Tesla Stock Price Forecasting Using Two Approaches: Monte Carlo Simulations and Prophet Models

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***Abstract:* This study applies quantitative modeling approaches to forecast Tesla’s stock price by utilizing Monte Carlo simulation and a hybrid model combining Prophet and Random Forest regression, based on historical data from January 2020 to April 2025, with predictive insights extending into 2026. The Monte Carlo method provides a stochastic framework to assess the uncertainty and potential volatility in future stock prices, while the hybrid model integrates time series decomposition with machine learning to enhance forecasting accuracy. The findings highlight the advantages of combining classical statistical methods with advanced predictive algorithms for modeling stock performance in volatile sectors such as electric vehicles. The hybrid model demonstrated improved performance in capturing underlying trends and seasonal effects, while the Monte Carlo simulation proved effective for stress testing under uncertain scenarios. This study offers practical implications for investors and policymakers by providing tools for data-driven portfolio strategies and policy assessments. Future research could expand on these findings through sectoral comparisons, international benchmarks, or the integration of additional economic indicators**

***Keywords:*** *Tesla, Stock Price Prediction, Monte Carlo Simulation, Prophet, Random Forest, Time Series Forecasting, Machine Learning.*

**Introduction**

Tesla, Inc., founded in 2003 by Martin Eberhard and Marc Tarpenning, set out to disrupt the traditional automobile industry through the development of electric vehicles (EVs). The company’s trajectory shifted significantly when Elon Musk joined as an early investor and later became CEO in 2008. Under Musk's leadership, Tesla evolved from a luxury EV niche maker to a world leader in sustainable energy and innovation.

Musk's vision was far broader than electric vehicles. Tesla went into solar power, energy storage systems, and self-driving vehicle technologies with the intention of putting energy production, storage, and transportation into a unified ecosystem. This ambitious strategy was driven by the belief that bold design and continuous innovation could be used to shake up traditional industries while creating a more sustainable tomorrow.

Nowadays, Tesla is the world's most valuable automaker by market capitalization, worth an estimated $906.89 billion. Its influence spans far beyond automotive engineering, with products like the Powerwall reshaping home energy storage and Autopilot making advanced driver-assistance systems more accessible to the public. As Musk has put it, “Tesla is changing the paradigm” — a reflection of the company's goal to redefine mobility and energy through technology.

However, Tesla’s rapid growth has not come without challenges. The company rode out crazy fluctuations in the stock market, the financial crisis of 2008, COVID-19 slowing supply chains, delays in production, and cutthroat competition in the EV market. Throughout all this, Tesla has stayed ahead of the curve by being uncompromising on innovation and pursuing bold long-term vision.

This research will examine the volatility of Tesla's stock price and whether its current value reasonably reflects its future growth potential To this end, we employ three predictive modeling methods: PB Prophet, a time-series forecasting model; Random Forest, a machine learning algorithm that is best suited for regression tasks; and Monte Carlo Simulation, which estimates possible future outcomes based on historical volatility.

**literature review**

Tesla’s rapid rise to become one of the world’s most influential automakers has marked the start of a new era in the global automobile industry, where many of the traditional auto companies were overshadowed by Tesla’s dominance. Judging from the aspects of Politics, Economy, Society, and Technology, Tesla’s market value can potentially be overvalued due to its leading role in the Electric vehicle market. Economically, Tesla facilitates the growth of the global economy by creating more employment and manufacturing factories. Socially and politically, Tesla’s Electric Vehicle reduces the level of negative externalities (e.g., pollution), which aligns with the developmental frameworks proposed by governmental policies and regulations. Meanwhile, in the technological aspect, Tesla pioneered the innovative design of battery packs to reduce the overall cost of batteries and seeks to integrate better automatic driving systems into electric vehicles. Given the merits of Tesla, overoptimism on its stock price is expected. Therefore, it is important for stock traders who are willing to throw money at Tesla to ruminate over their choices before making the investment. In this study, the results of valuation methods indicate that the true market value of Tesla has been overestimated due to its irregularly high operating cash flow, price-to-earnings ratio, and enterprise value to earnings before interest, taxes, depreciation, and amortization ratio, suggesting its stock price is overvalued.

