Apple Stock Price Forecasting

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ECON 47503

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April 30^{th}, 2025

Introduction

This project investigates the effectiveness of various time series forecasting techniques in projecting the stock price of Apple Inc. (AAPL) over a five-year horizon. Given Apple's significant influence in the global tech sector and the inherent fluctuations in its share price, the company presents a strong case for applying and assessing the forecasting methods introduced in this course. As one of the most valuable and actively traded corporations, Apple's stock is influenced by a range of factors, including product innovation, market perception, and macroeconomic trends.

According to Statista, Apple's market capitalization exceeded $2.8 trillion in 2024, reinforcing its status as a bellwether for both the technology sector and the broader economy (Statista, 2024). This study compares the performance of several forecasting models, ranging from straightforward linear regression to more complex frameworks such as ARIMA and seasonal-trend decomposition using LOESS (STL) combined with residual ARIMA modeling.

Our approach draws on foundational time series analysis by Box and Jenkins (1976), who introduced systematic strategies for modeling and forecasting financial data. Additionally, the STL decomposition method established by Cleveland et al. (1990) guided the structure of our most advanced model.

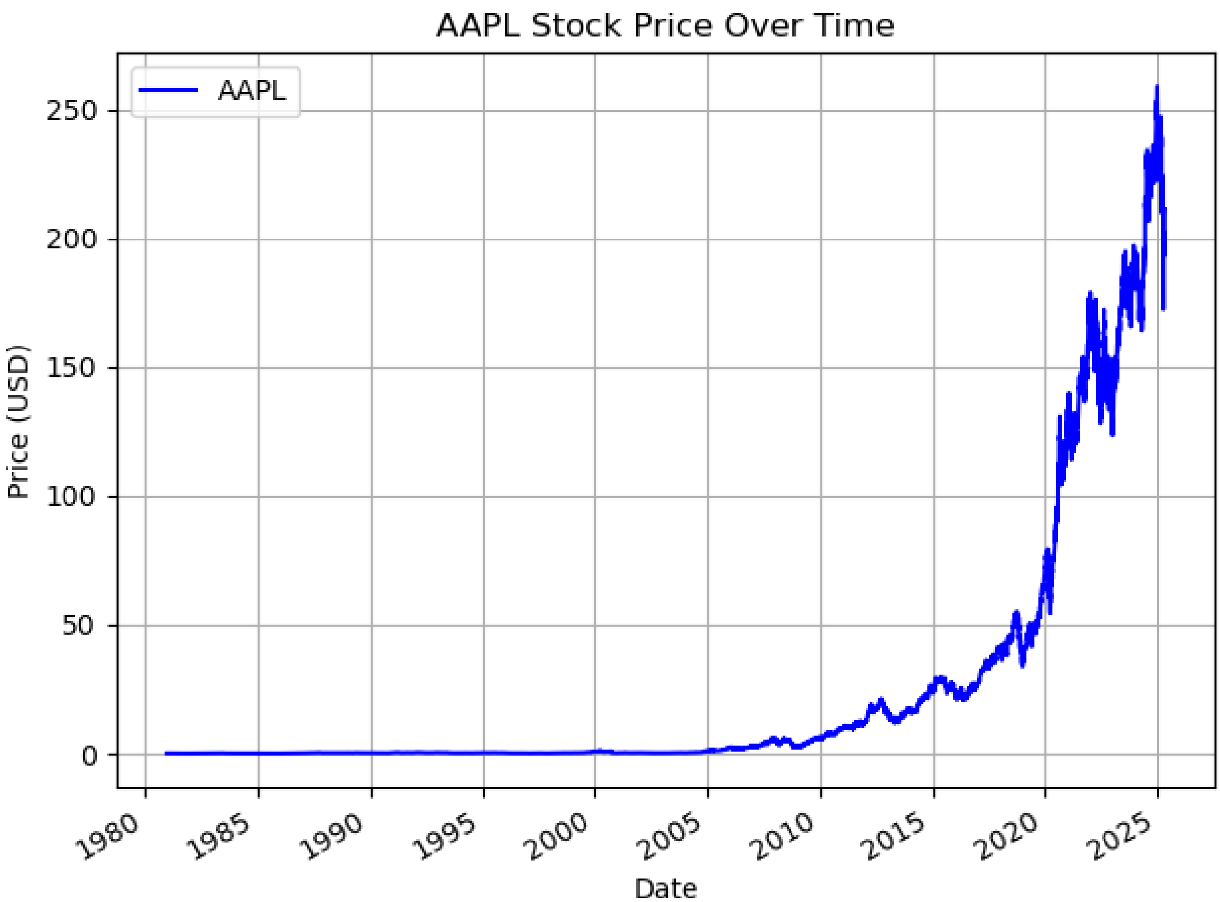
We evaluated five different forecasting methods: linear regression, a 12-month moving average, integrated moving average (IMA), ARIMA, and STL decomposition with ARIMA applied to the residuals. Historical stock data was used to produce forecasts through 2029, enabling a comparative assessment of each model's ability to capture past trends and predict future behavior.

