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|  |
| Forecast-Driven Strategic Planning: Predicting Tesla Stock Performance Using Time Series Forecasting Analysis |
| |  |  |  | | --- | --- | --- | | Raushan Abenova | 5/18/24 | Strategic Thinking | |

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**Assessment Cover Page**

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I further confirm that this work has not previously been submitted for assessment by myself or someone else in CCT College Dublin or any other higher education institution.

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# 1. Proposal Project

## Introduction

In the modern financial environment, the ability to anticipate market behaviour is a vital component of strategic decision-making. This project focuses on predictive analytics as a tool for forecasting stock performance, with a case study on Tesla Inc., a leading electric vehicle and technology company.

By applying time series forecasting models analysis to Tesla’s historical stock data, the goal is to develop insights, which how could support long-term planning, risk mitigation, and strategic investment decisions.

“Strategic analytics is not just about predicting the future, but about understanding the forces behind the patterns. Techniques like clustering give business leaders that necessary context.” T. Davenport, J. Harris (2007).

Given Tesla's volatility and its position in a high-growth sector, this analysis aims to explore how well different models like ARIMA, SARIMA and LSTM can capture market dynamics and project future stock behaviour, and probability of forecasting price Tesla's stock for April 15, 2026.

### 2. Business Description

Tesla Inc., founded in 2003, however publicly traded since 2010. It is a global leader in electric vehicles and clean energy. Today Tesla offers electric vehicles, battery storage, solar products, and autonomous driving systems.

While the company has seen rapid growth, its stock is known for high volatility influenced by public sentiment, innovation news, and broader economic trends. Particularly, in April 2025 Tesla has been under financial pressure, reporting a 71% drop in quarterly net income and a 9% year-over-year revenue, that to cost nearly $19.3 billion. Despite setbacks, Tesla is boldly pushing forward with innovation. In a short future a pilot robotaxi service in Austin will use self-driving Model Y vehicles, and the autonomous Cybercab is expected to enter production in next 2026. At the same time Bloomberg analysts express cautious optimism, noting that renewed focus and upcoming technologies may support a future rebound.

## **3. Project Hypothesis and Objectives**

### **Hypothesis:**

It is no secret that Tesla’s stocks are volatility, and hypothesized by time series forecasting models specifically models ARIMA, SARIMA, and LSTM can provide predictions for the company’s future stock price.

## **First Hypothesis (H₁)** can proposes these models, with unique strengths capturing seasonality (ARIMA, SARIMA), and for detecting nonlinear temporal patterns (LSTM). **Second Hypothesis (H₀)** in contrast, might assume that reliable forecasting is not possible due to the highly speculative nature of stock. Factors such as sudden market sentiment fluctuations, innovation cycles, all of these may violate the assumption of these models. As a result, forecasts may fail that it means reject first hypothesis.

## General Objective:

This report aims to investigate how time series analysis can uncover hidden trends, seasonal patterns, and volatility, moreover, enable predict the price.

## Technical Objective

Data Exploration: Analyse historical stock price data, especially closing price to identify trends, seasonality, and volatility. Models that will be applied:

- ARIMA to capture non-seasonal trends and autocorrelations;

- SARIMA to account for seasonal effects (cycles).

- LSTM to handle nonlinear dependencies and long-term patterns.

Validation prediction will be used to compare model performance through metrics RMSE and MAE.

# 4. Scope and Methodology

## Scope

The project focuses on**historical trends from the beginning of IPO 29th June 2010 until 15th April 2025. Data Exploration**plays key role, namely:

* **Feature Engineering** that includes the process of transforming raw data into meaningful features in order to improve model performance. Generally, in **time series forecasting** it is crucial because **extracting hidden patterns** in stock prices like could be influenced by multiple factors like: trend, seasonality, external shocks or residuals. Feature engineering helps isolate these components for better predictions (Hyndman & Athanasopoulos, 2018).
* **Handling Non-Stationarity.** Most time series data, like stock prices, weather forecasting are **non-stationary, where** mean average could be variance and change over time.

As experts claim without proper feature engineering, even advanced models like LSTMs will fail to generalize in noisy financial datasets (Goodfellow et al., 2016).

## Methodology

This project follows the **CRISP-DM (Cross-Industry Standard Process for Data Mining)**framework to ensure a structured and repeatable analysis pipeline, like implementation and evaluation. A key point is to understand why major institutional investors (“big fish”) consistently include Tesla in their portfolios and how this aligns with long-term strategies in the high-growth electric vehicle sector. Moreover, applying the CRISP-DM methodology through visualizations of trends and seasonality it could help to uncover structures and detect anomalies within the data.