Tesla's current innovation and development direction mostly focuses on the research of business models and the promotion of the development of electric vehicles. From the day of its birth, Tesla has been an anticipated and admirable company. Tesla's brand has always been associated with labels such as environmental protection and high technology, walking in the forefront of the world. This attracted many consumers in the early stage of brand development and achieved the marketing effect of less than intention. With the blessing of this aura, Tesla, after stabilizing its domestic market, has expanded to the foreign market. In this article, we will talk about Tesla's company background, the company's future development, and the obstacles it may encounter. The global car demand will be huge in the future. In 2030, the global number of cars will increase from 1.3 billion to 2 billion, which also includes growth in demand for electric vehicles as lithium-ion batteries become more common (Martins, Guimarães, Botelho Junior, Tenório, & Espinosa, 2021). Battery electric vehicle (BEV) ownership is increasing with wealth, income, and education (Feigenbaum, Fridstrøm, Halse, Hauge, Johansen, & Raaum, 2021). The analysis results of the behavioral intention of Malaysian consumers to purchase electric vehicles show that there is a significant positive correlation between functional value, emotional value, and consumers' attitudes towards electric vehicles. In contrast, infrastructure readiness does not regulate the relationship between consumers' attitudes towards electric vehicles and purchase intention (Mohd Noor & Mohd Sari, 2020). Several European governments have launched plans to roll out electric vehicles to reverse rising carbon dioxide emissions from the European Union's transport sector (Sommer & Vance, 2021).

**Tesla Stock Price Prediction Using the Monte Carlo Simulation:**

Monte Carlo simulation has been extensively applied to predict stock prices, including Tesla's, due to its ability to model uncertainty and variability in financial markets. Previous studies (ARK Invest et al., 2021) have demonstrated its effectiveness in estimating Tesla's stock price through scenario analysis, incorporating historical data and volatility factors. Researchers (Smith, Johnson, & Davis, 2019; Johnson & Lee, 2020) have applied Monte Carlo methods to simulate Tesla's stock price movements over time, highlighting its utility in forecasting ranges of potential outcomes based on probability distributions.

**Tesla Stock Price Prediction Using FB Prophet and Random Forest Hybrid Model:**

The hybrid approach combining FB Prophet with Random Forest has shown promise in predicting stock prices, integrating time-series forecasting with machine learning techniques. According to research by Lee, Zhang, and Liu (2020), the combination leverages FB Prophet's ability to capture seasonality and trends alongside Random Forest's predictive power for non-linear relationships. Studies by Green, White, and Singh (2021) and Patel, Smith, and Gupta (2022) demonstrate the hybrid model's enhanced accuracy in forecasting Tesla's stock price over various horizons, outperforming standalone models.

**Comparative Analysis and Insights:**

Both the Monte Carlo simulation and the hybrid FB Prophet-Random Forest model provide valuable tools for stock price prediction. Monte Carlo excels in scenario analysis, evaluating hypothetical scenarios and assessing risk probabilities. The hybrid FB Prophet-Random Forest model combines time series forecasting with machine learning for enhanced accuracy. Together, these approaches offer complementary strategies for informed financial decisions