Dataset

We utilized Apple's monthly adjusted closing prices sourced from Yahoo Finance, spanning from 1980 through the end of 2024. This extensive dataset provided over four decades of observations, offering a rich foundation for long-term trend analysis. The data was resampled to a monthly frequency to reduce short-term noise and highlight overarching movements in price.

For simplicity and clarity, only the 'Date' and 'Close' fields were preserved, allowing the focus to remain on temporal price dynamics. Figure 1 showcases the unmodeled data in line graph form.

Figure 1: Monthly AAPL Price



Apple's share price demonstrated prolonged periods of steady growth interspersed with sharp surges, especially after 2019. This combination of linear and nonlinear trends made it a strong candidate for evaluating forecasting models. Visualizing the entire historical trajectory allowed us to identify inflection points and shifts in price behavior.

Methods

We employed five distinct forecasting models using Python, with core implementation relying on the pandas, statsmodels, and matplotlib libraries. To ensure consistency and emphasize general patterns, AAPL stock prices were resampled to monthly intervals and logtransformed when suitable. Each model produced forecasts extending five years beyond the end of 2024.

The Linear Regression model offered a baseline by fitting a straight trend line to historical data. It treated the adjusted closing price as the dependent variable and indexed time sequentially as the predictor. The model equation takes the form: where is the closing price at time t, is the intercept, is the rate of change over time, and is the random error.

Moving Average (MA) smoothed short-term fluctuations by calculating a rolling average of the past 12 months. It provided a conservative forecast by holding the final smoothed value constant into the future: , where is the past 12 months' closing price.

Integrated Moving Average (IMA) captured monthly price momentum by first differencing the series, then applying a 12-month average to the differences: , and = - (representing month to month change).

ARIMA (Auto Regressive Integrated Moving Average) modeled stationary-adjusted prices using autoregressive and moving average components combined with differencing:

where and are lag polynomials for the AR and MA components, and , denotes the order of differencing.

STL + ARIMA separated the time series into trend, seasonal, and residual components using Seasonal-Trend Decomposition via LOESS (STL). An ARIMA model was then applied to the residuals to account for irregular patterns, resulting in the final forecast: Forecast = Trend + Seasonal + ARIMA(Residual). This decomposition-based approach allows the model to account for long-term structure and short-term volatility simultaneously.

All analysis was performed in a single Jupyter notebook using Visual Studio Code, allowing for reproducibility and consistency across models.

Results

Model Forecasting

Each forecasting model was visualized using a graph that featured three distinct colored lines to differentiate model components. The black line represents the actual historical stock prices. The blue line reflects the fitted values from the model within the sample period. The dotted orange line illustrates the model's forecasted stock price over the five-year future window. A red dot at the end of each projection marks the predicted price in 2029, which is also labeled in each figure for clarity.

