ENHANCED KNOWLEDGE IN SCIENCES AND TECHNOLOGY
e-ISSN: 2773-6385

EKST

Vol. 4 No. 2 (2024) 110-119
https://publisher.uthm.edu.my/periodicals/index.php/ekst

# Malaysia Stock Price Prediction Using ARIMA Model and Geometric Brownian Motion with Monte Carlo Simulation

**Tan Xiao Ying[1], Norzuria Ibrahim[1]***

[1] *Department of Mathematics and Statistics, Faculty of Applied Sciences and Technology, UTHM Kampus Cawangan Pagoh, Hab Pendidikan Tinggi Pagoh, KM 1, Jalan Panchor, 84600 Pagoh, Muar, Johor, MALAYSIA*

*Corresponding Author: norzuria@uthm.edu.my
DOI: https://doi.org/10.30880/ekst.2024.04.02.013

**Article Info**

Received: 27 December 2023
Accepted: 11 January 2024
Available online: 3 December 2024

**Keywords**

Stock Price Prediction, Autoregressive Integrated Moving Average, Geometric Brownian Motion, Monte Carlo Simulation, Mean Forecast Error, Root Mean Square Error, Mean Absolute Percentage Error

**Abstract**

The stock market serves as a platform for stock traders to issue and deal in stocks, offering the probability of financial gains. Information about stock price prediction is essential for considering the adoption of a trading strategy. Thus, this study is purposed to predict stock closing prices by implementing autoregressive integrated moving average (ARIMA) and geometric Brownian motion (GBM) models. Subsequently the study is aimed to obtain the highest, average, and lowest closing price paths through Monte Carlo simulation (MCS) for each method. The historical daily closing price of three Malaysian plantation companies' stock, including IOI Corporation Berhad, Kuala Lumpur Kepong Berhad and Sime Darby Plantation Berhad are used to fit the models. The predictions are evaluated with mean forecast error (MFE), root mean square error (RMSE) and mean absolute percentage error (MAPE). Based on the result, IOI is identified as the least risky stock. ARIMA outperformed GBM, and the combination of each model with MCS in predicting the average path had errors that closer to zero compared to each single model for most of the stocks. Hence, it is concluded that the application of MCS improved accuracy of prediction for both methods.

## 1. Introduction

The stock market is a public market to attract stock traders to issue and deal in stocks by offering the probability of financial earns [1]. A stock traded is known as an equity that represents fractional ownership in corporations and offered by a publicly traded company in terms of shares. The order flow of stock price moving up and down depends on buyers demand and sellers supply which is known as bid and offer principle. Besides, the stock market is critical to society's functioning as it directs investors investments into profitable business initiative and assists in capital production and economic growth of the country [2]. In subject to profit promptly from stock trading, traders familiarly practice a simple procedure of buying undervalued stock followed by selling at inflated prices. Since the stock market comes with high market risk such as recessions, changes in interest rates, and political instability that cannot be prevented by diversification, it leads to high volatility in the stock market [3]. Future stock price movement of a stock, whether the price will rise to a bull market or drop to a bear market is a major concern for investors. Hence, information about prediction plays a crucial in adopting a trading strategy [4].

There are several studies carried out by academic researchers that apply different models for the aim of comparing prediction performance. The research by [5] has stated machine learning as a modern method and superior traditional time series models such as autoregressive integrated moving average (ARIMA) and generalized autoregressive conditional heteroskedasticity. This is attributed to machine learning providing incredible improvements in regression and classification, while ARIMA is weak in tackling nonlinear pattern. In contrast, results from research published by [6] proven that both ARIMA and geometric Brownian motion (GBM) models, with relatively lower root mean square error (RMSE) surpassed artificial neural network, especially for short term daily stock price prediction. GBM also outperformed multilayer perceptron deep learning in Microsoft stock price forecasting with lower mean absolute percentage error (MAPE) value [7].

Besides, there is growing evidence that a combination of several models increases the accuracy of prediction in financial industry. [8] conducted stock price prediction using hybrid models. In their study, Markov chain-fuzzy model had lower MAPEs for more than half of stocks indicating better performance compared to hidden Markov models (HMM) and HMM-fuzzy. The work done by [9] demonstrated that a hybrid of ARIMA and Holt Winter had highly effective prediction no matter for long or short period. Furthermore, the combination of the complete empirical mode decomposition and long short-term memory outperformed other single multi-layer perceptron and long-short term model in financial time series forecasting [10].

Briefly, ARIMA is a linear model that applied to recognize trends in stock prices and assume stationarity of data [11] while GBM is a derivative of continuous model from discrete stochastics model that applied to assume uncertainty in stock returns using Brownian motion [12]. In addition, Monte Carlo simulation (MCS) is generally applied to consider randomness and various outcomes of predictions produced from the selected models and operate under assumption to reduce uncertainty [13]. Therefore, this study is purposed to produce stock closing price predictions using ARIMA and GBM models separately on closing prices of three Malaysian plantation companies. The predictions from each model are then extended by MCS where the highest, average and lowest predicted paths are selected. The prediction results of each single model and the hybrid of each model with MCS are compared in terms of mean forecast error (MFE), RMSE and MAPE to determine the superior model for stock closing price prediction in Malaysian plantation sector.

## 2. Methodology

The tool used to implement the prediction models and the process and steps involved in data preparation, ARIMA model building, GBM model building, the implementation of MCS into the models and measurement of prediction accuracy are illustrated as following sections below.

