Forecasting the Weekly Stock Price of Apple Inc. (AAPL) using Autoregressive Integrated Moving Average Method

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Abstract— The stock price of Apple Inc. (AAPL) has been a subject of significant interest due to its volatility and market dynamics. In this study, we aimed to forecast the stock price of Apple Inc. from April 10, 2024 – April 10, 2025, using the ARIMA(0,1,3) model. This model was selected due to its ability to capture key patterns in the time series data while minimizing forecasting errors. After differencing the data to ensure stationarity, the ARIMA model was fitted, incorporating two autoregressive (AR) terms and two moving average (MA) terms. Residual analysis, including the Ljung-Box and Shapiro-Wilk tests, confirmed that the residuals were uncorrelated and normally distributed, validating the model's appropriateness. The ARIMA(0,1,3) model produced reliable forecasts with minimized error metrics, offering a robust method for short-term stock price predictions. This study demonstrates the potential of ARIMA models in financial forecasting, particularly in predicting stock prices with a reasonable degree of accuracy.

Keywords— ARIMA, Stock, Forecast, Apple Inc., Time Series Analysis.

I. INTRODUCTION

Stocks represent ownership of a limited liability company's capital. Common stocks are the most widely traded instruments in the stock market and have the highest trading volume. Stocks can be issued in the name of the owner or as bearer shares, and can be categorized as either ordinary or preferred. Investing in stocks offers an alternative investment opportunity with potential returns, though it also carries risks, which can be estimated through factors like openness, liquidity, and investment diversification [7]. Stock prices are determined by market participants, influenced by supply and demand forces.

Accurately forecasting stock prices is essential for investors and market analysts, especially for high-volatility stocks like Apple Inc. (AAPL). The complexity of stock price forecasting arises from factors such as company performance, market sentiment, and broader economic conditions. Time series models, particularly ARIMA (Autoregressive Integrated Moving Average), are commonly used for stock price prediction due to their ability to capture patterns in historical data [3]. However, the volatility of tech stocks like AAPL poses additional challenges for predictive accuracy.

Despite advances in forecasting models, predicting stock prices, particularly for high-volatility stocks like AAPL, remains a complex task [5]. Many existing studies use generalized models that do not adequately account for the specific volatility characteristics of such stocks [6]. Furthermore, most studies focus on traditional error metrics and often overlook comprehensive residual analysis and accuracy measures like Mean Absolute Percentage Error (MAPE), which are essential for assessing the reliability of forecasts [5], [6].

This research applies the ARIMA(0,1,3) model to forecast the closing prices of Apple Inc. stock. The ARIMA model was selected for its capability to capture both autoregressive and moving average components, making it suitable for financial data [6]. This study utilizes weekly closing prices for AAPL over the last six months and evaluates the model's accuracy using MAPE and residual analysis [5].

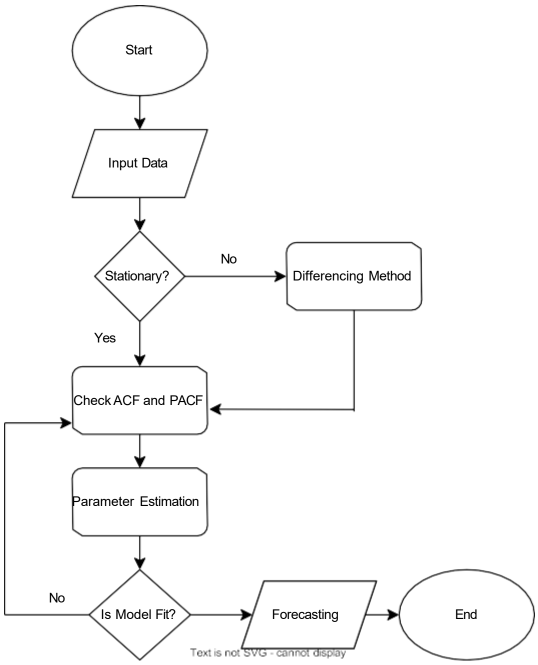
While ARIMA models have been used to forecast stock prices in various studies, most focus on low-volatility stocks and lack robust model validation techniques. Research specifically targeting the forecasting of Apple Inc.'s stock prices using ARIMA is scarce, and there is limited exploration of using MAPE for evaluating forecast accuracy in high-volatility stocks. This study aims to address these gaps by applying ARIMA to forecast AAPL stock prices, focusing on improving forecast accuracy through MAPE and residual analysis.