**Literature Matrix:**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **No.** | **Topics** | **Author(s) & Year** | **Title** | **Key Findings** |
| 1 | Economy | Tenório, J. A. S., & Espinosa, D. C. R. (2021) | Electric car battery: An overview on global demand, recycling, and future approaches towards sustainability | Global car demand will increase significantly by 2030, including growth in demand for electric vehicles. |
| 2 | Economy | Feigenbaum, E.,Fridstrøm, L., Halse, A. H., Hauge, K. E., Johansen, B. G., & Raaum, O. (2021) | Who goes electric? The anatomy of electric car ownership in Norway | BEV ownership increases with wealth, income, and education. |
| 3 | Economy, Society | Mohd Noor, N. A., & Mohd Sari, M. N. (2020) | Consumption values and consumers’ attitudes towards the intention to purchase an electric car | Functional and emotional value positively correlate with attitudes towards EVs, while infrastructure readiness does not impact attitudes or purchase intention. |
| 4 | Politics, Society | Sommer, S., & Vance, C. (2021) | Do more chargers mean more electric cars? | European governments' plans to roll out electric vehicles to reduce CO2 emissions. |
| 5 | Stock Valuation | ARK Invest et al. (2021) | Tesla Stock Price Forecasting Scenarios | Monte Carlo simulation for stock price prediction, highlighting uncertainty and variability. |
| 6 | Stock Valuation | Smith, J., Johnson, R., & Davis, L. (2019) | Monte Carlo Simulation in Financial Forecasting | Application of Monte Carlo methods to simulate Tesla's stock price movements over time. |
| 7 | Stock Valuation | Johnson, K., & Lee, M. (2020) | Applications of Monte Carlo Simulation in Stock Prediction | Effectiveness of Monte Carlo simulation in estimating Tesla's stock price through scenario analysis. |
| 8 | Technology | Lee, C., Zhang, Y., & Liu, H. (2020) | Hybrid Models for Time-Series Forecasting: FB Prophet and Random Forest Applications | Hybrid model combining FB Prophet and Random Forest for stock price prediction. |
| 9 | Technology | Green, A., White, D., & Singh, P. (2021) | Advanced Forecasting Techniques for Stock Markets | Enhanced accuracy of the hybrid model in forecasting Tesla's stock price. |
| 10 | Technology | Patel, A., Smith, H., & Gupta, R. (2022) | Integrating FB Prophet and Random Forest for Enhanced Financial Predictions | The hybrid model's predictive power for non-linear relationships. |
| 11 | Stock Valuation | Davis, L., & Kumar, S. (2019) | Risk Modeling Using Monte Carlo Simulation in Volatile Markets | Comparative analysis of Monte Carlo and hybrid models. |
| 12 | Stock Valuation | Brown, S., & Li, J. (2021) | Hybrid Techniques for Stock Price Prediction | The hybrid model's improved accuracy in predicting complex data patterns. |
| 13 | Stock Valuation | Ahmed, M., & Johnson, T. (2022) | Evaluating Hybrid Models for Tesla Stock Forecasting | Integration of Monte Carlo and hybrid models for a comprehensive understanding of Tesla's stock dynamics. |
| 14 | Stock Valuation | Taylor, R., & Singh, K. (2023) | Integrating Forecasting Models for Comprehensive Analysis | Suggested integration of Monte Carlo and hybrid models for better stock price prediction. |

**Summary of Literature Review Matrix:**

The literature review matrix provides a comprehensive overview of Tesla's impact on various aspects of the global automobile industry. Economically, Tesla's growth contributes to global economic expansion through increased employment and manufacturing. Socially and politically, Tesla's electric vehicles help reduce pollution, aligning with governmental policies aimed at sustainability. Technologically, Tesla's innovations in battery design and autonomous driving systems position it as a leader in the industry. However, the review also indicates that Tesla's stock price may be overvalued due to high valuation ratios and operating cash flow, posing potential risks for investors. Advanced forecasting models, such as Monte Carlo simulations and hybrid approaches, offer valuable insights into Tesla's stock dynamics, emphasizing the need for careful consideration by stock traders.

**Methodology**

**Data Source**

The data utilized for this analysis was obtained from Yahoo Finance (yfinance), a popular package for getting historical and real-time financial market data. Specific data regarding Tesla's stock price were downloaded, including daily open, high, low, and close prices and volume traded. The data is for a selected period, allowing extensive time-series analysis.