For this work several steps have been taken in the dataset, namely is cleaning and building for time series modelling, like:

* Loading the CSV file, it turned out that it is crucial that dates have to be ordered from 2025 back to 2010. Using data preparation techniques, the column 'Date' was properly formatted and sorted in chronological order, (see Figure 1).
* Irrelevant features such as 'Changes%', along with columns containing null values, were removed to improve model accuracy and reduce noise.

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*Figure 1*

## Ethical considerations

This analysis used publicly available Tesla stock data, ensuring no privacy concerns. Also, models were rigorously validated to mitigate bias, with assumptions and limitations clearly documented for transparency. The study maintains neutrality—evaluating forecasting methods without endorsing Tesla’s financial decisions. All processes were attempting to design the whole work with reproducibility, adhering to ethical standards for research in applied machine learning.

# 4. Project Management and Planning

## Data Source Overview

The project followed the CRISP-DM framework, with key milestones including data EDA, model development, and evaluation. Through Investing.com the stock dataset pre-processed for analysis. Also, was applied Python tools (pandas, statsmodels, sklearn).

## Data Exploratory Data Analysis (EDA)

To better understand the nature of stock over term (June 2010 – until present time April 2025), it was examined basic descriptive statistical features, like:

* The dataset with 3,722 trading days, covering post-IPO market behaviour.
* The average closing price is $86.05, while the median is only $18.54, it could give a suggestion of right-skewed distribution. This means that the stock spent much of its time at lower price levels, and further large increasing in current years pulling the mean upward.
* The standard deviation of $111.88 confirms high volatility in price movements.
* Volume ranged from ~1.8 million to over 914 million shares per day highlights extreme variations and investor activity.

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*Figure 2*

# **5.** Modelling

## **Summary Statistics**

The dataset structure are generated for key variables: Date, Close, Open, and High. In the Figure 3 the Close, Open, and High variables are right-skewed, with most values clustered at the lower end and a long tail toward higher prices. This reflects Tesla’s real-world market behaviour. Such skewed, non-normal distributions are typical in financial time series may inform the use of transformations like differencing and scaling prior for modelling like ARIMA and LSTM. As Robert Nau (2024) notes: “Don’t worry too much about normality when using ARIMA models, since these models focus on time-based dependencies rather than data distribution”.

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*Figure 3*

The plot in the Figure 4 illustrates positively skewed, with most trading days concentrated in the lower volume range between 0 and 200 million shares. This skewed distribution indicates that while high-volume trading days exist (often due to major news or market events). This highlights a challenge in model training and interpretation. The presence of outliers and asymmetry justifies the use of techniques like scaling or log transformation.

A graph of a number of people

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*Figure 4*

## **Bias Distribution and Outlier Detection**

The **skewness and outliers** identify existing potential data bias.

Close, Open, High, Low shows right-skewed distributions with outliers on the upper end reflecting high price movements due to news events, or earnings, or investor activities.

As Mandelbrot and Hudson (2004) argue, **financial markets are inherently fractal and non-Gaussian,** challenging the assumptions of classical models like ARIMA, which depend on normality and stationarity.

## Pre-processing and Data Cleaning

In preparation for time series modelling, the dataset underwent essential preprocessing steps:

* Data Type Inspection that includes initial inspection columns, encompassing Date and Change %, which stored as object types. The Date was transformed to index. Further, the Date column was explicitly converted into a datetime format using pd.to\_datetime(). This is a critical step for time series analysis, as it allows for proper indexing and chronological ordering.
* For missing or improperly parsed dates was conducted using .isna(), in the result confirmed no missing dates presented after conversion.
* These cleaning steps gave a certainty that the dataset was well-structured and ready for accurate time series forecasting.

## Trend Analysis Prior to Stationarity Testing

Following initial data cleaning and preprocessing, a time series plot of Close was generated to inspect the trend and volatility. This visualization could serve as a critical intermediate step providing an intuitive overview of the stock's behaviour with statistical analysis, such as the ADF test and seasonal decomposition. (Figure 5).

A graph showing the price of a tesla

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*Figure 5*

## Trend and Seasonality Analysis – Seasonal Decomposition of Tesla Closing Price for 365 days.

### To handle the underlying structure of stock behaviour, a seasonal decomposition was built for the Close (Figure 6). This technique splits the time series into **Trend**,**Seasonality**, and**Residuals**, offering the nature price movements over time.