Figure 2: Linear Regression Forecast

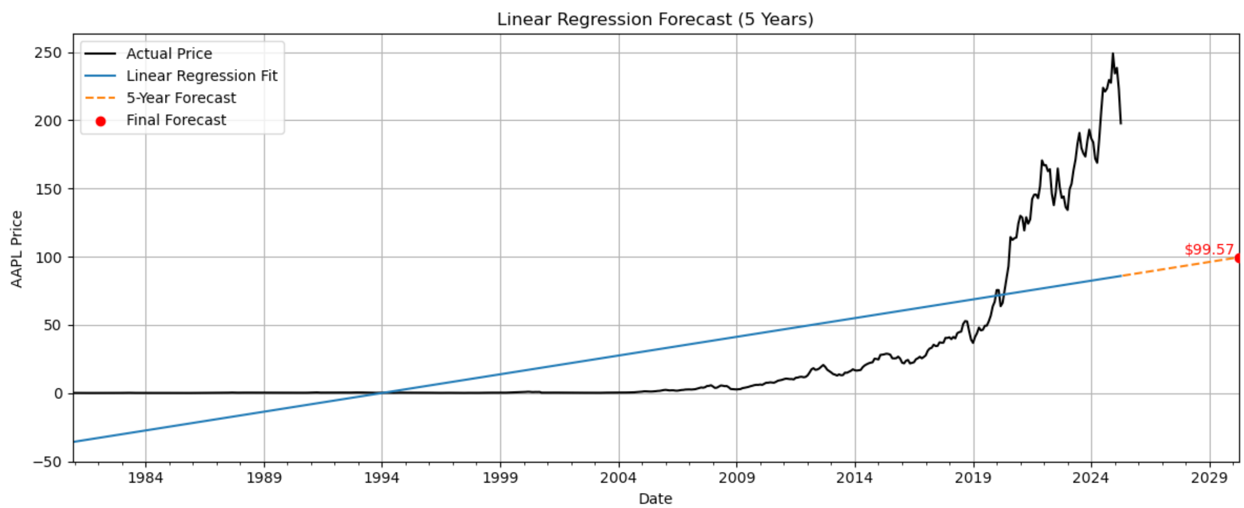
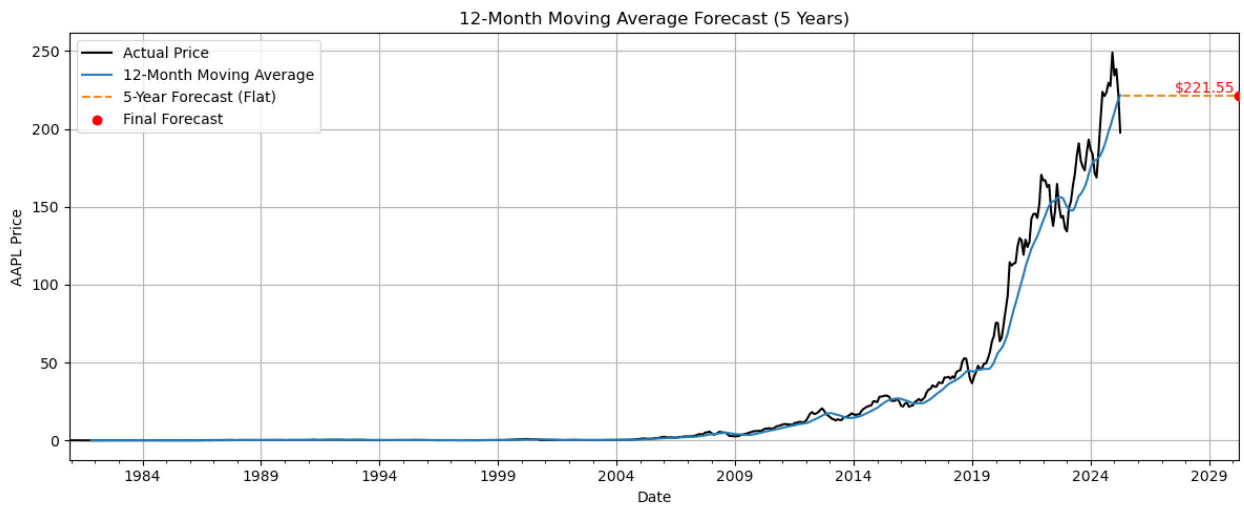


Figure 2 shows the linear regression projection, which assumes a constant rate of growth and projects a 2029 stock price of **$99.57**. However, the model underestimates Apple's more recent performance, particularly the accelerated growth observed since 2019. This gap between the projection and actual data suggests that while linear regression serves as a basic trend benchmark, it fails to capture the non-linear dynamics evident in recent years. This highlights the need for more flexible forecasting models.