### 2.1 Data Preparation

Spyder which is a free and open-source integrated development environment of Python will be used to perform all procedures in this study. Spyder is known for its user-friendly interface and powerful scientific computing and interactive programming [14]. One of its advantages is integrated support for popular scientific libraries, for example, Pandas and NumPy. Three selected Malaysian plantation companies implemented in this study were IOI Corporation Berhad, Kuala Lumpur Kepong Berhad and Sime Darby Plantation Berhad and represented by stock symbol of 1961.KL, 2445.KL and 5285.KL respectively. The historical stock closing prices of the stocks are loaded from Yahoo Finance which is a popular source that enable accessibility in Python. The dataset covered a period of four year and five months is collected from 1$^{st}$ July 2019 until 30$^{th}$ November 2023. The total of 1083 trading days of each stock is processed with data replacing from alternative source, Bursa Malaysia if there is missing value, data cleaning if there is redundant value and data splitting with ratio of 80:20 approximately. The first three and a half years or 860 observations are partitioned to training set and the data of the last 11 months or 223 observations are partitioned to testing set.

### 2.2 Autoregressive Integrated Moving Average (ARIMA) Model Building

ARIMA is a time-series forecasting method that integrates Box-Jenkins ARMA model [15]. Auto regressive (AR) implies the dependent association between an observation and a predetermined number of lagged observations. Integrated (I) is used to determine the stationary by differencing of raw observations. Moving average (MA) uses the relation that exists between the residual error and observations. Thus, the parameters involved in the model were the lag order (p), the degree of differencing (d) and the order of MA (q). ARIMA (p, d, q) model is built using Bos-Jenkins approach, which included of stationarity identification using Augmented Dickey Fuller (ADF) unit root test, parameters estimation and fitness checking of the best fitting ARIMA model.

The first phase involved the ADF unit root test which is applied to analyse the stationarity of the time series data of each stock [16]. This test can be performed using adfuller() function in statsmodels.tsa.stattools from statsmodel package. The outputs that will be obtained from ADF test included of the values of test statistics, $p$-value, considered number of lags and critical value. A time-series data is considered stationary if the value of test statistics is less than critical value and $p$-value is less than significance level of 0.05. Otherwise, converting the data to stationary data is required by subtracting MA from log of the closing price to get stationary data. The transformed data is evaluated with ADF test again. These steps are repeated until acquiring a stationary series. Subsequently, the series is partitioned with train-test split ratio as explained in section 2.1.

The determination of the best fitting ARIMA model depends on the number of differencing applied to the data. In this process, the auto_arima function from pmdarima package in Python is used to disclose an optimal ARIMA model order. The value of Akaike's information criterion (AIC) is considered as it measures the fitness of the data based on the order number of parameters used in setting up a model and likelihood estimation of the model [17]. The lower the AIC value, the better the fitting of the model. The fitness checking of each model is observed through standardized residual plot, histogram, normal Q-Q plot and correlogram of Autocorrelation Function (ACF) plot.

## 2.3 Geometric Brownian Motion (GBM) Model Building

In finance markets, GBM model is called as the log-normal asset return model, thus, only positive values of stock price are allowed in this model. This model is defined by the stochastic differential equation (SDE) that consists of Brownian motion (also known as Wiener process, W) that represents random walk, drift coefficient, $\mu$ and volatility coefficent , $\sigma$. This model presupposes that the expected return will cause the price to drift upward. Stock price drift frequently occurs when the stock price probably incapable to instantly reflect the new information. The volatility will be shocked by a random shock through multiplication of standard deviation and a random number. The calculations of stock return [18] is given by

$$r_k = \frac{S_k - S_{k-1}}{S_{k-1}}, \forall k, \tag{1}$$

where,

$k$ = time period,
$r_k$ = stock return value at time $k$,
$S_k$ = closing price at time $k$,
$S_{k-1}$ = closing price at time $k-1$.

The drift and volatility components [19] of stock return are computed as follow equations,

$$drift_k = \mu - \frac{1}{2}\sigma^2, \tag{2}$$

$$volatility_k = \sigma W_k, \tag{3}$$

where,

$\mu$ = mean of historical daily returns (drift coefficient),
$\sigma$ = standard deviation of historical daily returns (volatility coeffiicient),
$\sigma^2$ = variance of historical daily returns,
$W_k$ = array for Brownian path at period.

The GBM equation [18] which involved the drift and volatility components in GBM model building is expressed by

$$S_k = S_0 e^{\left(\left(\mu - \frac{1}{2}\sigma^2\right)k + \sigma \sum_{i=1}^{k} b_i\right)} \text{ for } k = 1, 2, \ldots, N, \tag{4}$$

where,

$S_0$ = starting closing price or the last observation in training data set,
$dt$ = time interval (daily),
$T$ = time frame for prediction (days),
$N$ = amount of time points in the time frame or dividing $T$ by $dt$,
$t$ = array for time points in the prediction time frame started from one,
$b$ = Brownian increments array where normal random shocks is included.

## 2.4 Implementation of MCS Into the Models

MCS not only keeps the properties of the original data but also considers randomness, which is similar to the unexpected movement of order flow of stock price [20]. Due to significantly larger computing power required as simulation number increases, therefore 1,000 simulations are used in this study [21]. The prediction result from ARIMA model is simulated using simulate() function with the repetition attribute while that of the GBM model is looped for the same simulation number as in ARIMA. The highest and lowest predicted paths are defined as the simulation paths where the last observation of the simulations is the highest and lowest stock price among the simulations, respectively. The average predicted path is determined as the average of the prices at each observation after 1000 simulations were produced. The highest, average and lowest paths can be represented as the optimistic, most likely and pessimistic paths, respectively, and are selected for visualisation and comparison.

The range between the optimistic and pessimistic paths will be considered to conduct scenario analysis that helps to compute risk of an investment. The higher the range, the higher the risk.