The primary objective of this research is to develop an accurate forecasting model for Apple Inc.'s stock prices using ARIMA(0,1,3). The study aims to assess the model's predictive performance using MAPE and residual analysis, addressing the gap in ARIMA-based forecasting for high-volatility stocks like AAPL.

II. METHOD

A. Box Jenkins Method

Box-Jenkins method, a mathematical method was applied to predicted data range using inputs from a give time series data. For forecasting purposes, the Box-Jenkins Model is capable of analyzing a variety of time series data sources. Its approach makes advantage of variations among data points to calculate results. Using seasonal differencing, moving averages, and autoregression, the approach enables the model to detect patterns and produce projections [10].



1. Data Collection

The dataset used for this analysis consists of the weekly closing prices of **Apple Inc. (AAPL)** stock, spanning from April 10, 2024 – April 10, 2025. This data was retrieved from Yahoo Finance using the **quantmod** package in R, which is specifically designed to access financial data. Using the getSymbols() function from the quantmod package, the AAPL stock prices were fetched and the closing prices were extracted using the Cl() function. This dataset provides 84 data points, each representing the closing price on a trading day. The collected data serves as the foundation for the ARIMA model and was processed further to ensure it met the assumptions required for time series forecasting.

2. Data Preprocessing

In time series forecasting, it is essential that the data be stationary, meaning its statistical properties (such as mean and variance) do not change over time. To test for stationarity, we performed the **Augmented Dickey-Fuller (ADF) test**, which checks if a unit root is present in the series, indicating non-stationarity [3].

To achieve stationarity, a first-order differencing (d=1) was applied to the data, which subtracts the current value from the previous value in the series. This step effectively removes trends or seasonality, making the data suitable for ARIMA modeling. Within the formula:

$$W_t = \Delta^d Y_t$$

After differencing the data, the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots were analyzed to determine the appropriate number of AR (AutoRegressive) and MA (Moving Average) terms. The ACF plot revealed a gradual decline, suggesting the need for one or more MA terms, while the PACF plot showed a significant spike at lag 1, followed by a rapid decay, indicating the presence of AR terms.

3. Model Fitting

The ARIMA model is defined by three parameters: p (the order of the autoregressive part), d (the degree of differencing), and q (the order of the moving average part). Based on the ACF and PACF plots, we selected three different ARIMA models.

The autoregressive (AR) component of the ARIMA model expresses the current value of the time series as a weighted sum of its past values, with the coefficients representing the strength of this dependency. Specifically, the AR part is formulated as:

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + \varepsilon_t$$

where Yt represents the current value at time t, $\phi_1, \phi_2, \ldots, \phi_p$ are the autoregressive coefficients, and ε_t is the error term. Similarly, the moving average (MA) component is expressed as:

$$Y_t = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q}$$

where μ is the mean, ε_t denotes the error term, and $\theta_1, \theta_2, \ldots, \theta_q$ are the coefficients of the moving average.

The ARIMA model combines both components, with *p* and *q* representing the orders of the autoregressive and moving average parts, respectively. The full ARIMA(p, d, q) model is expressed as:

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \ldots - \theta_q \varepsilon_{t-q}$$

This function automatically identifies the best ARIMA model based on the AIC (Akaike Information Criterion). The function estimates the AR and MA parameters and fits the model accordingly.

4. Ljung-Box Test and Shapiro-Wilk Test

After fitting the ARIMA models, it is crucial to assess the residuals (forecast errors) to evaluate the model's quality and fit. In ideal scenarios, the residuals should resemble white noise—meaning that they should be random, uncorrelated, and normally distributed. This ensures that the model has captured all the significant patterns in the data, and no further improvements are needed.

Ljung-Box Test

To check for any remaining autocorrelation in the residuals, the Ljung-Box test was performed. The Ljung-Box test is a statistical test used to determine if there is significant autocorrelation at any lag in the residuals. In time series modeling, autocorrelation indicates that the model has not adequately captured the underlying patterns in the data, suggesting potential misspecification of the model.