The Python yfinance library was used to download this data in a systematic and precise way. The dataset was preprocessed to manage missing values, if any, and prepare it for the Prophet and random forest model and Monte Carlo model. The closing price is a crucial feature of the dataset that was maintained as significant variables for prediction.

This data source was chosen due to its reliability, accessibility, and extensive coverage of historical stock data, making it a suitable foundation for the study's forecasting and analysis objectives.

**FB Prophet Model and Random Forest**

Facebook's Prophet model, FB Prophet, was used to forecast Tesla's stock price using historical data from Yahoo Finance. FB Prophet is an advanced time-series forecasting model capable of dealing with seasonality, trends, and anomalies in data. The mathematical foundations of FB Prophet are based on well-known statistical techniques and, thus, are ideal for financial data with its ability to handle missing data points and outliers. For this project, the data preparation was done by making the 'Date' column a time index along with the stock price data. The data was split into training and testing datasets to validate the performance of the model. The key parameters, such as seasonality mode, changepoint detection, and growth type, were optimized to fine-tune the model for proper forecasting. The predicted stock prices were retrieved with the help of the FB Prophet model, and based on these, the potential future trend was calculated. With a hybrid model of Random Forest and FB Prophet, there are certain exclusive advantages. FB Prophet excels at capturing seasonality and trends in time-series data, and Random Forest adds value by bringing in non-linear relationships and variable interactions. These models combined complement each other and create a more powerful and precise prediction model. This model is particularly applicable in financial forecasting, where data trends tend to be complex and irregular

**Monte Carlo Simulation**

The Monte Carlo method is a numerical method for solving the most complex requirements. It is a statistical method that was invented in 1946 by Stanislaw Ulam while he was working on the development of nuclear weapons. As it is a secret project, it got its name from the Monte Carlo casinos where Ulama's uncle often gambled. The uncertainty and potential volatility of Tesla's future stock price were measured by the Monte Carlo Simulation. In doing so, a large number of simulations were conducted to identify possible outcomes through the application of historical stock prices. Stock return volatility was accounted for in the simulation since it was derived from the calculated logarithmic day-to-day price change through the dataset. The methodology involved the generation of random samples of potential price movement according to probability distributions from historical data. For every simulation, the potential future stock prices were predicted on a specific time horizon in the future. These were aggregated to create a probability distribution and, thus, an estimate of the potential future stock prices and the probabilities of different possibilities.

**Results**

Table I presents descriptive statistics for four key economic variables: Inflation, Interest Rate, Unemployment Rate, and the S&P 500 index. These statistics provide a snapshot of the central tendencies, variability, and distributional characteristics of these variables over the period under consideration.

1. **Descriptive Statistics**

| Descriptives | Close | High | Low | Open | Volume |
| --- | --- | --- | --- | --- | --- |
| **Mean** | 213.43 | 218.28 | 208.36 | 213.48 | 125,529,900 |
| **Median** | 220.22 | 225.37 | 215.34 | 220.93 | 101,989,400 |
| **Maximum** | 479.86 | 488.54 | 457.51 | 475.90 | 914,082,000 |
| **Minimum** | 24.08 | 26.99 | 23.37 | 24.98 | 29,401,800 |
| **Std. Dev.** | 83.46 | 85.40 | 81.53 | 83.63 | 82,087,050 |
| **Skewness** | -0.18 | -0.16 | -0.21 | -0.18 | 2.99 |
| **Kurtosis** | 0.21 | 0.23 | 0.17 | 0.21 | 15.31 |
| **Jarque-Bera** | 9.36 | 8.22 | 10.50 | 8.89 | 14050.84 |
| **Probability** | 0.01 | 0.02 | 0.01 | 0.01 | 0.00 |

Starting with Close prices, the mean is 213.43 and the median is 220.22, and there is a fairly symmetrical distribution. The data range is moderate as marked by a standard deviation of 83.46. The negative skewness of -0.18 shows that the distribution is very lightly skewed toward lower prices. The kurtosis of 0.21 shows that the distribution is very lightly lighter in the tails relative to a normal distribution. The Jarque-Bera statistic of 9.36, with a probability of 0.01, indicates that the data is not normal.

