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Comparison of Apple Inc Stock Forecasting Accuracy Using Hybrid TSR Linear-ARIMA Model and ARIMA Model

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ABSTRACT

This study aims to compare the accuracy of Apple Inc. stock price forcasting using two time series models, namely the hybrid TSR Linear-ARIMA model and the ARIMA model. The background of this research is the need for more accurate forcasting methods in a dynamic stock market, especially for technology stocks such as Apple which have high volatility. The research methodology uses the quantitative approach with daily Apple stock price time series data for the period 2023. The hybrid TSR Linear-ARIMA model incorporates trend and residual components, while the ARIMA model uses the Box-Jenkins approach. Both models were implemented using statistical software R Studio and Minitab. The results that the ARIMA model provided better forcasting accuracy compared to the hybrid TSR Linear-ARIMA model. Comparative analysis using the MAPE shows the ARIMA model has a lowwer error rate. Specifically, the ARIMA model produces a MAPE of 2.909%, while the hybrid TSR Linear-ARIMA model produces a MAPE of 3.780%. in conclusion, the ARIMA model proved to be more effective in forecasting the stock price of Apple Inc. compared to the hybrid TSR Linear-ARIMA model. This research contributes to the development of forecasting techniques in finance and investment, especially for technology stock.

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1. INTRODUCTION

The rapid development of technology and globalization has significantly influenced the global financial industry, particularly the stock market. Stocks of major technology companies such as Apple Inc. have become attractive investment instruments due to their strong market performance, continuous innovation, and ability to introduce revolutionary products consistently. As one of the world's leading technology companies, Apple Inc. attracts considerable attention from investors seeking profitable and stable investment opportunities.

Successful stock investment requires a comprehensive understanding of market behavior and the ability to predict future stock price movements accurately. In the digital era, where information can be accessed quickly and widely, forecasting techniques play an essential role in supporting investment decision-making. Accurate forecasting models may provide competitive advantages for investors and stakeholders in minimizing risks and maximizing returns.

Various methods have been developed for time series forecasting, including exponential smoothing, fuzzy methods, and statistical forecasting approaches. Exponential smoothing methods are widely used because of their simplicity; however, they are less effective in handling data with complex trends. Fuzzy methods are also commonly applied in forecasting problems, but these methods tend to focus only on fuzzy variables and may not optimally capture linear patterns in time series data.

One of the statistical approaches that is effective in modeling trends and linear relationships in time series data is the Time Series Regression (TSR) method. In addition, the Autoregressive Integrated Moving Average (ARIMA) method is frequently used because of its strong capability in short-term forecasting using historical data without requiring specific data patterns. Several previous studies have shown that hybrid forecasting models can improve forecasting accuracy by combining the strengths of different methods.

In general, forecasting accuracy can be improved through two approaches, namely developing new forecasting methods or combining existing forecasting models into hybrid models. However, studies comparing the TSR linear-ARIMA hybrid model with the classical ARIMA model on Apple Inc. stock data are still limited, particularly for recent stock market conditions in 2023. Therefore, this study aims to compare the forecasting performance of the TSR linear-ARIMA hybrid model and the ARIMA model using Apple Inc. stock price data in 2023.

2. METHOD

This study employed a quantitative approach using time series data of Apple Inc. stock prices during the period January–December 2023. The research focused on comparing the forecasting accuracy between the hybrid TSR Linear-ARIMA model and the ARIMA model. The analysis process was conducted using R Studio and Minitab software. The research stages included data collection, identification of data patterns, model formation, parameter estimation, diagnostic checking, forecasting, and model accuracy evaluation using Mean Absolute Percentage Error (MAPE) [4], [5].

The data used in this research were secondary data obtained from Yahoo Finance in the form of daily closing stock prices of Apple Inc. The collected data were divided into training data and testing data. The training data were used to construct forecasting models, while the testing data were used to evaluate forecasting performance. Time series plots were initially used to identify data patterns and determine whether the data contained trend, seasonal, cyclical, or stationary characteristics [7].

The first forecasting method applied in this study was the Time Series Regression (TSR) linear model. The TSR model was formed by regressing the time variable as the independent variable and stock price as the dependent variable using the Ordinary Least Squares (OLS) method [2], [10]. After obtaining the TSR linear model, residual analysis was conducted to determine whether the residuals satisfied the white noise assumption. If the residuals still contained autocorrelation patterns, the residuals were further modeled using the ARIMA approach to form the hybrid TSR Linear-ARIMA model [4].

The ARIMA modeling procedure followed the Box-Jenkins methodology, which consists of several stages, namely stationarity testing, model identification, parameter estimation, diagnostic checking, and forecasting [14]. Stationarity testing in variance was performed using the Box-Cox transformation, while stationarity in mean was examined through differencing and analysis of Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots [5], [13]. The identification of ARIMA model orders was determined based on ACF and PACF patterns.