## 2.5 Prediction Accuracy Measurement

There are three errors computed which included of a prediction error, MFE, a scale-dependent error, RMSE and a percentage error, MAPE. A positive MFE implies that the model underestimates the actual data while a negative MFE indicates that the model overestimates the actual data. The unbiasedness and performance increase as MFE and RMSE approach to zero. The predicting power is highly accurate if the MAPE is less than 10%. The formulae of MFE [4], RMSE [22] and MAPE [23] are represented as

$$MFE = \frac{\sum_{t=1}^{n}(y_t - \hat{y}_t)}{n}, \tag{5}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}, \tag{6}$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{y_t - \hat{y}_t}{y_t}\right|(100), \tag{7}$$

where,

$n$ = the number of sample size,
$y_t$ = the actual value in testing set at time $t$,
$\hat{y}_t$ = the predict value obtained from the data in training set at time $t$.

# 3. Result and Discussion

## 3.1 ARIMA Model Building

Referred to the results of ADF test shown in Table 1, both datasets of 1961.KL and 2445.KL stocks were stationary except the dataset of 5285.KL. Hence, data transformation is applied on dataset of 5285.KL. The transformed dataset is evaluated with ADF test again. The stationarity of dataset of all three stocks are identified and supported by ADF test as their test statistics was less than $p$-value and critical value was less than significance level of 0.05.

**Table 1** ADF unit root test result

| Values | ADF 1961.KL | ADF 2445.KL | ADF 5285.KL | $2^{nd}$ ADF 5285.KL |
|---|---|---|---|---|
| Test statistics | -3.0355 | -3.5059 | -2.7302 | -10.1654 |
| $p$-value | 0.0317 | 0.0078 | 0.0689 | 7.3199E-18 |
| No. of lags used | 1 | 10 | 1 | 5 |
| Critical value | -2.8642 | -2.8642 | -2.8642 | -2.8643 |
| Condition | Test statistics < critical value and $p$-value < significance level of 0.05 | Test statistics < critical value and $p$-value < significance level of 0.05 | Test statistics > critical value and $p$-value > significance level of 0.05 | Test statistics < critical value and $p$-value < significance level of 0.05 |
| Conclusion | Stationary | Stationary | Non-stationary | Stationary |

The parameters estimation for the best fitting ARIMA (p, d, q) model is selected from the models with the smallest AIC value. Thus, the best fitting ARIMA models for 1961.KL, 2445.KL and 5285.KL stocks were ARIMA (1, 0, 1) with AIC value of -2339.881, ARIMA (2, 1, 0) with AIC value of 597.087 and ARIMA (1, 1, 0) with AIC value of -4146.155 respectively.

Residual is the different between actual and predicted value. The residual with mean zero in (a) of each Fig 1, Fig. 2 and Fig. 3 indicated the model was fitting well and suitable for prediction. There was only a few of standardized residuals surpass three standard deviations in size which tend to be outlier. The (b) and (c) of Fig. 1, Fig. 2 and Fig. 3 demonstrated that the normality of residual of each stock was reasonable except some possible outliers. The (d) of Fig. 1, Fig. 2 and Fig. 3 shown that the residual is uncorrelated as the lags were greater than zero and there was no apparent move away from the model assumptions.

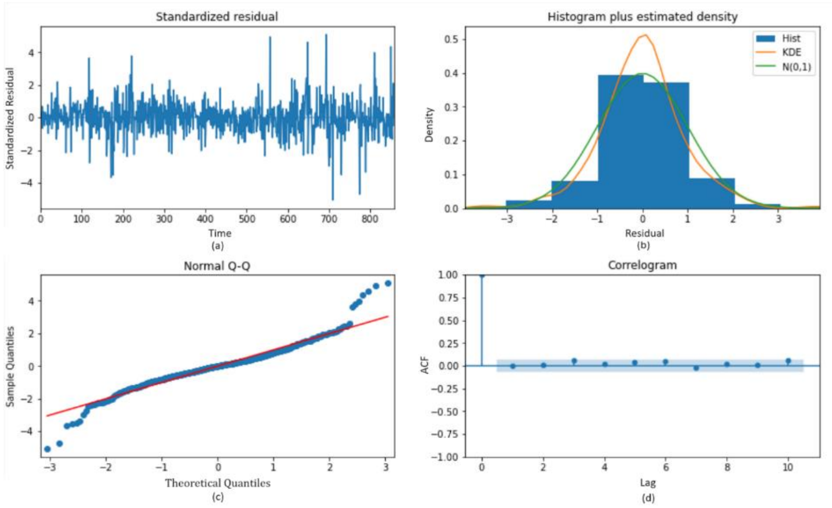


**Fig. 1** Diagnostics checking for 1961.KL stock: (a) Standardized Residual; (b) Histogram; (c) Normal Q-Q; (d) Correlogram of ACF

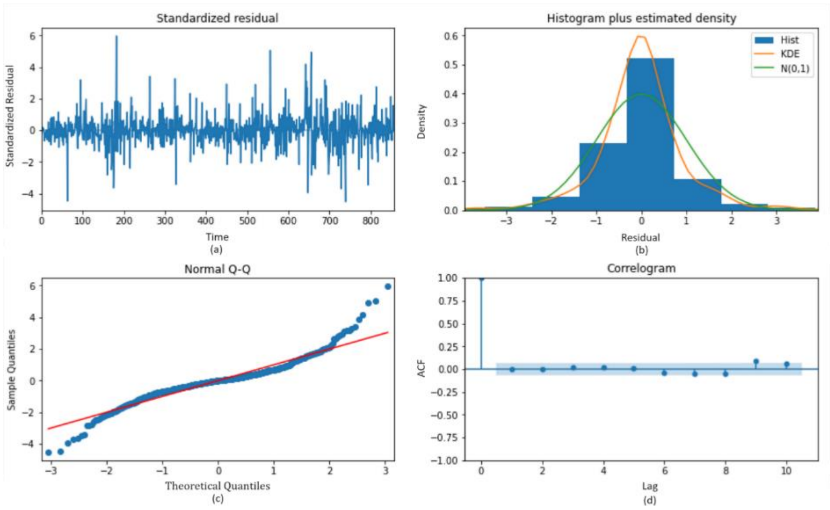


**Fig. 2** Diagnostics checking for 2445.KL stock: (a) Standardized Residual; (b) Histogram; (c) Normal Q-Q; (d) Correlogram of ACF