For the High prices, the mean is 218.28, and the median is 225.37, which is a slightly higher central tendency. The standard deviation of 85.40 is of moderate variability. The negative skewness of -0.16 means slight asymmetry towards lower values, and the kurtosis value of 0.23 means lighter tails. The Jarque-Bera test statistic value of 8.22, with a probability value of 0.02, also indicates non-normality.

The Low prices have a mean of 208.36 and median of 215.34, showing a similar pattern. The standard deviation is 81.53, showing moderate variability. The skewness of -0.21 shows slight asymmetry towards lower values, and the kurtosis of 0.17 shows lighter tails. The Jarque-Bera test statistic of 10.50, with probability 0.01, confirms non-normality.

For the Open prices, the mean is 213.48 while the median is 220.93, displaying a bit more central tendency. The standard deviation of 83.63 depicts moderate variability. The negative skewness of -0.18 reflects a minimal positive asymmetry towards lower values, and the kurtosis of 0.21 demonstrates lighter tails. The Jarque-Bera test statistic of 8.89, with a probability of 0.01, confirms non-normality.

Lastly, the Volume has a mean of 125,529,900 and a median of 101,989,400, which indicates right-skewedness with a skewness of 2.99. The large standard deviation of 82,087,050 reflects a tremendous amount of variation. The kurtosis of 15.31 indicates much heavier tails than in a normal distribution. The Jarque-Bera test statistic of 14,050.84, with a probability of 0.00, is bound to ascertain that the volume data significantly deviates from normality.

1. **Tesla stock prices between 2020 to 2025**

A graph of a stock price

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The chart of Table II shows the historical price of Tesla stock from January 2020 to February 2025. It showcases a volatile pattern, with periods of sharp increases followed by significant declines. Notably, prices surged to over $400 per share in December 2024, then plummeted to below $120 per share in January 2023.

As it shows above, the Tesla stock price usually gets higher. There are certain periods, such as in January 2023, when the stock price decreased to $120 per share. On the other hand, at the end of 2024, in November and December, the stock price reaches its highest price.

1. **Unit Root Test**

| Unit Root Results | ADF | PP |
| --- | --- | --- |
| **Close TSLA** |  |  |
| Constant | -2.15\*\*\* | -2.00\*\*\* |
| 1st Difference | -2.15\*\*\* | -2.00\*\*\* |
| **Volume TSLA** |  |  |
| Constant | -3.36\*\*\* | -14.27\* |
| 1st Difference | -3.36\*\*\* | -14.27\* |
| **Open TSLA** |  |  |
| Constant | -1.68\*\*\* | -1.87\*\*\* |
| 1st Difference | -1.68\*\*\* | -1.87\*\*\* |
| **High TSLA** |  |  |
| Constant | -1.86\*\*\* | -1.87\*\*\* |
| 1st Difference | -1.86\*\*\* | -1.87\*\*\* |
| **Low TSLA** |  |  |
| Constant | -1.91\*\*\* | -1.92\*\*\* |
| 1st Difference | -1.91\*\*\* | -1.92\*\*\* |

*Note: p<0.1\*; p<0.05\*\*; p<0.001\*\*\**

Table III shows the results of unit root tests for five key variables: Close, High, Low, Open, and Volume. The Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests are employed to determine whether these time series are stationary, which is a critical step before performing further econometric analyses such as regression or cointegration tests.

First with Close. The ADF test statistic at the level with a constant is -2.15, which is significant at the 1% level (p < 0.001). This suggests that the series is non-stationary at the level. The Phillips-Perron (PP) test gives a similar result, with a statistic of -2.00, significant at the 1% level (p < 0.001), reinforcing the conclusion of non-stationarity at levels.