Parameter estimation for the ARIMA model was carried out using the Maximum Likelihood Estimation (MLE) method. Furthermore, significance testing of model parameters was conducted using p-values at a significance level of 5%. The best ARIMA model was selected based on the smallest Akaike Information Criterion (AIC) value [13], [14].

After obtaining the best forecasting models, diagnostic checking was performed to ensure that the residuals satisfied the assumptions of normality and white noise. Residual normality testing was conducted using the Kolmogorov-Smirnov test, while the white noise assumption was tested using the Ljung-Box test [8]. Models that satisfied all diagnostic assumptions were then used for forecasting Apple Inc. stock prices.

Finally, the forecasting accuracy of both models was evaluated using Mean Absolute Percentage Error (MAPE). The model with the smaller MAPE value was considered to have better forecasting performance [3], [9].

3. RESULTS AND DISCUSSION

3.1 Time Series Plot

The first step in this analysis process is to identify the pattern of stock price data. The following is a time series plot of Apple Inc. stock price data for the period January 1, 2023 to December 31, 2023.

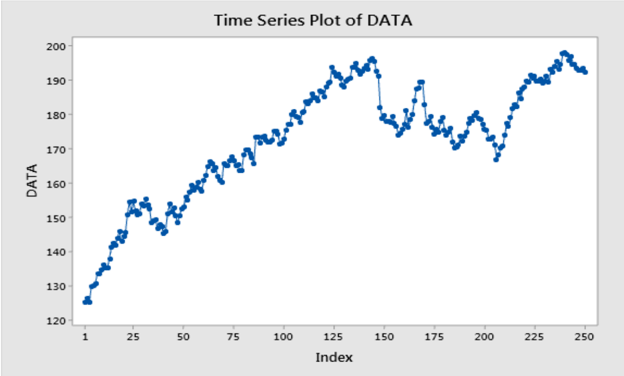

Figure 1 Time Series Plot of Apple Inc. Data

Based on Figure 1, it can be seen that there is a fairly stable and consistent increase in stock prices in indexes 1 to 100 or the period from January 1 to around May 25. The highest peak in stock prices occurred around index 100 to 125 or May 25 to July 3. Subsequently, there was a significant decline in share prices. Between index 150 to 200 or August 8 to October 18, the data showed considerable fluctuations. Towards the end, the data again shows an upward trend. Such a pattern of Apple Inc. stock price data shows the characteristics of data that are not yet stationary. A data is said to be stationary if the data pattern does not show changes in the tendency of both the mean and variance. The data pattern formed can be categorized as an upward trend pattern. The pattern also does not show any seasonal patterns.

3.2 Hybrid Time Series Regression Linear-ARIMA Method

3.2.1 Time Series Regression Linear

3.2.1.1 Parameter Estimation

The linear TSR model (time series regression linear) was formed using Apple Inc. stock price data. The linear TSR model is created by regressing the independent variables on the dependent variable using the ordinary least square (OLS) method, the TSR model is obtained

$$Z_t = 148{,}0017019 + 0{,}195596004t$$

3.2.1.2 Cheking Residual Fulfil the White Noise Assumption

Based on the calculation of the ljung-box test $Q = 236{,}3616747$ for lag 1, the $p-value = 2{,}4437E - 53$ is smaller then the significance level of 0,05. Therefor, rejected H_0 ameaning that the residuals are not white noise. The linear TSR model does not meet the white noise assumption, meaning that the model is not good enough to capture the pattern and dynamics of the data. Thus, the residual data of the linear TSR model needs to be hybridized, because there is still information from the data that has not been captured by the linear TSR model.

3.2.2 ARIMA on TSR Residual

3.2.2.1 Stationarity Test

Checking the stationarity of the data in variance is done using box-cox plots.

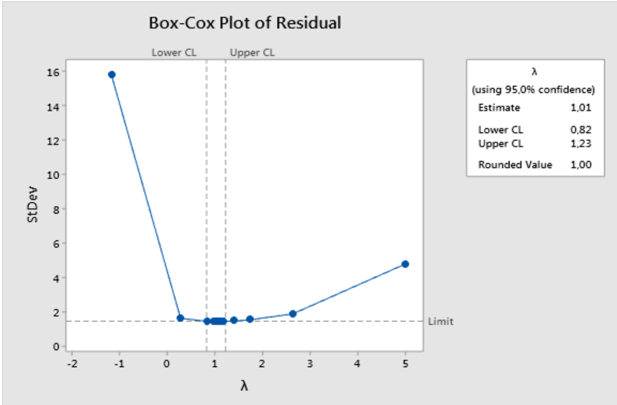

Figure 2 Box-Cox Plot of Residual Data

Based on Figure 2, it can be seen that the lambda value indicated by the rounded value is 1.00. Because the lambda value shows a value of 1.00, it means that the data is stationary in variance. The next step is to check stationarity in the mean. The following is an image of the ACF plot and PACF plot of data that has been stationary in variance