Figure 3: Moving Average Forecast



In Figure 3, the moving average approach captures smoothed historical trends by computing a rolling 12-month average. The model assumes that the final smoothed value remains stable into the forecast period, resulting in a projected 2029 value of **$221.55**, denoted by the red marker. This method more closely tracks recent levels than linear regression but assumes no future growth beyond the current average. It effectively filters out volatility but lacks responsiveness to shifts in long-term momentum, making it best suited for short-term stabilization rather than long-term forecasting.

Figure 4: Integrated Moving Average Forecast

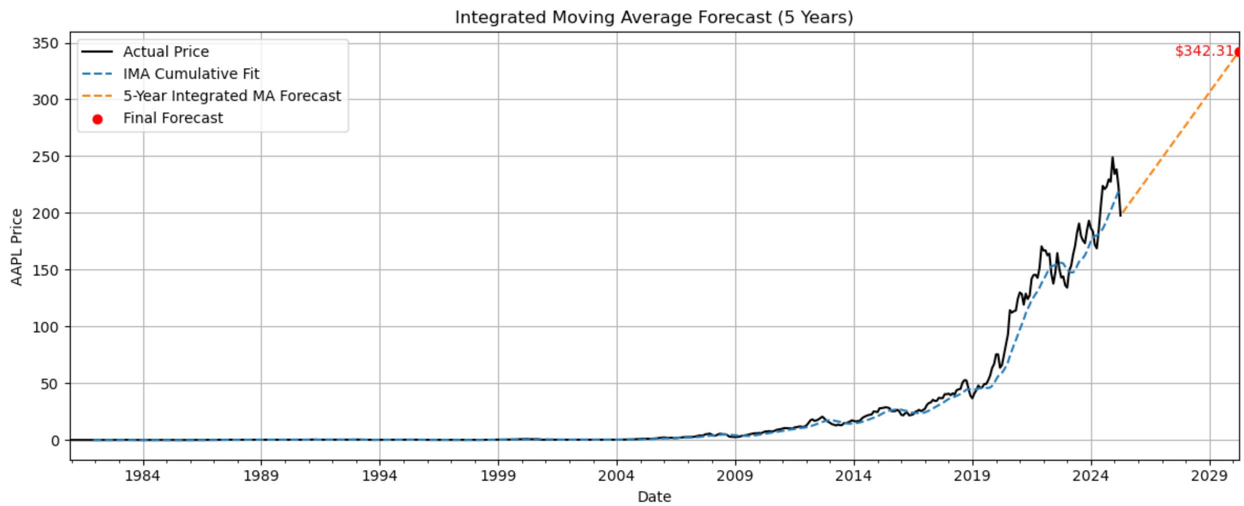
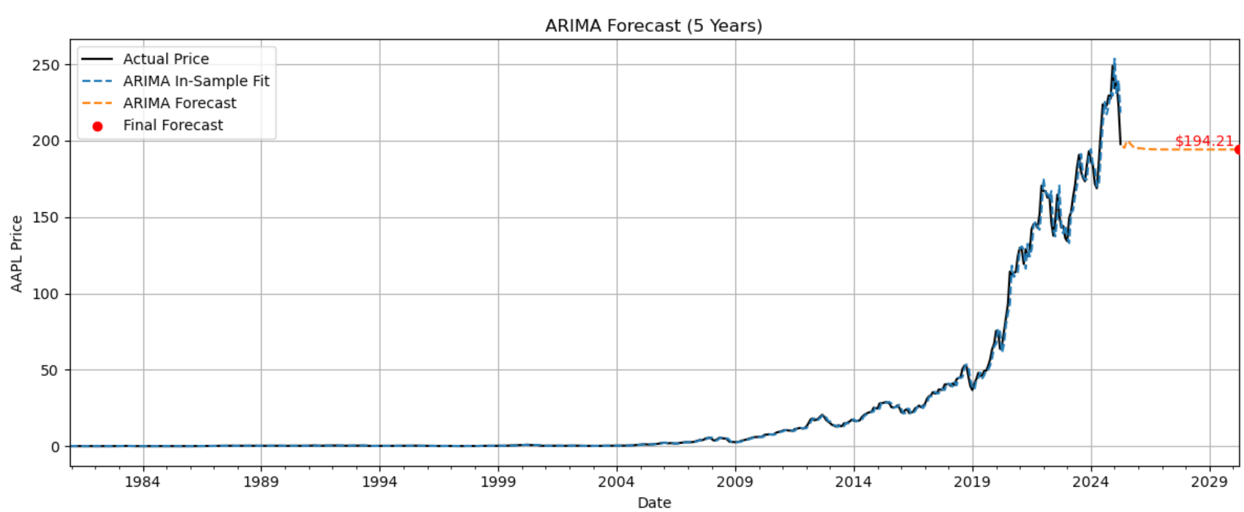