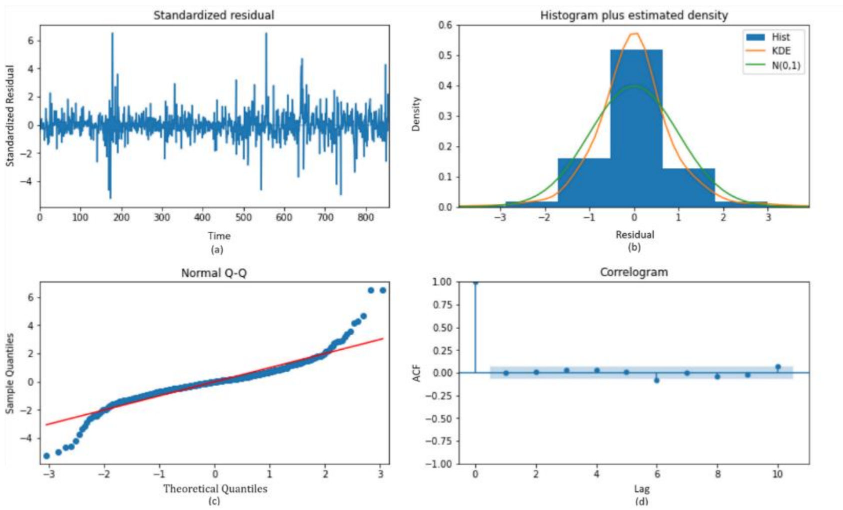


**Fig. 3** Diagnosis checking for 5285.KL stock: (a) Standardized Residual; (b) Histogram; (c) Normal Q-Q; (d) Correlogram of ACF

## 3.2 GBM Model Building

The parameters used in GBM equation for each stock are calculated and shown in Table 2. The parameters below are then substituted into equation (4) to obtain prediction for each time point.

**Table 2** The values of parameters used in GBM equation

| Parameters | 1961.KL | 2445.KL | 5285.KL |
|---|---|---|---|
| $S_0$ | 4.05 | 22.36 | 4.65 |
| $dt$ | 1 | 1 | 1 |
| $T$ | 390 | 390 | 390 |
| $N$ | 390 | 390 | 390 |
| $\mu$ | 0.00006310 | 0.000007811 | 0.0001824 |
| $\sigma$ | 0.01528 | 0.01539 | 0.02213 |
| $\sigma^2$ | 0.0002336 | 0.0002370 | 0.0004898 |

## 3.3 Comparison of the Predictions of ARIMA Model to That of GBM Model

As demonstrated in Fig. 4 and 5, the future trends of each stock predicted by ARIMA and GBM respectively, were different. The behaviour of future price movements produced by ARIMA model were constant and linearly with slightly up trending for all the three stocks. Conversely, the behaviour of future price movements produced by GBM were volatile as it consisted of random fluctuations by Brownian motion which is also known as Wiener process. The appearance of GBM predictions was more alike to real stock market. The trending for each stock by GBM was dissimilar where it was a downward trend for both 1961.KL and 5285.KL, while an upward trend for 2445.KL. The prices of 5285.KL used for ARIMA was lower than that of GBM as log transformation and subtraction MA took place.