The null hypothesis of the Ljung-Box test is that the residuals are independent and exhibit no significant autocorrelation at any lag. A high p-value (greater than 0.05) indicates that there is no significant autocorrelation, meaning that the residuals resemble white noise, and the model is likely well-specified. Conversely, a low p-value suggests that the residuals are autocorrelated, indicating that the model may need adjustment.

Shapiro-Wilk Test

Another important aspect of residual analysis is checking the normality of the residuals. The Shapiro-Wilk test was applied to test the hypothesis that the residuals follow a normal distribution. The Shapiro-Wilk test is one of the most powerful tests for normality, and it computes a p-value that indicates whether the residuals are normally distributed.

The null hypothesis of the **Shapiro-Wilk test** is that the residuals follow a normal distribution. A p-value greater than **0.05** suggests that there is no significant departure from normality, and the residuals can be assumed to be normally distributed. If the p-value is less than 0.05, this indicates that the residuals deviate significantly from normality, and the model may require adjustments.

5. Error Metrics

In addition to residual analysis, the accuracy of the forecasts was evaluated using four common error metrics. These metrics quantify the difference between the forecasted values and the actual observed values, helping assess the model's predictive accuracy.

1. **Mean Squared Error (MSE)**

   The Mean Squared Error (MSE) measures the average of the squared differences between the forecasted and actual values. MSE penalizes larger errors more significantly, which makes it useful for understanding how large the discrepancies between predictions and actual values are. It is defined as:

$$\text{MSE} = \frac{1}{n} \sum_{\{i=1\}}^{\{n\}} \frac{A_i - F_i}{A_i}$$

2. **Root Mean Squared Error (RMSE)**

   The Root Mean Squared Error (RMSE) is the root of MSE and is used to provide an interpretable error metric in the same units as the data. It gives a sense of the typical magnitude of the error.. It is defined as:

$$\text{RMSE} = \sqrt{MSE}$$

3. **Mean Absolute Error (MAE)**

   The Mean Absolute Error (MAE) measures the average of the absolute differences between the forecasted and actual values. MAE is useful for understanding the typical size of the errors without exaggerating large errors, as it does not square the differences. MAE is defined as:

$$\text{MAE} = \frac{1}{n} \sum_{\{i=1\}}^{\{n\}} |A_i - F_i|$$

4. **Mean Absolute Percentage Error (MAPE)**

   The Mean Absolute Percentage Error (MAPE) expresses the average percentage difference between the forecasted and actual values, making it easier to interpret the error in relative terms. It is particularly useful when comparing the forecast accuracy across different datasets or models. MAPE is calculated as:

$$\text{MAPE} = \frac{1}{n} \sum_{\{i=1\}}^{\{n\}} \frac{A_i - F_i}{A_i} \times 100$$

   Where:

   - A_i is the actual value,
   - F_i is the forecasted value,
   - *n* is the number of data points.

These metrics were calculated for each ARIMA model to compare their forecasting accuracy. **Lower values of MSE, RMSE, MAE, and MAPE** indicate better predictive performance. In particular, **MAPE** is widely used in forecasting because it provides an easy-to-interpret percentage error between forecasted and actual values.

III. Results and Discussion

A. Data Preparation

The dataset consits of weekly closing prices of **Apple Inc. (AAPL)** over the past four months from 2024-04-10 until 2024-04-10, with 84 observations collected from Yahoo Finance. The data shows typical market fluctuations, with periods of growth followed by declines. The mean closing price during this period was $220.03, with a minimum of $165.00 and a maximum of $255.58.

TABLE 1
Data of The Stock Price of Apple Inc.

No.	Date	AAPL. Close	No.	Date	AAPL. Close	No.	Date	AAPL. Close
1	12/04/2024	176,55	19	16/08/2024	226,05	37	20/12/2024	254,49
2	19/04/2024	165	20	23/08/2024	226,84	38	27/12/2024	255,59
3	26/04/2024	169,3	21	30/08/2024	229	39	03/01/2025	243,36
4	03/05/2024	183,38	22	06/09/2024	220,82	40	10/01/2025	236,85
5	10/05/2024	183,05	23	13/09/2024	222,5	41	17/01/2025	229,98