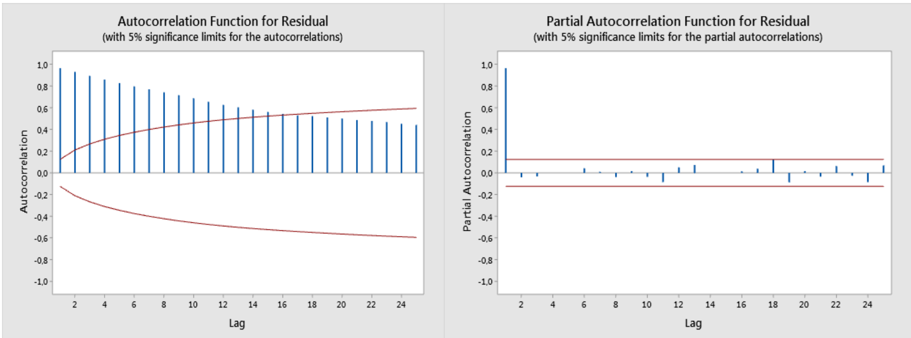

Figure 3 ACF and PACF Plot

Based on Figure 3 the ACF and PACF graphs above, the data is not yet stationary in the mean. It can be seen that the ACF plot shows a very slow downward pattern and there are still many lags out of the boundary line. In the PACF plot there is also a very high spike at lag 1 which shows a pattern that the data is not stationary and needs to be differenced. After differencing 1 time, the following ACF and PACF plots are obtained.

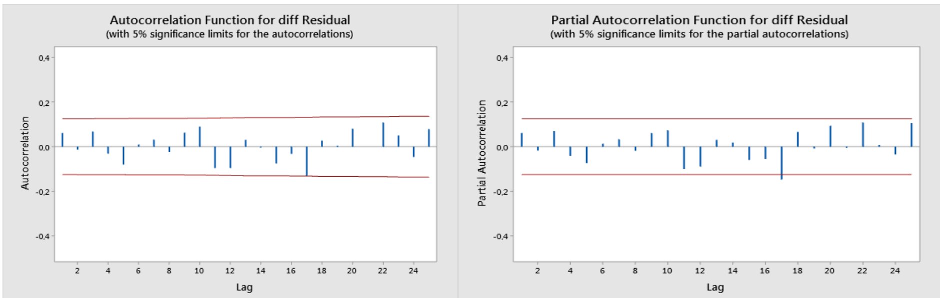

Figure 4 ACF and PACF After Differencing

Based on Figure 4 the ACF and PACF above, it can be seen that most of the lags are already on the boundary line, meaning that the data is stationary in the mean.

3.2.2.2 Model Identification

Based on the ACF and PACF plots in Figure 2.4, it can be seen that most of the lags do not cross the boundary line. The lag that comes out of the boundary line can be used as a reference to determine the order of AR and MA. However, because the lag is too far out, so the AR and MA orders that are tried to be used as ARIMA models are ARIMA(3,1,3) with a combination of ARIMA(3,1,3), ARIMA(3,1,2), ARIMA(3,1,1), ARIMA(3,1,0), ARIMA(2,1,3), ARIMA(2,1,2), ARIMA(2,1,1), ARIMA(2,1,0), ARIMA(1,1,3), ARIMA(1,1,2), ARIMA(1,1,1), ARIMA(1,1,0), ARIMA(0,1,3), ARIMA(0,1,2), ARIMA(0,1,1).

3.2.2.3 Parameter Estimation and Significance Test

The estimation results of a number of temporary ARIMA models that have been obtained with the help of the R Studio program are summarized in Table 1.