Figure 4 displays the output from the integrated moving average model, which builds its forecast by averaging the monthly changes in price over the previous year and extending that pattern into the future. This results in a much more bullish projection of **$342.31** by 2029. By emphasizing recent upward momentum, the IMA model anticipates continued strong growth. While optimistic, this method rests heavily on the assumption that past momentum will persist, making it more sensitive to shifts in market conditions.

Figure 5: ARIMA Forecast



The ARIMA forecast, shown in Figure 5, demonstrates a closer in-sample fit to recent data than the simpler models. Its forecast predicts a 2029 stock price of approximately **$194.21**, marked by the red dot. ARIMA accounts for autoregressive patterns, differencing (to address non-stationarity), and moving averages, making it capable of capturing both trend and noise. This model suggests a potential plateau in AAPL's growth trajectory, reflecting a more tempered outlook that balances previous surges with possible stabilization.

Figure 6: Decomposed ARIMA Forecast

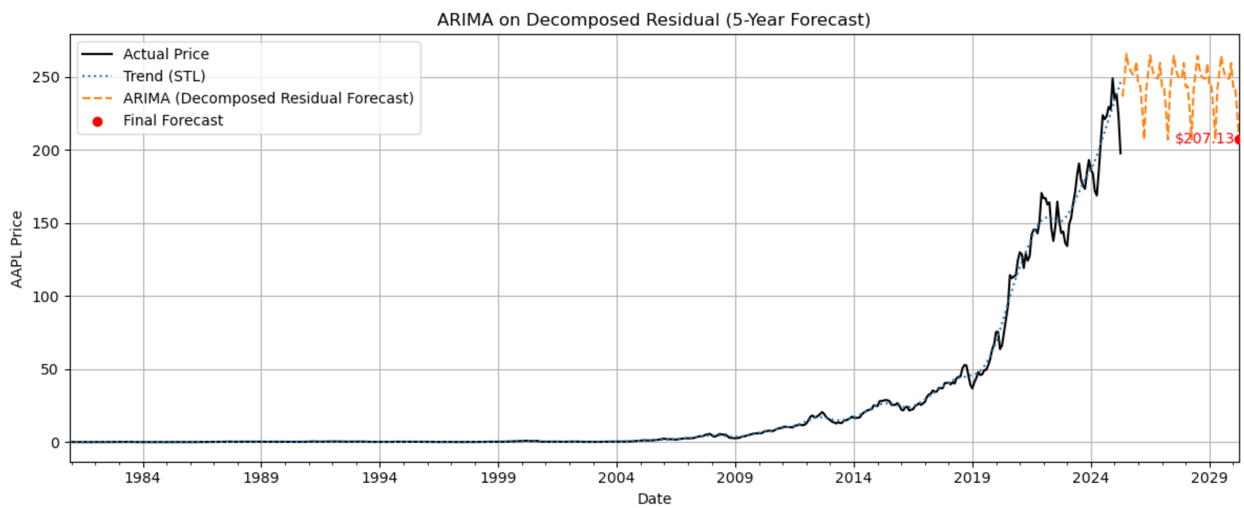


Figure 6 presents the most advanced model, which first decomposes the time series using STL into trend, seasonal, and residual components. An ARIMA model was applied to the residuals and recombined with the trend to form the final forecast. This hybrid approach led to a projected stock price of $207.13 in 2029. The resulting forecast incorporates structural trends and cyclical patterns, offering a comprehensive view that captures both consistent growth and short-term fluctuations. This model reflects a more nuanced forecast that smooths volatility while retaining realism in projecting future behavior.