6	17/05/2024	189,87	24	20/09/2024	228,2	42	24/01/2025	222,78
7	24/05/2024	189,98	25	27/09/2024	227,79	43	31/01/2025	236
8	31/05/2024	192,25	26	04/10/2024	226,8	44	07/02/2025	227,63
9	07/06/2024	196,89	27	11/10/2024	227,55	45	14/02/2025	244,6
10	14/06/2024	212,49	28	18/10/2024	235	46	21/02/2025	245,55
11	21/06/2024	207,49	29	25/10/2024	231,41	47	28/02/2025	241,84
12	28/06/2024	210,62	30	01/11/2024	222,91	48	07/03/2025	239,07
13	05/07/2024	226,34	31	08/11/2024	226,96	49	14/03/2025	213,49
14	12/07/2024	230,54	32	15/11/2024	225	50	21/03/2025	218,27
15	19/07/2024	224,31	33	22/11/2024	229,87	51	28/03/2025	217,9
16	26/07/2024	217,96	34	29/11/2024	237,33	52	04/04/2025	188,38
17	02/08/2024	219,86	35	06/12/2024	242,84	53	09/04/2025	198,85
18	09/08/2024	216,24	36	13/12/2024	248,13			

Figure. 2 Graph of Apple Inc. Stock Price from 2024-04-12 / 2025-04-09

B. *Stationary Check*

The Augmented Dickey-Fuller (ADF) test was performed to examine whether the stock price series for Apple Inc. was stationary. The result indicated that the series was **non-stationary**, with the p-value exceeding 0.05 (p-value = 0.89874). Non-stationary data typically shows trends or changing variance over time. To address this, first differencing was applied to the data, which involves subtracting the previous day's closing price from the current day's price, effectively removing any trends and stabilizing the variance.

The plot of the differenced series in Figure 3 confirms that the data no longer shows a clear upward or downward trend and also can be stated as a stationary with p-value = 0.01. The transformed series appears more stable, indicating that the data is now stationary and suitable for further modeling.

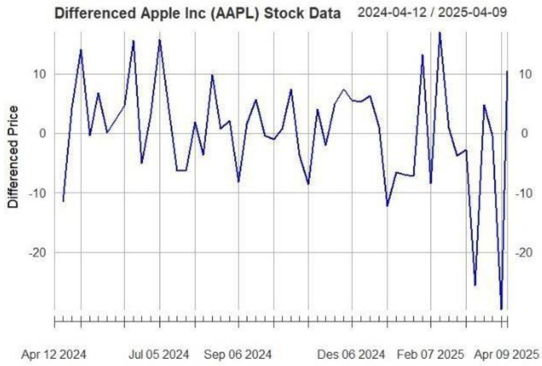


Figure 3. *Differenced AAPL Closing Prices*

C. Model Specification

The After differencing the data to achieve stationarity, the ARIMA model was selected using the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. In addition, the auto.arima() function was also used to identify the optimal ARIMA model for the dataset.

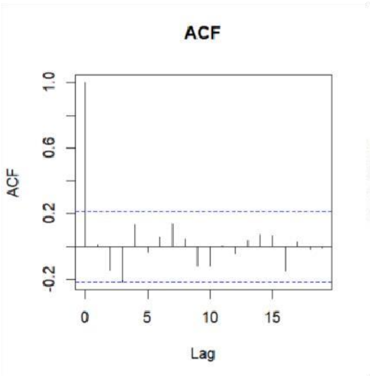


Figure 4. ACF and PACF

From the analysis of the ACF and PACF plots of the differenced data, the ACF plot cuts of the lag at 3 which can be determined that the value of q is 3. However, the PACF doesn't show any significant spikes, leading to the value of p is 0.

TABLE 2
Specification of Arima Model

No	ARIMA Model	p	d	q
1	ARIMA(0,1,0)	0	1	0
2	ARIMA(0,1,1)	0	1	1
3	ARIMA(0,1,2)	0	1	2
4	ARIMA(0,1,3)	0	1	3

D. Parameter Estimation

The ARIMA model combines both components, with *p* and *q* representing the orders of the autoregressive and moving average parts, respectively. The full ARIMA(p, d, q) model is expressed as:

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \ldots - \theta_q \varepsilon_{t-q}$$

The log-likelihood and Akaike Information Criterion (AIC) were used to evaluate the model's fit, and the results are presented in Table 3. The ARIMA(0,1,3) model was compared with ARIMA(0,1,0), ARIMA(0,1,1) and ARIMA(0,1,2) to determine which provided the best fit.