Table 1. ARIMA Model Significance Testing Results

Model	Parameter Estimasition	$p-value$	Significance
ARIMA(3,1,3)	$\hat{\phi}_1 = -0{,}238994$	0,008218	Significant
	$\hat{\phi}_2 = -0{,}903732$	0,0000	Significant
	$\hat{\phi}_3 = 0{,}108465$	0,157389	Insignificant
	$\hat{\theta}_1 = -0{,}686146$	0,0000	Significant
	$\hat{\theta}_2 = 0{,}645165$	0,0000	Significant
	$\hat{\theta}_3 = -0{,}936203$	0,0000	Significant
ARIMA(3,1,2)	$\hat{\phi}_1 = -0{,}114885$	0,81273	Insignificant
	$\hat{\phi}_2 = -0{,}011069$	0,87668	Insignificant
	$\hat{\phi}_3 = 0{,}071940$	0,27913	Insignificant
	$\hat{\theta}_1 = -0{,}810327$	0,09392	Insignificant
	$\hat{\theta}_2 = -0{,}178653$	0,70833	Insignificant
ARIMA(3,1,1)	$\hat{\phi}_1 = 0{,}064725$	0,3140	Insignificant
	$\hat{\phi}_2 = -0{,}021929$	0,7329	Insignificant
	$\hat{\phi}_3 = 0{,}072823$	0,2590	Insignificant
	$\hat{\theta}_1 = -0{,}990973$	0,0000	Significant
ARIMA(3,1,0)	$\hat{\phi}_1 = -0{,}700678$	0,0000	Significant
	$\hat{\phi}_2 = -0{,}493949$	0,0000	Significant
	$\hat{\phi}_3 = -0{,}187875$	0,002679	Significant
ARIMA(2,1,3)	$\hat{\phi}_1 = -0{,}815130$	0,0000	Significant
	$\hat{\phi}_2 = -0{,}977606$	0,0000	Significant
	$\hat{\theta}_1 = -0{,}110273$	0,0000	Significant
	$\hat{\theta}_2 = 0{,}136773$	0,0000	Significant
	$\hat{\theta}_3 = -0{,}985870$	0,0000	Significant
ARIMA(2,1,2)	$\hat{\phi}_1 = -0{,}5269310$	0,3109	Insignificant
	$\hat{\phi}_2 = -0{,}0053807$	0,9476	Insignificant
	$\hat{\theta}_1 = -0{,}3975644$	0,4410	Insignificant
	$\hat{\theta}_2 = -0{,}5832882$	0,2537	Insignificant
ARIMA(2,1,1)	$\hat{\phi}_1 = 0{,}060870$	0,3446	Insignificant
	$\hat{\phi}_2 = -0{,}019049$	0,7675	Insignificant
	$\hat{\theta}_1 = -0{,}988307$	0,0000	Significant
ARIMA(2,1,0)	$\hat{\phi}_1 = -0{,}630161$	0,0000	Significant

Model	Parameter Estimasition	$p-value$	Significance
ARIMA(1,1,3)	$\hat{\phi}_2 = -0,376889$	0,0000	Significant
	$\hat{\phi}_1 = -0,522997$	0,3695	Insignificant
	$\hat{\theta}_1 = -0,401167$	0,4905	Insignificant
	$\hat{\theta}_2 = -0,584627$	0,2615	Insignificant
	$\hat{\theta}_3 = 0,004779$	0,9532	Insignificant
ARIMA(1,1,2)	$\hat{\phi}_1 = -0,53903$	0,2055	Insignificant
	$\hat{\theta}_1 = -0,38342$	0,3415	Insignificant
	$\hat{\theta}_2 = -0,59758$	0,1318	Insignificant
ARIMA(1,1,1)	$\hat{\phi}_1 = 0,060384$	0,3482	Insignificant
	$\hat{\theta}_1 = -0,989111$	0,0000	Significant
ARIMA(1,1,0)	$\hat{\phi}_1 = -0,458689$	0,0000	Significant
ARIMA(0,1,3)	$\hat{\theta}_1 = -0,923496$	0,0000	Significant
	$\hat{\theta}_2 = -0,089470$	0,3383	Insignificant
	$\hat{\theta}_3 = 0,025338$	0,6966	Insignificant
ARIMA(0,1,2)	$\hat{\theta}_1 = -0,925752$	0,0000	Significant
	$\hat{\theta}_2 = -0,062623$	0,339	Insignificant
ARIMA(0,1,1)	$\hat{\theta}_1 = -0,986614$	0,0000	Significant

Based on Table 1 the ARIMA model parameter estimation results in Table 2.1, there are several ARIMA models that pass the parameter significance test. Some temporary ARIMA models that pass the significant test are ARIMA(3,1,0), ARIMA(2,1,3), ARIMA(2,1,0), ARIMA(1,1,0), ARIMA(0,1,1). Of these models, the ARIMA(2,1,3) model shows the best performance with the lowest AIC value of 1080,37.