Model Comparison and Evaluation

Each model was assessed on various regression model metrics, including Mean Squared Error, R-Squared, Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC).

Table 1: Model Comparison – Accuracy Metrics

Model	**MSE**	**R-Squared**	**AIC**	**BIC**
Linear Regression	1502.4394	0.4521	3902.81	3911.37
Moving Average	59.7245	0.9786	2138.85	2147.36
IMA	59.7536	0.9786	2135.01	2143.52
ARIMA	12.5585	0.9954	1366.70	1405.21
Decomposed ARIMA	**3.5118**	**0.9987**	**685.51**	**719.74**

As shown in Table 1, the STL + ARIMA model outperformed all other forecasting approaches across each of the evaluation metrics. It achieved the lowest Mean Squared Error (MSE) of 3.51, signifying minimal average deviation from actual values, and the highest R-squared score (0.9987), meaning it explained nearly all observed variance in AAPL's stock prices. Additionally, it registered substantially lower Akaike (AIC = 685.51) and Bayesian Information Criteria (BIC = 719.74) compared to the other models, underscoring its ability to deliver high accuracy without overfitting.

These findings emphasize the strength of combining STL decomposition with ARIMA modeling. The decomposition process successfully isolates seasonality and long-term trends, allowing ARIMA to focus purely on modeling the remaining residual variation. The result is a model that not only captures structural patterns but also offers enhanced precision in forecasting.

To further validate model performance, we compared each forecast's output to AAPL's actual market price on April 15, 2025, when the stock closed at $202.14. The predicted prices from all five models were recorded and assessed for how closely they approximated this observed value, shown in Table 2.

Table 2: Model Comparison – Prediction Validation

Model Name	**Predicted Value**	**Difference From Actual**

Linear Regression	\$86.07	\$116.07
Moving Average	\$221.65	-\$19.51
IMA	**\$201.38**	**\$0.76**
ARIMA	\$199.63	\$2.51
Decomposed ARIMA	\$237.04	-\$34.90

As reflected in the table's results, the Integrated Moving Average (IMA) model offered a very accurate forecast when compared to AAPL's actual stock price on April 15, 2025. Its predicted value came within a narrow margin of the real price, reinforcing its reliability in this instance. Coupled with its solid evaluation metrics from Table 1, the IMA model emerges as a strong performer, competing closely with the more complex ARIMA-based models in terms of predictive accuracy.

Conclusion

This study illustrates the varying effectiveness of different forecasting approaches applied to Apple Inc.'s stock price. Simpler models such as Linear Regression were helpful in identifying general growth patterns but lacked precision, as evidenced by their relatively high error rates. On the other hand, more advanced techniques (particularly the STL + ARIMA model) offered substantial improvements in performance, achieving the lowest error values (MSE, AIC, and BIC) and the highest R^2, indicating a strong fit to historical data.

When compared against AAPL's actual market closing price on April 15, 2025, the IMA model produced the most accurate forecast, missing by just \$0.76. However, this high level of precision is likely attributable to recent market disruptions. Since early 2025, heightened policy uncertainty and renewed trade tensions during Donald Trump's second term have introduced significant volatility. Research from the Wharton School at the University of Pennsylvania (Boller et al., 2025) confirms that these developments have materially altered investor behavior and financial market dynamics. In a more stable context, models like the decomposed ARIMA may yield greater predictive consistency.

These findings highlight an important limitation of traditional time series methods—their reliance on historical continuity. External shocks and structural breaks can significantly reduce model effectiveness. To address this, future work should consider incorporating exogenous variables through models like ARIMAX, which adjust dynamically based on real-world economic indicators. This would enable forecasts to better reflect rapidly evolving conditions and offer more resilience to volatility.

Additional strategies, such as rolling-window validation, real-time model updating, and ensemble modeling, could also enhance adaptability. While the decomposed ARIMA model stood out under historically stable conditions, adaptive and hybrid techniques will be essential for maintaining accuracy in unpredictable market environments.

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