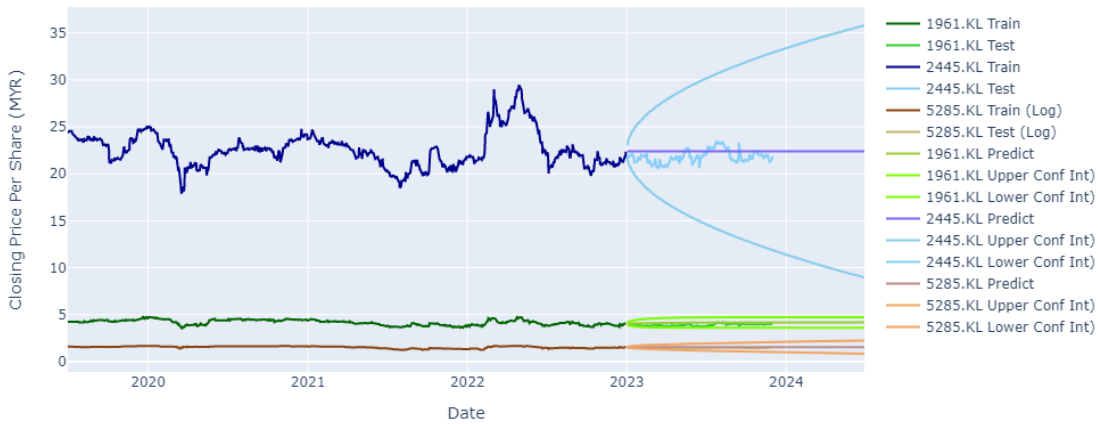


**Fig. 4** Closing price prediction of 1961.KL, 2445.KL and 5285.KL by ARIMA model

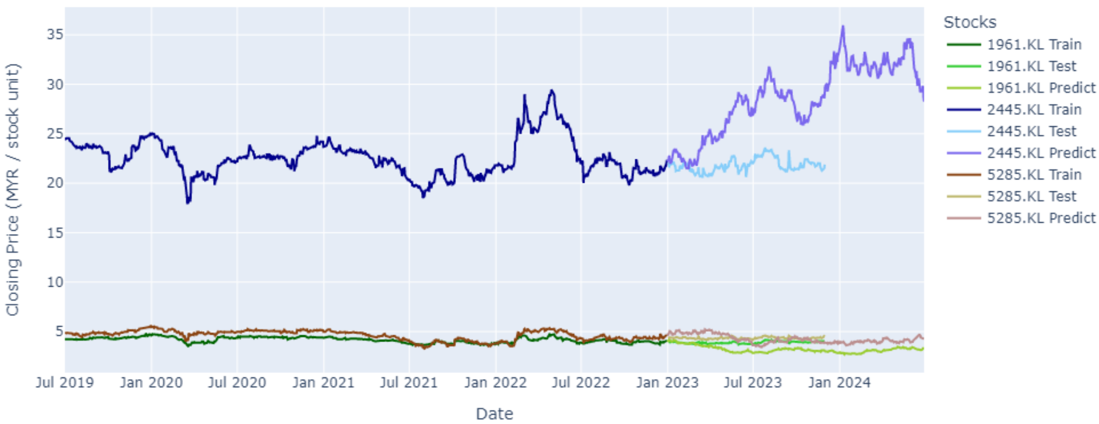


**Fig. 5** Closing price prediction of 1961.KL, 2445.KL and 5285.KL by GBM model

## 3.4 Implementation of MCS to the predictions

The predictions produced by each model are simulated for 1000 times as shown as in Fig. 6 and 8 respectively. This is an estimation of a variety of possible price movement that considered randomness as a market risk. The highest, average and lowest predicted paths of ARIMA-MCS and GBM-MCS are evaluated from the 1000 simulations produced and plotted in Fig. 7 and 9 respectively. It can be observed that the range of GBM-MCS for each stock was greater than ARIMA-MCS. This was the result of underlying characteristics and assumptions of these two methods. The broader range of GBM-MCS was due to GBM that considered the inherent volatility of training data and continuous stochastic process that allowed more erratic future price movements, whereas the more moderate range of ARIMA-MCS was due to ARIMA that exhibited stationary with constant mean and variance over time, trends and seasonality that were captured from the training data and restriction of upper and lower bounds. Based on Table 3, 1961.KL had the smallest range among the three selected stocks in both GBM-MCS and ARIMA-MCS models. Hence, 1961.KL stock can be prioritized for investment as the least risky stock.