3.2.2.4 Residual Assumption Testing (Diagnostic Cheking)

3.2.2.4.1 Normalitiy Test

The following are the results of the calculation of the Kolmogorov-Smirnov statistical value

Table 2 Calculation of Kolmogorov-Smirnov Statistical Value

Residual	F	FK	F(S)	Z	F(T)	ǀF(T)-F(S)ǀ
−9,20798	1	1	0,004	−4,42271	0,00000	0,00401
−6,91791	1	2	0,008	−3,30218	0,00048	0,00755
⋮	⋮	⋮	⋮	⋮	⋮	⋮
−2,15469	**1**	**32**	**0,129**	**−0,97153**	**0,16564**	**0,03713**
⋮	⋮	⋮	⋮	⋮	⋮	⋮
6,64327	1	249	1,000	3,33332	0,99957	0,00043

$|F_T - F_S|$ the largest is 0,03713

$KS_{table} = 0,08601$

Based on Tabke 2 the calculation value of Kolmogorov-Smirnov Statistics, the largest value of $|F_T - F_S|$ is 0,03713. Because the largest $|F_T - F_S|\ value < KS_{table}$ it can be concluded that the residuals are normally distributed.

3.2.2.4.2 White Noise Test

The following are the results of white noise residual testing displayed in graph form.

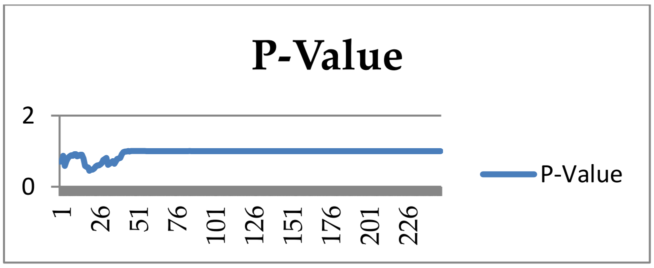

Figure 5. White Noise Residual Testing on ARIMA Model on TSR Residuals

Based on Figure 5, it is known that each lag has a $p - value >$ 0.05 so that it can be decided to fail to reject H_0 and it can be concluded that the residual data of the TSR linear ARIMA hybrid model meets the white noise assumption.

3.2.3 *Hybrid* TSR Linear-ARIMA Model

After obtaining the linear TSR model and ARIMA model of the linear TSR residuals, the next step is to form a hybrid linear TSR-ARIMA model based on equation 1.8

$$H_t = 148{,}0017019 + 0{,}195596004t + Y_{t-1} - 0{,}815130(Y_{t-1} - Y_{t-2}) - 0{,}977606(Y_{t-2} - Y_{t-3}) + 0{,}110273\varepsilon_{t-1} - 0{,}136773\varepsilon_{t-2} + 0{,}985870\varepsilon_{t-3} + \varepsilon_t$$

Forecasting results using the hybrid TSR linear-ARIMA model are obtained in the following table.

Table 3 Forecast Results Using the Hybrid TSR Linear-ARIMA Model

Period	*Hybrid* TSR Linear-ARIMA forecast result	Actual
251	192,6444197	185,639999
252	193,6370973	184,250000
253	193,2184721	181,910004
254	193,0925255	181,179993
255	194,1075427	185,559998
256	193,9063793	185,139999
257	193,5813337	186,190002
258	194,5450506	185,589996
259	194,5805288	185,919998
260	194,1125785	183,630005
261	194,9624169	182,679993
262	195,2304254	188,630005
263	194,6832608	191,559998

264	195,3705311	193,889999
265	195,8483315	195,179993
266	195,2900644	194,500000
267	195,7812909	194,169998
268	196,4287464	192,419998
269	195,9240266	191,729996
270	196,2055869	188,039993
271	196,9725771	184,399994

3.3 ARIMA Method

3.3.1 Stationary Test

To ensure the stationarity of the data, a stationarity test in variance is carried out using a box-cox plot and a stationarity test in the mean with the ADF test. The following is a box-cox plot of stock price data from January 1, 2023 to December 31, 2023.

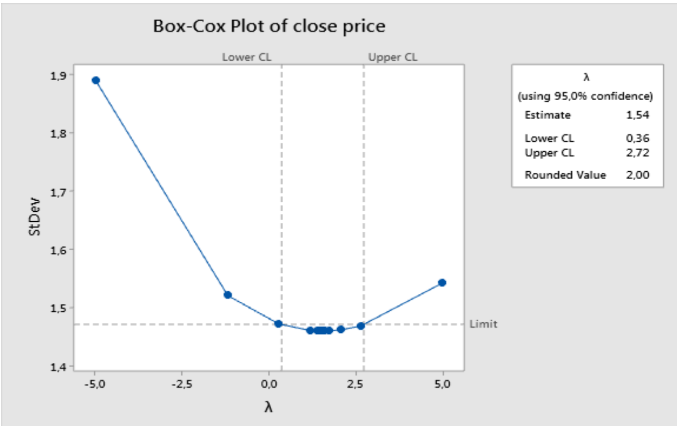

Figure 6 Box-Cox Plot of Stock Price Data

Based on Figure 6, the lambda value shown by the rounded value of 2.00 indicates that the data is not yet stationary with respect to variance. The data shows stationarity after being transformed once. The next step is to check stationarity in the mean. The following is an image of the ACF plot and PACF plot of data that has been stationary in variance.