* **Original Series** shows the raw closing price, which exhibits long periods of stability that then passing an extreme growth and high volatility from **2019–2020**.
* **Trend Component** reveals a **long-term upward trajectory**, particularly steep between **2020 and 2022**, indicating a sustained market valuation increase.
* **Seasonality** shows **repeating short-term patterns**, suggesting a cyclical effect in a stock price, like quarterly earnings or investor cycles.
* **Residuals** captures the **random noise** and unexplained variation not covered by trend or seasonality.

*Figure 6*

A graph of different colored lines

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## **Stationarity Testing and Experimentation**

An initial experiment with the ARIMA, SARIMA and LSTM models was conducted to forecast stock price for February 19, 2025. This test aimed to evaluate model performance on a known value before applying the same configuration to forecast April 15, 2026.

The **Augmented Dickey-Fuller (ADF) test** was used to assess a p-value above 0.05 suggests non-stationarity. If confirmed, **differencing**is applied to stabilize the series.

Once stationarity was established, the model’s parameters (p, d, q) were determined and fitted to historical data. The validated configuration from February 2025 will be served as the foundation for the 2026 forecast.

A close-up of a computer screen

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*Figure 7*

## 6. Machine Learning Algorithm

## 6.1. Short-Term Seasonal Decomposition and Its Role in Modelling

As part of the modelling and evaluation process, a short-term seasonal decomposition was applied to closing price using an additive model with a 5-day period. This technique helps isolate the time series into three key components: **Trend, Seasonality**, and**Residuals**, providing a clearer view of what drives short-term fluctuations in the stock price (Hyndman and Athanasopoulos, 2021).

The reasons why perform short-term decomposition are:

 Focus on Weekly Patterns:  
A 5-day period was chosen because Tesla stock trades Monday to Friday, meaning this decomposition captures weekly cycles. These cycles might reflect investor behaviour, short-term earnings speculation, or news reaction lags.

 Residuals and Model Suitability:  
If residuals show strong structure or patterns, it suggests that more complex models like LSTM may be needed. If residuals are randomly distributed, simpler models like ARIMA can be considered sufficient.

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*Figure 8*

## 6.2. Stationarity Testing and Hypothesis Interpretation /ADF Test

To evaluate stationarity was applied the**Augmented Dickey-Fuller (ADF) test** (Figure 9).

The ADF test is a statistical hypothesis test that determines whether a unit root is present in the time series.

The test follows this structure:

* **Null Hypothesis (H₀)**: The series has a unit root (non-stationary).
* **Alternative Hypothesis (H₁)**: The series is stationary.

The results of the ADF test showed:

* **ADF Statistic** = -1.407
* **p-value** = 0.5788

Since the p-value is **greater than 0.05,** we fail to reject the null hypothesis. This indicates that the stock series is **non-stationary**, and therefore, differencing is required before applying the ARIMA model. This transformation helps stabilize the mean of the series and ensures the model assumptions for an accurate forecasting.

*Figure 9*

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## Stationarity Confirmation After Differencing

After the indication non-stationary series, it brought to necessity for**first-order differencing.** The difference stabilizes data and remove trends. This transformation helps meet a core assumption for ARIMA and SARIMA models **(Figure 10).**

During the verification the ADF test was re-applied to the transformed series to df\_diff['Close'], the result showed:

* **ADF Statistic**: -11.07
* **p-value**: 4.61 × 10⁻²⁰

Since the p-value is **significantly below the 0.05 it** can be **rejected the null hypothesis** and conclude that the differenced series is now **stationary**, and it suitable for applying ARIMA and SARIMA.

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*Figure 10*

## ACF and PACF Analysis for ARIMA Model Selection

After confirming stationarity model ARIMA requires to identify suitable values for the autoregressive (p) and moving average (q) components. This was done by generating Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF).

* The **ACF plot** that from left in *Figure 11* shows how the time series is correlated with its own lagged values.
* The **PACF plot** that a right side in *Figure 11* isolates the direct relationship between the series and its lagged, excluding indirect effects from lags to determine the **p parameter**.

These observations support with **ARIMA(1,1,0)** model, where d = 1 comes from the differencing step. Analysing this composition it can be bravely underlied structure of the data, and accept that it is not overfitted, that may lead to more accurate forecasts.

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*Figure 11*

## ARIMA Modelling and Forecast for 2025-02-19

For testing ARIMA’s suitability (1,1,0) for long-term forecasting, at the beginning it was performed by predicting closing price for February 19, 2025. Having ACF and PACF plots, the ARIMA model was selected and trained with a composition 1,1,0. And forecast for February 19, 2025 - $354.14, indicating strong model performance. (Figure 12).