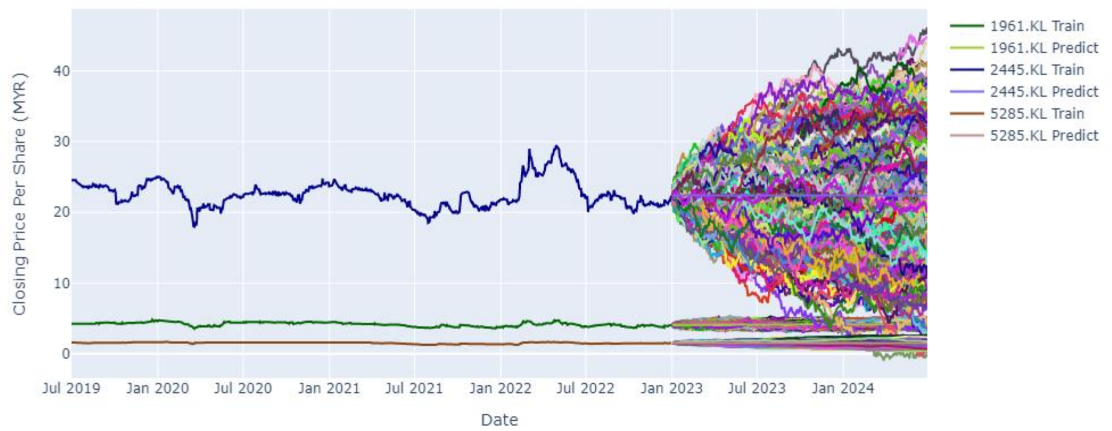


**Fig. 6** ARIMA-MCS prediction

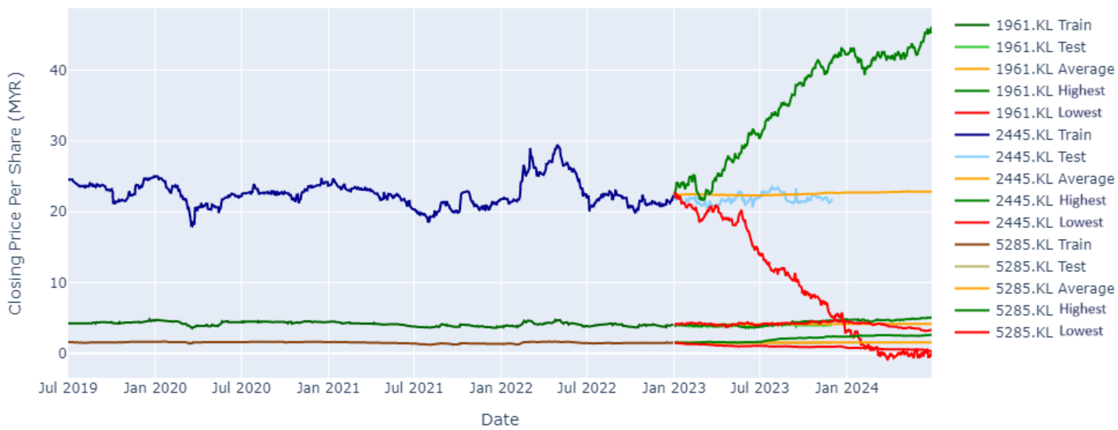


**Fig. 7** The highest, average and lowest paths of 1961.KL, 2445.KL, and 5285.KL selected from ARIMA-MCS

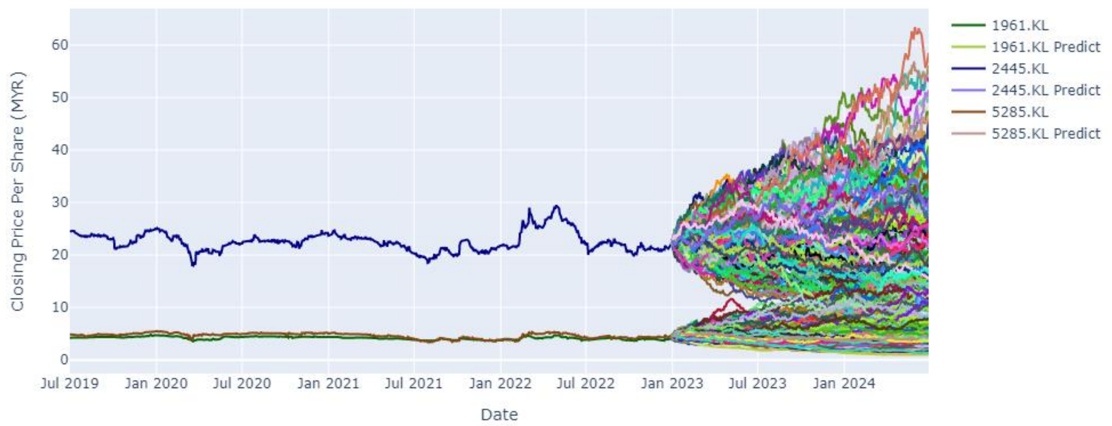


**Fig. 8** GBM-MCS prediction

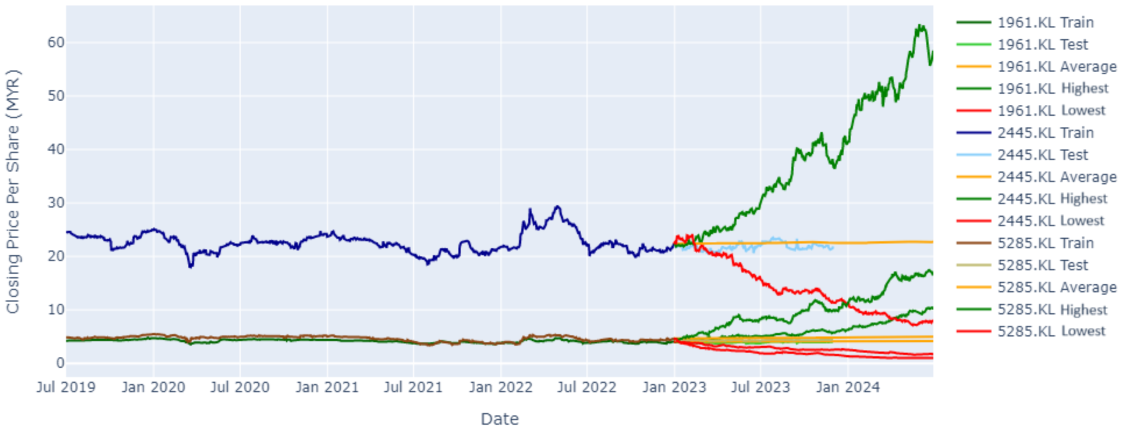


**Fig. 9** The highest, average and lowest paths of 1961.KL, 2445.KL, and 5285.KL selected from GBM-MCS

**Table 3** The range between the highest and lowest paths on 30th June 2024

| Models | | 1961.KL | | | 2445.KL | | | 5285.KL | |
|---|---|---|---|---|---|---|---|---|---|
| | Highest | Lowest | Range | Highest | Lowest | Range | Highest | Lowest | Range |
| ARIMA-MCS | 5.15 | 3.24 | 1.91 | 46.12 | 0.10 | 46.02 | 2.63 | 0.34 | 2.29 |
| GBM-MCS | 10.12 | 1.72 | 8.40 | 58.51 | 8.06 | 50.45 | 16.68 | 1.03 | 15.65 |

## 3.5 Accuracy Comparison

According to the MFE, RMSE and MAPE values of each model shown in Table 3 and 4, most of the models tend to overestimate the actual price over time as indicated by negative MFE. Additionally, in comparison of ARIMA to GBM, ARIMA had errors that were closer to zero than that of GBM for two out of three stocks. It can be concluded that each model had different performance in different stock prediction. For 1961.KL stock, the average path prediction by GBM-MCS was superior with the MFE, RMSE and MAPE closest to zero which were -0.1603, 0.1881 and 4.35% respectively. For 2445.KL, ARIMA was the best option as the prediction model as it had MFE, RMSE and MAPE of -0.5473, 0.8750 and 3.52%, respectively, that were the nearest to zero. However, the performance of ARIMA-MCS and GBM-MCS predictions on average path of 2445.KL were also compatible with slight difference of errors compared to ARIMA model. Thus, three of these models, ARIMA, ARIMA-MCS and GBM-MCS were reliable in 2445.KL stock price prediction. For 5285.KL stock, prediction on average path by ARIMA-MCS outperformed with MFE of -0.0650, RMSE of 0.0686 and MAPE of 4.44%. Overall, ARIMA superior GBM and application of MCS on each model improved the prediction performance with errors that were nearer to zero in the majority.