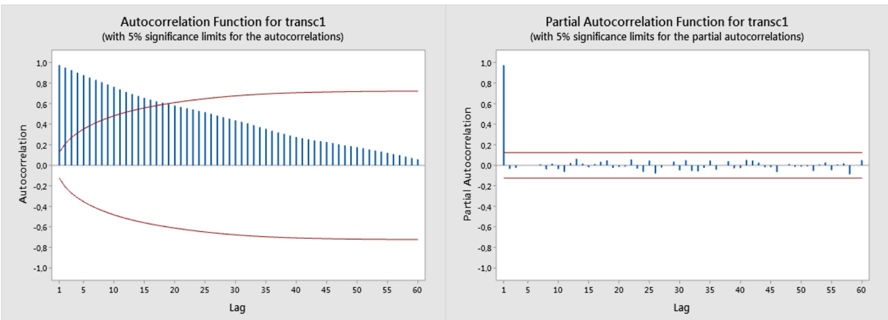

Figure 7 ACF and PACF Plot Stock Price Data

Based on the ACF and PACF graphs above, the data is not yet stationary in the mean. It can be seen that the ACF plot shows a very slow downward pattern and there are still many lags out of the boundary line. In the PACF plot there is also a very high spike at lag 1 which shows a non-stationary data pattern. After differencing once, the data is stationary in the mean.

3.3.2 Model Identification

Based on the stationary ACF and PACF plots, most of the lags do not cross the boundary line. The lag that comes out of the boundary line can be used as a reference to determine the AR and MA orders. However, because the lag that comes out is too far, so the AR and MA orders that are tried to be used as ARIMA models are ARIMA(3,1,3) with a combination of ARIMA(3,1,3), ARIMA(3,1,2), ARIMA(3,1,1), ARIMA(3,1,0), ARIMA(2,1,3), ARIMA(2,1,2), ARIMA(2,1,1), ARIMA(2,1,0), ARIMA(1,1,3), ARIMA(1,1,2), ARIMA(1,1,1), ARIMA(1,1,0), ARIMA(0,1,3), ARIMA(0,1,2), ARIMA(0,1,1).

3.3.3 Parameter Estimation and Significance Test

The estimation results using the help of the R Studio program for a number of temporary ARIMA models that have been obtained are summarized in Table 2.4

Table 4 Results of Significance Testing of ARIMA Models

Model	Parameter Estimation	*p-value*	Significance
ARIMA(3,1,3)	$\hat{\phi}_1 = -0{,}039444$	0,92544	Insignificant
	$\hat{\phi}_2 = -0{,}347441$	0,31183	Insignificant
	$\hat{\phi}_3 = 0{,}754866$	0,06317	Insignificant
	$\hat{\theta}_1 = 0{,}151376$	0,74986	Insignificant
	$\hat{\theta}_2 = 0{,}367051$	0,38245	Insignificant
	$\hat{\theta}_3 = -0{,}723277$	0,12794	Insignificant
ARIMA(3,1,2)	$\hat{\phi}_1 = -0{,}759645$	0,0000	Significant
	$\hat{\phi}_2 = -0{,}932485$	0,0000	Significant
	$\hat{\phi}_3 = 0{,}053601$	0,4077	Insignificant
	$\hat{\theta}_1 = 0{,}873871$	0,0000	Significant
	$\hat{\theta}_2 = 0{,}999964$	0,0000	Signifikan
ARIMA(3,1,1)	$\hat{\phi}_1 = -0{,}0455797$	0,9226	Insignificant
	$\hat{\phi}_2 = 0{,}001061$	0,9223	Insignificant
	$\hat{\phi}_3 = 0{,}0826688$	0,1913	Insignificant
	$\hat{\theta}_1 = 0{,}1239449$	0,7912	Insignificant
ARIMA(3,1,0)	$\hat{\phi}_1 = 0{,}0775009$	0,2193	Insignificant
	$\hat{\phi}_2 = -0{,}0023524$	0,9703	Insignificant
	$\hat{\phi}_3 = 0{,}081030$	0,1999	Insignificant
ARIMA(2,1,3)	$\hat{\phi}_1 = -0{,}325638$	0,006438	Significant
	$\hat{\phi}_2 = -0{,}861069$	0,0000	Significant
	$\hat{\theta}_1 = 0{,}408083$	0,001923	Significant
	$\hat{\theta}_2 = 0{,}910139$	0,0000	Significant
	$\hat{\theta}_3 = 0{,}141331$	0,033790	Significant
ARIMA(2,1,2)	$\hat{\phi}_1 = 0{,}029652$	0,9723	Insignificant
	$\hat{\phi}_2 = 0{,}383898$	0,3683	Insignificant
	$\hat{\theta}_1 = 0{,}057630$	0,9465	Insignificant
	$\hat{\theta}_2 = -0{,}384567$	0,4006	Insignificant
ARIMA(2,1,1)	$\hat{\phi}_1 = 0{,}0390574$	NaN	Insignificant