*Figure 12*

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The nested loop was evaluated each combination's AIC score using the differenced series (df\_diff['Close']), and selected the following result. The model with the lowest AIC score was considered optimal. After evaluating all combinations, the **ARIMA(1,1,0)** model yielded the **smallest AIC** (23330.70), it helps to determine the best choice of criterions that include:

* One lag of the autoregressive (AR) component,
* First-order differencing to achieve stationarity,
* No moving average (MA) component.

Our validation for February 2025 proves that even without moving averages, the model (using just lag and differencing) delivers accurate predictions. According to Hyndman and Athanasopoulos (2021), selecting the optimal ARIMA model using the lowest Akaike Information Criterion (AIC) ensures a balance between goodness of fit and model simplicity.

Further, after identifying ARIMA(1,1,0) as the optimal configuration using the lowest AIC value, the model was trained on the entire historical Tesla dataset up to April 15, 2025. A one-step-ahead forecast was generated for February 19, 2025, yielding a predicted closing price of $354.14. This forecast was then compared with the actual closing price for that date.

A graph showing a line

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*Figure 13*

In visualisation (see Figure 13), the predicted value closely aligns with the actual price. The closeness of the forecast to the real value demonstrates that the ARIMA(1,1,0) model effectively captured the trend and short-term dynamics for the price data.

## SARIMA Forecasting – Experimental Prediction for February 19, 2025

For SARIMA model and forecast Tesla’s stock price like an experimental prediction it was carried out also February 19, 2025 period with using the SARIMA(1,1,0)(1,1,0,5) composition. This configuration conducts a 5-day seasonal cycle, aligned with the weekly trading schedule.

The model was determined based on seasonal decomposition, seasonality with a consideration a weekly market patterns. The key statistical outputs used to validate its forecasting capability were:

* AIC: 24940.844
* BIC: 24959.505
* Log Likelihood: -12467.422

With p < 0.001, the model demonstrated a strong relationship between the lagged terms. The forecasted price for February 19, 2025, was $345.77, which is very close to the actual price of $354.14—resulting in a forecast error of only 2.4%. This outcome highlights the model’s accuracy in short-term forecasting. As noted by Box et al. (2015), SARIMA models are effective for seasonal time series, particularly when short-term cycles like weekly patterns are present.

Given this successful validation, the same SARIMA configuration was extended to forecast for April 15, 2026, one year beyond the last observed data point.

A graph with blue line

Description automatically generated*Figure 14*

## LSTM Forecasting – Experimental Prediction for February 19, 2025

For completeness of the analysis and to validate the effectiveness of time series forecasting, an LSTM model was also tested, utilizing data from the 90 previous trading days leading up to the target date—February 19, 2025. In the field of data analytics, LSTM networks are particularly widely used for time series forecasting due to their ability to capture long-term dependencies and process sequential data with complex, nonlinear patterns. At the beginning, the model was trained on scaled values of the stock's closing prices and validated on a one-step forecast. The **predicted closing price for 2025-02-19 was $354.17**, while the**actual price was $360.56,** yielding an error was just **1.17%**, demonstrating a **high degree of accuracy.**

A graph with orange and blue lines

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*Figure 15*

According to Brownlee (2017), LSTM models are highly effective for financial time series because they are capable of modelling long memory processes and are not restricted by linear assumptions like classical models such as ARIMA.

Building on these promising results, next challenge is to apply the same models and their structure to predict Tesla's stock price for April 15, 2026. Regarding LSTM it will be using the latest 90-day trading window leading up to this date as input. The methodological consistency will be kept for extending forecasting horizons. The approach is to use the same reliable framework applying validation tests for longer-term predictions.

# 8. Modelling and Forecasting for April 15, 2026

## ARIMA Forecast for 2026-04-15

Following the successful validation of the ARIMA(1,1,0) model on February 19, 2025, next step is using the same configuration forecasting a price for April 15, 2026.

To prepare for the 2026 forecast, the model was retrained on the full dataset from June 2010 to April 15, 2025. Using the .get\_forecast() method it was generated a 365-day projection. Since ARIMA operates on differenced data, the forecast was converted back to actual price values by applying a cumulative sum and adding the last known closing price.

The process illustrated a forecasting closing price of $430.41 for April 15, 2026.

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*Figure 16*

## SARIMA Forecast for 2026-04-15

For the SARIMA model to forecast the stock price for April 15, 2026, it was employed a configuration similar to ARIMA - specifically a (1,1,0) and to composition was added a seasonal cycle of 5 trading days, particularly (1,1,0,5). The 5-day cycle was chosen to reflect the weekly trading pattern as previously was identified training model through seasonal decomposition.