**Table 3** Error measurement of predictions by ARIMA and ARIMA-MCS

| Stocks and Models | MFE | RMSE | MAPE (%) |
|---|---|---|---|
| 1961.KL ARIMA | -0.2319 | 0.2541 | 6.02 |
| 1961.KL ARIMA-MCS (Highest) | -0.1538 | 0.2854 | 5.60 |
| 1961.KL ARIMA-MCS (Average) | -0.2272 | 0.2498 | 5.91 |
| 1961.KL ARIMA-MCS (Lowest) | -0.2750 | 0.3195 | 7.20 |
| 2445.KL ARIMA | -0.5473 | 0.8750 | 3.52 |
| 2445.KL ARIMA-MCS (Highest) | -8.4175 | 10.1787 | 38.40 |
| 2445.KL ARIMA-MCS (Average) | -0.5675 | 0.9083 | 3.70 |
| 2445.KL ARIMA-MCS (Lowest) | 6.2275 | 7.9907 | 28.36 |
| 5285.KL ARIMA | -0.0673 | 0.0707 | 4.60 |
| 5285.KL ARIMA-MCS (Highest) | -0.3018 | 0.4052 | 20.55 |
| 5285.KL ARIMA-MCS (Average) | -0.0650 | 0.0686 | 4.44 |
| 5285.KL ARIMA-MCS (Lowest) | 0.3758 | 0.4103 | 25.57 |

**Table 4** Error measurement of predictions by GBM and GBM-MCS

| Stocks and Models | MFE | RMSE | MAPE (%) |
|---|---|---|---|
| 1961.KL GBM | 0.6012 | 0.7300 | 15.88 |
| 1961.KL GBM-MCS (Highest) | -1.1343 | 1.2508 | 28.98 |
| 1961.KL GBM-MCS (Average) | -0.1603 | 0.1881 | 4.35 |
| 1961.KL GBM-MCS (Lowest) | 0.7729 | 0.9310 | 20.37 |
| 2445.KL GBM | -4.4565 | 5.1154 | 20.38 |
| 2445.KL GBM-MCS (Highest) | -7.8990 | 9.9942 | 36.09 |
| 2445.KL GBM-MCS (Average) | -0.6679 | 0.9486 | 3.88 |
| 2445.KL GBM-MCS (Lowest) | 4.3309 | 5.8792 | 21.82 |
| 5285.KL GBM | -0.0717 | 0.5184 | 9.94 |
| 5285.KL GBM-MCS (Highest) | -3.3234 | 3.8163 | 76.39 |
| 5285.KL GBM-MCS (Average) | -0.4063 | 0.4185 | 9.39 |
| 5285.KL GBM-MCS (Lowest) | 1.9169 | 2.0386 | 44.22 |

## 4. Conclusion

This study implemented two different statistical and mathematical methods, which were ARIMA and GBM models to predict stock closing price for one-and-a-half-year period on three selected Malaysian plantation companies. It can be observed obviously that the pattern of prediction result plotted among these two approaches was different. ARIMA created prediction linearly whereas GBM recognized prediction with fluctuations. Although the upper and lower confidence intervals of ARIMA prediction are plotted to represent the range of possible price movement, the result of GBM seem to be more likely to real stock market phenomena where volatile is unavoidable.

In addition, the result from both ARIMA and GBM models is developed with MCS for 1000 times to estimate a variety of possible outcomes by considering randomness as equivalent to an unknown factor that is affecting the stock market. The highest, average and lowest predicted paths of each method are demonstrated as two possible extreme scenarios and a preserve scenario on price movements. The range between the highest and lowest paths of GBM-MCS was greater than that of ARIMA-MCS due to the underlying assumptions of each GBM and ARIMA models. By the reason of the compatible range in both ARIMA-MCS and GBM-MCS, therefore 1961.KL stock can be prioritised for investment as it had the smallest risk.

Furthermore, the error measurement that included of MFE, RMSE and MAPE is evaluated to determine the superior prediction model. Most of the models tend to overestimate the actual price over time as shown as negative MFE. ARIMA performed better than GBM for most of the stocks. GBM-MCS on average path prediction, ARIMA prediction and ARIMA-MCS on average path prediction had MFE, RMSE and MAPE that were the closest to zero for 1961.KL stock, 2445.KL and 5285.KL respectively. Besides, ARIMA-MCS and GBM-MCS on average path predictions for 2445.KL were also reliable with slight difference of errors compared to ARIMA. Hence, these three models, ARIMA, ARIMA-MCS and GBM-MCS can be considered in 2445.KL stock price predictions. As a result, the application of MCS on each ARIMA and GBM model is supposed to improve the performance in prediction as the error of prediction result approaches to zero. This study has proven that the claim as the accuracy of average paths produced from combination of each model with MCS was higher compared to each single model.

Last but not least, there are limits of large range between the highest and lowest path produced from MCS and the predictive power for each approach. Thus, there are three ways that the study can explore to broaden its foundation for additional enhancements. Firstly, it is advised to increase the number of observations in both training and testing dataset to enhance model fitting and achieve more accurate error measurement. Additionally, it is recommended to amplify the number of Monte Carlo simulation to obtain more accurate average predicted path by averaging more possible outcomes. It is suggested to implement MCS on other methods such as long short-term memory, artificial neural networks and other. The predictions produced can be compared to obtain more appropriate stock price predictions model.