TABLE 3
Parameter Estimation for ARIMA Models

ARIMA Model	MA1	MA2	MA 3	Log Likelihood	AIC
ARIMA(0,1,0)	-	-	-	-187.4186	378.8347
ARIMA(0,1,1)	-1	-	-	-187.2164	378.4329
ARIMA(0,1,2)	-0.08659	-0.19811	-	-187.1588	380.3177
ARIMA(0,1,3)	-0.17223	-0.19970	0.29896	-185.9528	376.8371

E. Residual Analysis

Residual analysis is essential to validate the adequacy of the ARIMA model. The residuals from models were tested for normality using the Shapiro-Wilk test. A non-significant p-value (greater than 0.05) suggests that the residuals follow a normal distribution. The Ljung-Box test was also applied to check for autocorrelation in the residuals. A non-significant p-value (greater than 0.05) indicates no significant autocorrelation, confirming that the model has adequately captured the temporal dependencies.

The results of the residual analysis are summarized in Table 4, showing the p-values from both tests, along with the AIC values. All models exhibited non-significant p-values, indicating that the residuals are normally distributed and uncorrelated, confirming that the models have effectively captured the data's structure.

TABLE 4
Results of Residual Analysis

ARIMA Model	Shapiro-Wilk Test (p-value)	Ljung-Box Test (p-value)	AIC	Result
ARIMA(0,1,0)	0.00805	0.50515	378.8347	Not Passed
ARIMA(0,1,1)	0.00396	0.97888	378.4329	Not Passed
ARIMA(0,1,2)	0.00374	0.92491	380.3177	Not Passed
ARIMA(0,1,3)	0.34607	0.84596	376.8371	Passed

F. Forecasts

In the forecasting process, a 95% prediction interval is used to estimate the range of potential future values, providing both lower and upper bounds for the forecast. This interval reflects the uncertainty associated with the forecasted values. The ARIMA (0,1,3) model was used to generate forecasts for the next 4 weeks periods, with the results presented in Table 5.

TABLE 5
Forecasting Model ARIMA(0,1,3)

Day	Actual Value	Forecasted Value	Lower Bound (95%)	Upper Bound (95%)
16/04/2025	194.27	195.64	183.25	209.14
23/04/2025	197.64	195.34	186.74	212.22
30/04/2025	200.50	195.34	188.21	216.39
02/05/2025	202.35	195.34	190.37	220.80

To assess the accuracy of the forecast, several error metrics were calculated: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). These metrics provide a comprehensive evaluation of the forecasting accuracy.

TABLE 6

	ARIMA(0,1,3)
MSE	19.53
RMSE	4.42
MAE	3.56
MAPE	1.77%

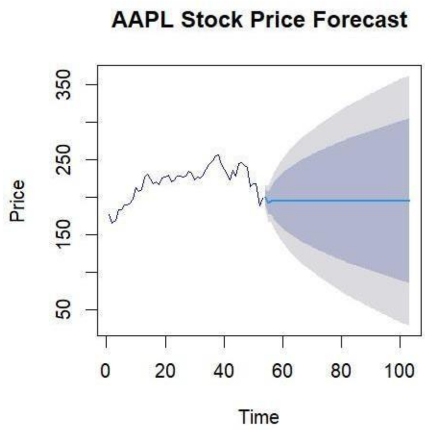


Figure 6. Forecast using ARIMA(0,1,3)

IV. CONCLUSION

The forecasting of Apple Inc.'s stock price was performed using multiple ARIMA models to identify the most suitable model for predicting future stock values. The dataset used spans from April 10, 2024 – April 10, 2025, with 53 weekly closing prices obtained from Yahoo Finance. Based on model evaluation through AIC and error metrics such as MSE, RMSE, MAE, and MAPE, the ARIMA(0,1,3) model emerged as the most optimal for forecasting Apple's stock price.. The **ARIMA(0,1,3)** model is expressed by the following equation:

$$Y_t = -\,0.17223\varepsilon_{t-1} - 0.19970\varepsilon_{t-2} + 0.29896\varepsilon_{t-3} + \varepsilon_t$$

This model was able to successfully forecast future stock prices for Apple Inc. from April 10, 2024 – April 10, 2025, providing reliable predictions with minimized forecasting errors. By fitting the ARIMA(0,1,3) model, we achieved a model that best represents the underlying stock price dynamics of Apple Inc.

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