	$\hat{\phi}_2 = 0{,}0042117$	0,9468	Insignificant
	$\hat{\theta}_1 = 0{,}0387769$	NaN	Insignificant
ARIMA(2,1,0)	$\hat{\phi}_1 = 0{,}0776113$	0,2202	Insignificant
	$\hat{\phi}_2 = 0{,}0043491$	0,9452	Insignificant
ARIMA(1,1,3)	$\hat{\phi}_1 = -0{,}029873$	0,9496	Insignificant
	$\hat{\theta}_1 = 0{,}108521$	0,8169	Insignificant
	$\hat{\theta}_2 = 0{,}017261$	0,8142	Insignificant
	$\hat{\theta}_3 = 0{,}086422$	0,1816	Insignificant
ARIMA(1,1,2)	$\hat{\phi}_1 = 0{,}0395604$	NaN	Insignificant
	$\hat{\theta}_1 = 0{,}0387378$	NaN	Insignificant
	$\hat{\theta}_2 = -0{,}0022683$	0,9718	Insignificant
ARIMA(1,1,1)	$\hat{\phi}_1 = 0{,}039125$	NaN	Insignificant
	$\hat{\theta}_1 = 0{,}038881$	NaN	Insignificant
ARIMA(1,1,0)	$\hat{\phi}_1 = 0{,}077959$	0,2167	Insignificant
ARIMA(0,1,3)	$\hat{\theta}_1 = 0{,}079144$	0,2072	Insignificant
	$\hat{\theta}_2 = 0{,}015020$	0,8156	Insignificant
	$\hat{\theta}_3 = 0{,}086094$	0,1819	Insignificant
ARIMA(0,1,2)	$\hat{\theta}_1 = 0{,}0785507$	0,2182	Insignificant
	$\hat{\theta}_2 = -0{,}0024923$	0,9687	Insignificant
ARIMA(0,1,1)	$\hat{\theta}_1 = 0{,}078326$	0,2189	Insignificant

Based on the ARIMA model parameter estimation results in Table 2.4, the ARIMA model that passes the parameter significance test is the ARIMA (2,1,3) model. The AIC value of the ARIMA (2,1,3) model is 3999.74.

3.3.4 Residual Assumption Testing (Diagnostic Cheking)

3.3.4. 1 Normalitiy Test

The following are the results of the calculation of the Kolmogorov-Smirnov statistical value

Table 5 Calculation of Kolmogorov-Smirnov Statistical Value

Residual	F	FK	F(S)	Z	F(T)	ǀF(T)-F(S)ǀ
−3273,23753	1	1	0,004	−4,63562	0,00000	0,00400
−2519,08771	1	2	0,008	−3,59179	0,00016	0,00784
⋮	⋮	⋮	⋮	⋮	⋮	⋮
−535,74544	**1**	**41**	**0,164**	**−0,84661**	**0,19861**	**0,03461**
⋮	⋮	⋮	⋮	⋮	⋮	⋮
2685,66146	1	250	1	3,61220	0,99985	0,00015

$|F_T - F_S|$ the largest is 0,03461

$KS_{table} = 0{,}08601$

Based on Table 4 the calculation value of Kolmogorov-Smirnov Statistics, the largest value of $|F_T - F_S|$ is 0,03461. Because the largest $|F_T - F_S|\ value < KS_{table}$, it can be concluded that the residuals are normally distributed.

3.3.4.2 White Noise Test

The following are the results of white noise residual testing displayed in graph form.

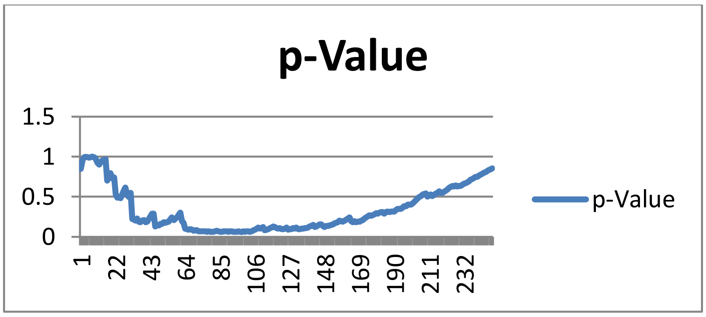

Figure 8 White Noise Residual Test on ARIMA Model

Based on Figure 8, it is known that each lag has a $p - value > 0{,}05$ s so that it can be decided to fail to reject H_0 and it can be concluded that the ARIMA model residual data meets the white noise assumption.
The ARIMA (2,1,3) model can be written as follows:

$$Y_t = Y_{t-1} - 0{,}325638(Y_{t-1} - Y_{t-2}) - 0{,}861069(Y_{t-2} - Y_{t-3}) - 0{,}408083\varepsilon_{t-1} - 0{,}910139\varepsilon_{t-2} - 0{,}141331\varepsilon_{t-3} + \varepsilon_t$$