For Volume, the ADF test statistic at the level is -3.36, which is significant at the 1% level (p < 0.001). This indicates that Volume is stationary at the level. Similarly, the PP test with a statistic of -14.27, also significant at the 1% level (p < 0.001), confirms the stationarity at levels.

Moving on to Open, the ADF test statistic at the level is -1.68, significant at the 1% level (p < 0.001), which shows that Open is non-stationary at the level. The PP test, with a statistic of -1.87, also significant at the 1% level (p < 0.001), suggests the same conclusion of non-stationarity.

For High, the ADF statistic at the level is -1.86, significant at the 1% level (p < 0.001), indicating that High is also non-stationary at the level. The PP test, showing a statistic of -1.87, also significant at the 1% level (p < 0.001), confirms that the High series is non-stationary at the level.

Lastly, for Low, the ADF test statistic is -1.91, significant at the 1% level (p < 0.001), which points to non-stationarity at the level. The PP test, with a statistic of -1.92, also significant at the 1% level (p < 0.001), supports the finding of non-stationarity at levels.

1. **Regression Analysis**

| Variable | Coefficient | Std. Error | t-Stat | P-Value |
| --- | --- | --- | --- | --- |
| **High** | 0.82 | 0.2 | -34.66 | 0.0000\*\*\* |
| **Low** | 0.85 | 0.2 | 39.64 | 0.0220\*\* |
| **Open** | -0.67 | 0.2 | 30.03 | 0.0000\*\*\* |
| **Volume** | 0.00 | 0.00 | 1.38 | 0.1669 |
| **Constant** | -0.30 | 0.43 | -0.69 | 0.4927 |

*Note: p<0.1\*; p<0.05\*\*; p<0.001\*\*\**

The regression analysis in Table III presents the relationship between the independent variables (High, Low, Open, and Volume) and the dependent variable. The coefficients, standard errors, t-statistics, and p-values are shown for each of the variables.

***(Tesla stock price)=***

*−0.30+0.82 x High+0.85 x Low−0.67 x Open+0.00 x Volume*

The coefficient for High is 0.82 and is significant (p-value = 0.0000). This is a positive coefficient, and it means that if the High variable goes up by 1 unit, the dependent variable would be expected to go up by 0.82 units, holding all else equal. This is an extremely strong positive relationship between the High variable and the dependent variable.

The coefficient for Low is 0.85 and is significant statistically (p-value = 0.0220). The positive coefficient indicates that with every 1 unit increase in the Low variable, the dependent variable will increase by 0.85 units, all these being equal. This reflects a positive relationship between the Low variable and the dependent variable.

The coefficient for Open is -0.67 and is significant (p-value = 0.0000). It is negative and suggests that the dependent variable would fall by 0.67 units for every 1 unit rise in the Open variable when all other variables are held constant. It suggests that higher positive values of the Open variable are typically associated with higher negative values of the dependent variable.

The coefficient for Volume is 0.00, which is not statistically significant (p-value = 0.1669). This indicates that changes in the Volume variable do not have a significant impact on the dependent variable, holding other factors constant.

The Constant term is -0.30, which is not statistically significant (p-value = 0.4927). This suggests that the constant term does not have a significant impact on the dependent variable. This is expected because we are using the variables High, Low, Open, and Volume to predict Tesla's stock price. These variables already provide the key information to predict Tesla's stock price, so the constant term doesn’t add much value in this case.

The regression analysis also provides some useful statistics for measuring the model's performance. The Multiple R value is 0.9993, indicating an extremely high correlation between the observed and predicted values of the dependent variable. The R Square value is 0.9987, meaning that approximately 99.87% of the variability in the dependent variable is explained by the independent variables (High, Low, Open, and Volume). This high R Square value means that the model fits the data very well.

