Junianto, E., Rabbani, M. I., & Mayangsari, A. D. (2025). Stock's selection and trend prediction using technical analysis and artificial neural network. *International Journal of Advances in Applied Sciences*, *14*(1), 151–163. https://doi.org/10.11591/ijaas.v14.i1.pp151-163

Almira, N. P. A. K., & Wiagustini, N. L. P. (2020). Return on Asset, Return on Equity, Dan Earning Per Share Berpengaruh Terhadap Return Saham. *E-Jurnal Manajemen Universitas Udayana*, *9*(3), 1069. https://doi.org/10.24843/ejmunud.2020.v09.i03.p13

Ashraf, S., Khalid, A., Batool, B., Tlija, M., Jana, C., & Pamucar, D. (2025). Stock Market Prediction Based Multi-Attribute Decision Making Model Using Picture Fuzzy Z^-Information. *International Journal of Computational Intelligence Systems*, *18*(1). https://doi.org/10.1007/s44196-024-00664-9

Babarinde, T. O., & Madyira, D. M. (2022). Dataset and ANFIS model prediction of the performance of graphene nano-LPG in domestic refrigerator system. *Data in Brief*, *44*, 108548. https://doi.org/10.1016/j.dib.2022.108548

Cappello, C., Congedi, A., De Iaco, S., & Mariella, L. (2025). Traditional Prediction Techniques and Machine Learning Approaches for Financial Time Series Analysis. *Mathematics*, *13*(3), 1–21. https://doi.org/10.3390/math13030537

Chang, V., Xu, Q. A., Chidozie, A., & Wang, H. (2024). Predicting Economic Trends and Stock Market Prices with Deep Learning and Advanced Machine Learning Techniques. *Electronics (Switzerland)*, *13*(17). https://doi.org/10.3390/electronics13173396

Cipra, T. (2020). *Time Series in Economics and Finance*. Springer Nature Switzerland. https://doi.org/10.1007/978-3-030-46347-2

de Myttenaere, A., Golden, B., Le Grand, B., & Rossi, F. (2016). Mean Absolute Percentage Error for regression models. *Neurocomputing*, *192*, 38–48. https://doi.org/10.1016/j.neucom.2015.12.114

Deistler, M., Scherrer, W. (2022). *Time Series Models*. Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-13213-1

Demir, S. (2022). Comparison of Normality Tests in Terms of Sample Sizes under Different Skewness and Kurtosis Coefficients. *Journal of Assessment Tools in Education, 9*(2), 397–409. https://doi.org/10.21449/ijate.1101295

Fränti, P., & Sieranoja, S. (2019). How much can k-means be improved by using better initialization and repeats? *Pattern Recognition*, *93*, 95–112. https://doi.org/10.1016/j.patcog.2019.04.014

Geni, B. Y., Santony, J., & Sumijan. (2019). Prediksi Pendapatan Terbesar pada Penjualan Produk Cat dengan Menggunakan Metode Monte Carlo. *Jurnal Informatika Ekonomi Bisnis*, *1*(4), 15–20. https://doi.org/10.37034/infeb.v1i4.5

Hartanto, B. (2022). Analisis Prediksi Indeks Saham Syariah Indonesia (ISSI) Menggunakan Metode Garch. *EKONOMIKA45 : Jurnal Ilmiah Manajemen, Ekonomi Bisnis, Kewirausahaan*, *10*(1), 281–288. https://doi.org/10.30640/ekonomika45.v10i1.893

He, G., Li, Z., Yu, L., & Zhou, Z. (2025). Does commercial reform embracing digital technologies mitigate stock price crash risk? *Journal of Corporate Finance*, *91*, 102741. https://doi.org/10.1016/j.jcorpfin.2025.102741

Hery., Haryani, C. A., Widjaja, A. E., & Mitra, A. R. (2024). Harnessing the Power of Prophet Algorithm for Advanced Predictive Modeling of Grab Holdings Stock Prices. *Journal of Applied Data Sciences, 5*(2), 326–341. https://doi.org/10.47738/jads.v5i2.181

He, G., Li, Z., Yu, L., & Zhou, Z. (2025). Does commercial reform embracing digital technologies mitigate stock price crash risk? *Journal of Corporate Finance*, *91*, 102741. https://doi.org/10.1016/j.jcorpfin.2025.102741

Inayati, S., Iriawan, N., & Irhamah. (2024). A Markov Switching Autoregressive Model with Time-Varying Parameters. *Forecasting*, *6,* 568–590. https://doi.org/10.3390/forecast6030031

Javier, L., & Héctor, H. (2021). *Theory and Applications of Time Series Analysis and Forecasting*. Springer Nature Switzerland. https://doi.org/10.3390/forecast6030031

Karmakar, R., Chatterjee, S., Datta, D., & Chakraborty, D. (2024). Application of harmony search algorithm in optimizing autoregressive integrated moving average : A study on a data set of Coronavirus Disease 2019. *Systems and Soft Computing, 6*.

https://doi.org/10.1016/j.sasc.2023.200067

Kim, S., & Kim, H. (2016). A new metric of absolute percentage error for intermittent demand forecasts. *International Journal of Forecasting*, *32*(3), 669–679. https://doi.org/10.1016/j.ijforecast.2015.12.003

Kolambe, M., & Arora, S. (2025). Time Series Forecasting Enhanced by Integrating GRU and N-BEATS. *International Journal of Information Engineering and Electronic Business*, *17*(1), 140–158. https://doi.org/10.5815/ijieeb.2025.01.07