The results of forecasting using the ARIMA (2,1,3) model are obtained in the following table.

Table 6 Forecast Results Using the ARIMA Model

Period	Forecast Result	Actual
251	192,1994537	185,639999
252	192,2613066	184,250000
253	192,3753363	181,910004
254	192,2849708	181,179993
255	192,2162064	185,559998
256	192,316432	185,139999
257	192,3430009	186,190002
258	192,2480429	185,589996
259	192,2560792	185,919998
260	192,3352282	183,630005
261	192,3025481	182,679993
262	192,2450259	188,630005
263	192,2919135	191,559998
264	192,3261553	193,889999
265	192,3266492	195,179993
266	192,2619307	194,500000
267	192,3104261	194,169998
268	192,3055901	192,419998
269	192,2654155	191,729996
270	192,2826565	188,039993
271	192,3116481	184,399994

3.4 MAPE (Mean Absolute Percentage Error)

The following is a summary of the comparison of the MAPE values of the two models

Table 7 Comparison of MAPE Value

Model	Data	
	Training	*Testing*
Hybrid TSR linear-ARIMA	4,65%	3,79%
ARIMA	0,9%	2,90%

Based on Table 7 above, the two models are categorized as models that have a very accurate forecasting accuracy value because the MAPE value of the two models is below 10%, which means that the average deviation of the predicted value is below 10% of the actual value. Among the two models, the ARIMA model has a smaller MAPE value in both testing and training data, besides that the difference in MAPE values is also not much different (< 2%), it can be said that the model is quite stable.

4. CONCLUSION

Based on the results of the research that has been done, the conclusions in this study can be drawn as follows: (1) The form of hybrid TSR linear-ARIMA model on Apple Inc. stock price data is $H_t = 148{,}0017019 + 0{,}195596004t + Y_{t-1} - 0{,}815130(Y_{t-1} - Y_{t-2}) - 0{,}977606(Y_{t-2} - Y_{t-3}) + 0{,}110273\varepsilon_{t-1} - 0{,}136773\varepsilon_{t-2} + 0{,}985870\varepsilon_{t-3} + \varepsilon_t$. (2) The form of ARIMA model on the stock price of Apple Inc. is $Y_t = Y_{t-1} - 0{,}325638(Y_{t-1} - Y_{t-2}) - 0{,}861069(Y_{t-2} - Y_{t-3}) - 0{,}408083\varepsilon_{t-1} - 0{,}910139\varepsilon_{t-2} - 0{,}141331\varepsilon_{t-3} + \varepsilon_t$. (3) The ARIMA model has a better forecasting accuracy value with a MAPE value of 2,909%. (4) The results of forecasting the daily Apple Inc. stock price using the ARIMA (2,1,3) model for the period January 2024 in USD units are: period 1 = \$192,1994537; period 2 = \$192,2613066; period 3 = \$192,3753363; period 4 = \$192,2849708; period 5 = \$192,2162064; period 6 = \$192,316432; period 7 = \$192,3430009; period 8 = \$192,2480429; period 9 = \$192,2560792; period 10 = \$192,3352282; period 11 = \$192,3025481; period 12 = \$192,2450259; period 13 = \$192,2919135; period 14 = \$192,3261553; period 15 = \$192,3266492; period 16 = \$192,2619307; period 17 = \$192,3104261; period 18 = \$192,3055901; period 19 = \$192,2654155; period 20 = \$192,2826565; period 21 = \$192,3116481.

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Author Contributions Statement

Aulia Padhila Ersu: Conceptualization, methodology, data curation, software, formal analysis, visualization, writing-original draft.
Muhammad Rijal Alfian: Supervision, validation, methodology, writing-review & editing.
Nur Asmita Purnamasari: Formal analysis, validation, resources, writing-review & editing.
All authors discussed the results and contributed to the final manuscript.

Conflict of Interest Statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

The data that support the findings of this study are publicly available from Yahoo Finance at https://finance.yahoo.com/. Additional processed data are available from the corresponding author upon reasonable request.

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