## Acknowledgement

The authors would thank the Faculty of Applied Sciences and Technology, Universiti Tun Hussein Onn Malaysia for its support.

## Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

## Author Contribution

*The authors confirm contribution to the paper as follows:* ***study conception and design:*** *Tan XiaoYing, Norzuria Ibrahim;* ***data collection:*** *Tan XiaoYing, Norzuria Ibrahim;* ***analysis and interpretation of results:*** *Tan XiaoYing, Norzuria Ibrahim;* ***draft manuscript preparation:*** *Tan XiaoYing[1], Norzuria Ibrahim. All authors reviewed the results and approved the final version of the manuscript.*

## References

[1] Barber, B. M., Huang, X., Odean, T., & Schwarz, C. (2022). Attention-Induced Trading and Returns: Evidence From Robinhood Users. *The Journal of Finance*, 77(6), pp. 3141-3190.
[2] Addy, C., Chorengel, M., Collins, M., & Etzel, M. (2019). Calculating the Value of Impact Investing. *Harward Business Review, 97(1),* pp. 102-109.
[3] Pflueger, C., Siriwardane, E., & Sunderam, A. (2020). Financial Market Risk Perceptions And The Macroeconomy. *The Quarterly Journal of Economics*, *135*(3), pp. 1443-1491.
[4] Tang, E. C. H. & Nor, M. E. (2022). Aggregate Versus Disaggregate Data in Artificial Neural Network for Stock Market Forecasting. *Enhanced Knowledge in Sciences and Technology, 2*(1), pp. 143-152.
[5] Qian, X. Y., & Gao, S. (2017). Financial Series Prediction: Comparison Between Precision of Time Series Models and Machine Learning Methods. *arXiv preprint arXiv:1706.00948*, pp. 1-9.
[6] Islam, M. R., & Nguyen, N. (2020). Comparison of Financial Models for Stock Price Prediction. *Mdpi.Com. Journal of Risk and Financial Management*, *13*(8), pp.181.
[7] Azizah, M., Irawan, M. I., & Putri, E. R. M. (2020). Comparison of Stock Price Prediction Using Geometric Brownian Motion and Multilayer Perceptron. *AIP Conference Proceedings*, 2242(1). AIP Publishing LLC.
[8] Ky, D. X., Tuyen, L. T. (2016). A Markov-fuzzy Combination Model for Stock Market Forecasting. *International Journal of Applied Mathematics and Statistics*, *55(3),* 110-121.
[9] Jagwani, J., Gupta, M., Sachdeva, H., & Singhal, A. (2019). Stock Price Forecasting Using Data from Yahoo Finance and Analysing Seasonal and Nonseasonal Trend. In *2018 Second International Conference on Intelligent Computing and Control Systems (ICICCS)*, pp. 462-467. IEEE.
[10] Cao, J., Li, Z., & Li, J. (2019). Financial Time Series Forecasting Model Based On CEEMDAN And LSTM. *Physica A: Statistical mechanics and its applications*, *519*, pp. 127-139.
[11] Wang, Z., & Sobey, A. (2020). A Comparative Review Between Genetic Algorithm Use In Composite Optimisation and The State-Of-The-Art In Evolutionary Computation. *Composite Structures*.
[12] Abidin, S. N. Z. & Jaffar, M. M. (2014). Forecasting Share Prices of Small Size Companies in Bursa Malaysia Using Geometric Brownian Motion. *Applied Mathematics & Information Sciences*, *8*(1), pp. 107–112.
[13] Thakkar, J. J. (2020). Structural Equation Modelling. *Application for Research and Practice*.
[14] Kendhe, S., Nishad, A., Labhade, D., & Magar, V. (2023). Comparative Analysis of Different Python Editors. *Vidhyayana-An International Multidisciplinary Peer-Reviewed E-Journal-ISSN 2454-8596*, *8*(si7), pp. 562-574.
[15] Shumway, R. H., & Stoffer, D. S. (2000). Time series analysis and its applications (Vol. 3). New York: springer.
[16] Naseem, S., Fu, G. L., ThaiLan, V., Mohsin, M., & Zia-Ur-Rehman, M. (2019). Macroeconomic Variables and The Pakistan Stock Market: Exploring Long and Short Run Relationship. *Pacific Business Review International*, *11*(7), pp. 621-72.
[17] Meher, B. K., Hawaldar, I. T., Spulbar, C. M., & Birau, F. R. (2021). Forecasting Stock Market Prices Using Mixed ARIMA Model: A Case Study of Indian Pharmaceutical Companies. *Investment Management and Financial Innovations*, *18*(1), pp. 42-54.
[18] Yildiz, U. (2019). Simulating stock prices in Python using Geometric Brownian Motion. *Towards Data Science.*
[19] Ross, S. M. (2011). An elementary introduction to mathematical finance. Cambridge University Press.
[20] Tsay, R. S. (2005). Analysis of Financial Time Series Second Edition. John Wiley & Sons.
[21] Parungrojrat, N., & Kidsom, A. (2019). Stock Price Forecasting: Geometric Brownian Motion and Monte Carlo Simulation Techniques. *MUT Journal of Business Administration*, *16*(1), pp. 90-103.
[22] Cheng, C. T., Feng, Z. K., Niu, W. J., & Liao, S. L. (2015). Heuristic Methods For Reservoir Monthly Inflow Forecasting: A Case Study of Xinfengjiang Reservoir In Pearl River, China. *7(8)*, pp. 4477–4495.
[23] Koutsandreas, D., Spiliotis, E., Petropoulos, F., & Assimakopoulos, V. (2022). On the Selection of Forecasting Accuracy Measures. *Article in Journal of the Operational Research Society*, *73*(5), pp. 937-954.