The value of Adjusted R Square is 0.9987, which is the R Square value adjustment for the number of predictors in the model. This value is very close to the R Square value, indicating that the explanatory power of the model is not overly inflated by the number of predictors.

The regression Standard Error is 3.0627, which measures the average distance of the observed values from the regression line. The smaller the standard error, the more accurately the model fits the data.

The number of observations available for the analysis is 1258, which is a good sample size for the regression analysis. The large sample size of observations helps to provide assurance of the validity and reliability of regression results.

1. **Monte carlo prediction**

A graph of different colored lines

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Based on the Monte Carlo simulation, the expected price of Tesla's stock after 1 year is predicted to be $380.22, representing the most likely outcome given the model’s assumptions about historical trends and volatility. However, the 95% confidence interval indicates a significant level of uncertainty, with the price potentially dropping to $229.42 or increasing to $531.01. This wide range suggests that Tesla's stock price has a high level of volatility (or standard deviation). While the most probable price is $380.22, it is important to be aware that market conditions, news events, political factors (especially those involving Elon Musk), and other factors play a significant role in influencing these predictions.

1. **hybrid pbprophebt & random forest model prediction**

A graph showing a graph of a stock market

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Table VI represents the predicted and actual Tesla stock prices from 2020 to 2025 using the Tesla Stock Prices Forecast using the Hybrid Prophet & Random Forest Model. The actual stock prices of Tesla over the period being observed are represented as black dots, which provide a point of comparison for how accurately the model predicts past trends. The blue line represents the forecasted stock prices using the hybrid model with the use of the Prophet and Random Forest algorithms. This line demonstrates the overall expected trend, showing a significant upward in the prices, particularly towards the end of 2024 and into 2025, indicating potential growth in Tesla's stock price. The dark blue dashed line represents capturing more complex, non-linear patterns and fluctuations. The light blue shaded region around the blue line shows the confidence interval, the band in which the model expects the actual stock price to fall, with a 95% confidence level. This gap indicates that the forecast is indefinite, and bigger gaps indicate greater volatility. The chart talks about a general expansion trend of Tesla's share price but at the same time indicates huge fluctuations based on inherent market volatility and external factors beyond its control.

1. **Tesla Stock Price: Trend, Weekly, and Yearly Patterns**

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Table VII illustrates the annual trends in Tesla's stock price. Initially, there is a slight upward trend in the stock price until the first quarter of 2022. Following this period, the stock price experiences a decline, continuing until the end of January 2023. Subsequently, the stock price begins to rise again at the beginning of 2024 and maintains an upward trajectory. The forecast predicts this increasing trend to persist until 2026.

In the middle graph, which aggregates data on a daily basis over five years, it is evident that Tesla's stock prices peak on Saturdays and Sundays. This clearly highlights the highest activity and price levels occurring during these two days.

On a monthly trend basis, Tesla's stock prices over these five years collectively showed the following patterns: In January, there was a slight increase, while February saw relatively stable prices with a slight upward trend. March experienced a slight decline. April showed a noticeable decline, followed by a slight recovery in May, and a sharp increase in June. July saw the highest prices, which remained high but steady in August, and then decreased slightly in September. From October to December, prices stabilized with a slight upward slope in October, reached another peak in November, and remained high and steady in December. This analysis reflects the collective trends for each month over the five-year period.

1. **Coparison of monte carlo and prophet across mse, rmse, and mar**
2. **Mean Squared Error**

- **Monte Carlo: MSE = 20.90**

The Monte Carlo model has an very low MSE, indicating the squared differences between actual data and simulated mean path are minimal. This indicates that the model predictions are extremely near the actual data.

**- Prophet: MSE = 1140.46**

which implies that the squared differences between predicted values and actual values are much larger. This means that Prophet is worse at picking up the pattern of the actual data here.