Kömm, H., & Küsters, U. (2015). Forecasting zero-inflated price changes with a Markov switching mixture model for autoregressive and heteroscedastic time series. *International Journal of Forecasting*, *31*(3), 598–608. https://doi.org/10.1016/j.ijforecast.2014.10.008

Liantoni, F., & Agusti, A. (2020). Forecasting bitcoin using double exponential smoothing method based on mean absolute percentage error. *International Journal on Informatics Visualization*, *4*(2), 91–95. https://doi.org/10.30630/joiv.4.2.335

Lim, S., Flores, E., Barnett, C., & Islam, M. M. (2025). Analyzing Cambodia Securities Exchange Index Returns using the Markov-Switching Autoregressive Model. *International Journal of Economics and Financial Issues* , *15*(2), 98–105. https://doi.org/10.32479/ijefi.17647

Lu, X., Zeng, Q., Zhong, J., & Zhu, B. (2024). International stock market volatility: A global tail risk sight. *Journal of International Financial Markets, Institutions and Money*, *91*. https://doi.org/10.1016/j.intfin.2023.101904

Luiz, A. J. B., & de LIMA, M. A. (2021). Application of the kolmogorov-smirnov test to compare greenhouse gas emissions over time. *Revista Brasileira de Biometria*, *39*(1), 60–70. https://doi.org/10.28951/RBB.V39I1.498

Maitra, S., & Politis, D. N. (2024). Prepivoted Augmented Dickey-Fuller Test with Bootstrap-Assisted Lag Length Selection. *Stats*, *7*(4), 1226–1243. https://doi.org/10.3390/stats7040072

Makoni, T., & Ndlovu, N. T. (2024). Modelling and forecasting Masvingo Province maternal mortality using time series models. *Statistics Optimization and Information Computing, 12*, 1543–1552. https://doi.org/10.19139/soic-2310-5070-2011

Myint, K. N., & Khaing, M. (2025). Predictive Analytics System for Time Series Stock Data Using LSTM with Residual Unit and Attention Mechanism. *International Journal of Intelligent Engineering and Systems*, *18*(1), 1137–1150. https://doi.org/10.22266/ijies2025.0229.82

Patriya, E. (2020). Implementasi support vector machine pada prediksi harga saham gabungan (IHSG). *Jurnal Ilmiah Teknologi dan Rekayasa, 25*(100), 24–38. https://doi.org?10.35760/tr.2020.v25i1.2571

Primawati, A., & Trinoto, A. A. (2024). Evaluasi Kinerja Prophet untuk Prediksi Harga Emas Berjangka. *Faktor Exacta*, *17*(1), 40–46. https://doi.org/10.30998/faktorexacta.v17i1.22013

Privalsky, V. (2023). *Progress in Geophysics Practical Time Series Analysis in Natural Sciences*. Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-16891-8

Rahmadewi, P. W., & Abundanti, N. (2018). Pengaruh Eps, Per, Cr Dan Roe Terhadap Harga Saham Di Bursa Efek Indonesia. *E-Jurnal Manajemen Universitas Udayana*, *7*(4), 2106. https://doi.org/10.24843/ejmunud.2018.v07.i04.p14

Ruppert, D., & Matteson, D. S. (2015). *Statistics and Data Analysis for Financial Engineering*. Springer. https://doi.org/10.1007/978-1-4939-2614-5

Sanjaya, H., Angga Kurniawan, Ibnu Ickwantoro, Abdul Ra'uf Alfansani, Kusrini, & Dina Maulina. (2023). Prediksi Jumlah Kejadian Titik Panas Pada Lahan Gambut Di Indonesia Menggunakan Prophet. *INFOTECH Journal*, *9*(2), 354–360. https://doi.org/10.31949/infotech.v9i2.6073

Shaju, B., & Narayan, V. (2023). Prediction Model for Stock Trading using Combined Long Short Term Memory and Neural Prophet with Regressors. *International Journal of Intelligent Engineering and Systems*, *16*(6), 956–964. https://doi.org/10.22266/ijies2023.1231.79

Singh, R. K., Singh, Y., Kumar, S., Kumar, A., & Alruwaili, W. S. (2024). Mapping Risk – Return Linkages and Volatility Spillover in BRICS Stock Markets through the Lens of Linear and Non-Linear GARCH Models. *Journal of Risk and Financial Management, 17*(10), 1-26. https://doi.org/10.3390.jrfm17100437

Sukartaatmadja, I., Khim, S., & Lestari, M. N. (2023). Faktor-faktor Yang Mempengaruhi Harga Saham Perusahaan. *Jurnal Ilmiah Manajemen Kesatuan*, *11*(1), 21–40.

https://doi.org/10.37641/jimkes.v11i1.1627
Taylor, S. J., & Letham, B. (2018). Forecasting at Scale. *American Statistician*, *72*(1), 37–45. https://doi.org/10.1080/00031305.2017.1380080
Wang, P. C., & Vo, T. T. H. (2025). Stock price prediction based on dual important indicators using ARIMAX: A case study in Vietnam. *Journal of Intelligent Systems*, *34*(1). https://doi.org/10.1515/jisys-2024-0101
Yamamoto, H., Ano, S., & Yamazaki, K. (2015). Modeling of Dynamic Latency Variations Using Auto-Regressive Model and Markov Regime Switching. *Journal of Information Processing, 23*(4), 420–429. https://doi.org/10.2197/ipsjjip.23.420
Zhang, Y., Lei, L., & Wei, Y. (2020). Forecasting the Chinese stock market volatility with international market volatilities: The role of regime switching. *North American Journal of Economics and Finance*, *52*. https://doi.org/10.1016/j.najef.2020.101145