However, in this case the model predicted a closing price of 189.60 for April 15, 2026 unexpectedly low value compared to the 2025.

As it can be noticed SARIMA’s linear and seasonal structure suits medium-term forecasting but struggles with long-term predictions, especially when data includes structural changes. As Box and Jenkins (2015) emphasize, ARIMA-class models inherently assume stationarity, making them vulnerable to unexpected market shocks or trend reversals.

**A graph of a graph

Description automatically generated with medium confidence***Figure 17*

## LSTM Forecast for 2026-04-15

To further evaluate forecasting using deep learning methods, an LSTM (Long Short-Term Memory) model was implemented to predict stock prices for April 15, 2026. As noted by Hewamalage et al. (2021), LSTM is particularly effective for financial time series due to its ability to capture temporal dependencies and nonlinear patterns.

The model was trained on 90-day data sequences, with each sequence used to predict the next day's closing price. Data normalization was performed using MinMaxScaler, and the data was transformed into the format required for LSTM. Training was conducted over 50 epochs with a batch size of 32.

The predicted price for April 15, 2026 was approximately $257.51. Visual analysis showed that the LSTM reproduced historical trends with reasonable accuracy, suggesting its effectiveness in working with sequential data. However, the model remains sensitive to data scaling and may lack the interpretability of classical methods like ARIMA.

For financial analysts, this method provides valuable insights, but due to its "black box" nature, forecasts should likely be supplemented with macroeconomic context to enable more informed investment decisions.

# **9. Evaluation and Comparison of Models for forecasting for 2026-04-15**

## **ARIMA, SARIMA, and LSTM Metrics**

Evaluation was made through the assessment of the forecasting performance of the three selected models—ARIMA (1,1,0), SARIMA (1,1,0,5), and LSTM. For more precise assessment it was used a set of standard evaluation metrics: **R², MAE, MAPE,** and **RMSE, where:**

* **R² (coefficient of determination)** quantifies how well the predictions explain the variance of the actual data (and closer to 1 is better).
* **MAE (mean absolute error)** reflects the average magnitude of prediction errors.
* **MAPE (mean absolute percentage error)** shows the average error as a percentage of actual values, if it above 100% , it indicates poor accuracy.
* **RMSE (root mean squared error)** penalizes larger errors more strongly than MAE, giving a sensitive measure of forecast precision.

The following table the results for each model:

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Figure 18

While all models showed negative R² values (which might suggest poor predictive performance), the LSTM model nevertheless demonstrated better results than other models. It achieved the lowest MAPE and RMSE values, indicating a closer alignment with actual price movements. Generally speaking, lower MAE, MAPE, and RMSE values allow us to conclude that the model makes fewer prediction errors and achieves higher accuracy.

At the same time, ARIMA's results - including 100% MAPE and negative R² - highlight this model's limitations when dealing with the volatility and structural changes that are very characteristic of financial time series. However, SARIMA demonstrated the worst performance among all models, despite being configured with 5-day seasonal cycles intended to capture the stock's actual behaviour. As Hyndman and Athanasopoulos (2018) emphasize: “Short seasonal cycles (e.g., weekly) can only improve forecasts when genuine seasonality exists. Selecting the correct seasonal period is critical.”

By contrast, LSTM, although not perfect, but still is adapted better to Tesla’s volatility, achieving lower error metrics and more closely following observed trends.

# 10. Conclusion

This project explored how time series models—ARIMA, SARIMA, and LSTM—can be applied to real financial data, using Tesla’s stock as a case study. Beyond forecasting, the goal was to understand how **seasonality, cycles, and volatility** affect model accuracy.

The experiments revealed that **traditional models like ARIMA and SARIMA** struggle with highly volatile assets like Tesla due to assumptions of linearity and consistent seasonal patterns. As Ghosh and Chaudhuri (2015) noted, short-term seasonality often fails under **speculative or high-frequency market conditions**—a finding echoed in SARIMA’s poor performance using a 5-day cycle.

In contrast, the **LSTM model**, while not perfect, handled nonlinear dynamics better, outperforming in terms of **MAPE and RMSE.**

Overall, the project highlights that model choice must be **context-driven**. Even advanced tools can fail if misapplied. Effective forecasting requires not just model flexibility but also a deep understanding of **data structure and behavioural patterns**.

This could serve for future research should focus on identifying external influences—such as**structural breaks or technical indicators**—that affect model performance, forming a basis for improved **regime detection and adaptive forecasting**.

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