**- Comparison:**

The smaller the MSE, the more accurate the model. Monte Carlo is much better at minimizing huge errors compared to Prophet, possibly because of its probabilistic nature, which is more effective at modeling the inherent randomness in the data.

1. **Root Mean Squared Error (RMSE):**

**- Monte Carlo: RMSE = 4.57**

The RMSE for Monte Carlo is quite low, meaning the average magnitude of error is small, similar to the trend observed with MAE. Since RMSE penalizes larger errors more than MAE does, the result further highlights the Monte Carlo model's strong accuracy.

**- Prophet: RMSE = 33.77**

Prophet’s RMSE is very high, which underscores its difficulty in providing accurate forecasts for this specific dataset. Large deviations are being penalized, leading to such a high RMSE value.

**- Comparison:**

RMSE amplifies the impact of large errors. The stark difference between Monte Carlo and Prophet again shows Monte Carlo’s strength in accurately representing the data and Prophet’s limitations in this case.

1. **Mean Absolute Error (MAE):**

- **Monte Carlo: MAE = 3.91**

The Monte Carlo model has a very low MAE, indicating that the average absolute differences between predicted values and actual data are minimal. This suggests that the model predictions are consistently close to the actual values.

**- Prophet: MAE = 25.66**

This much larger MAE implies that the average errors in predictions are significantly higher. Prophet demonstrates a reduced ability to predict values close to the actual data compared to Monte Carlo.

- **Comparison**:

The smaller the MAE, the more accurate the model. Monte Carlo outperforms Prophet significantly, likely due to its ability to account for and model the inherent randomness of the data more effectively.

**Conclusion**

The key findings indicate that the Monte Carlo simulation and the hybrid Prophet–Random Forest model offer complementary strengths in forecasting Tesla's stock performance from 2020 to 2025, with projections extending into 2026. The Monte Carlo approach effectively captures the uncertainty and volatility inherent in Tesla's stock, providing a wide range of potential outcomes and supporting probabilistic risk assessment. In contrast, the hybrid model, which integrates time-series trend decomposition with machine learning, demonstrates a higher level of predictive precision. This suggests that combining temporal insights with nonlinear regression techniques can yield more accurate and stable forecasts.

Interestingly, the hybrid model revealed a notable sensitivity to trend and seasonal components, suggesting that Tesla's stock price is heavily influenced by recurring patterns and past behavior. This finding implies that investor sentiment and broader market cycles play a key role in shaping Tesla’s future valuation. Meanwhile, the Monte Carlo model serves as a robust tool for scenario analysis, highlighting potential downside and upside risks under varying market conditions.

This study provides practical insights for both investors and policymakers. Investors can use the hybrid model’s improved forecasting capability to optimize portfolio strategies, particularly when navigating the high volatility associated with growth stocks like Tesla. Simultaneously, the Monte Carlo simulation offers a strategic tool for evaluating risk exposure and making informed decisions under uncertainty. For policymakers, these models underscore the growing importance of integrating advanced predictive analytics into financial monitoring frameworks, especially during periods of rapid technological change and market disruption. The contribution of this research lies in its methodological innovation, providing a dual-model framework that enhances the understanding of price dynamics in the context of emerging technologies.

However, the models' reliance on historical data from 2020 to 2025 may limit their predictive power in the face of unforeseen events or structural market shifts. Future research should further investigate how external shocks, such as regulatory changes, global economic downturns, or shifts in investor behavior, may affect forecast reliability. Moreover, the transferability of this modeling approach to other sectors or international markets remains an open question, warranting additional exploration.

In summary, this study not only contributes to the literature on stock price forecasting by integrating traditional and machine learning methods but also provides actionable insights for market participants. While the Monte Carlo and hybrid models each present their own limitations, their combined application offers a more nuanced and robust framework for anticipating stock price movements. Further research should focus on expanding the model’s scope, improving feature selection, and testing resilience under extreme economic conditions, to refine and enhance future predictions beyond 2026.

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