Predicting Delta Flight Departure Delays from Hartsfield-Jackson Atlanta International Airport

*Note: Project Completed in partial fulfillment of credit in the Predictive Analytics course led by Dr. Mehmet Aktas

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***Abstract*—The airline industry faces the persistent challenge of flight delays, resulting in financial losses and reduced customer satisfaction. Delta Airlines, with its primary operations centered at Hartsfield-Jackson Atlanta International Airport, encounters difficulties in effectively predicting and managing these delays. This study focuses on the development of predictive models to forecast flight delays for Delta Airlines departures from this major hub. Accurate delay prediction is essential for optimizing operational efficiency, improving passenger experience, and maintaining competitiveness within the airline industry. This research employs a data-driven approach, leveraging historical flight data and various analytical techniques to identify patterns and predict delays. Through the use of machine learning models, the study aims to provide valuable insights and strategies for Delta Airlines to enhance strategic planning, regulatory compliance, and overall operational performance. The results of this study have the potential to contribute significantly to the airline's efforts in mitigating flight delays and improving customer satisfaction.**

***Index Terms*—Prediction, Delay, Flights, Airlines, SARIMA, Prophet, LSTM**

I. Introduction

The airline industry regularly faces the challenge of flight delays, which can disrupt operations, lead to financial losses, and negatively impact customer satisfaction. Delta Airlines, primarily operating from Hartsfield-Jackson Atlanta International Airport, experiences these challenges firsthand. Accurate prediction and management of flight delays are crucial for optimizing operational efficiency, maintaining competitive advantages, and ensuring positive passenger experiences.

The objective of this research is to employ three predictive analytics methods—SARIMA, LSTM, and Prophet Model—to forecast flight delays for Delta Airlines flights departing from Atlanta Airport. By leveraging approximately 429,000 records of flight departure data from the Bureau of Transportation Statistics, covering Delta Airlines flights from Hartsfield-Jackson Atlanta International Airport in 2022 and 2023, the study aims to enhance Delta's ability to manage and anticipate delays effectively.

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The research utilizes historical data, including flight timings, airport traffic, and delay reasons, to develop predictive models. SARIMA is applied to analyze delays influenced by seasonal travel trends and operational factors. Long Short-Term Memory (LSTM) networks are used to capture complex nonlinear dependencies and long-term historical contexts within the delay data. The Prophet Model forecasts flight delays by accommodating yearly, weekly, and daily seasonality, as well as holiday effects.

By exploring these models, the study seeks to provide Delta Airlines with actionable insights into predicting flight delays more accurately, improving overall efficiency, and optimizing operations. This research contributes to the airline's efforts in strategic planning, regulatory compliance, and delivering superior customer experiences

II. Models and Algorithms Used

A. Preprocessing

Preprocessing of the flight delay data was essential for preparing it for use in the predictive models. The data set of approximately 429,000 records from the Bureau of Transportation Statistics contained Delta Airlines flights departing from Hartsfield-Jackson Atlanta International Airport in 2022 and 2023. The data did not contain many missing values, but the two records with missing values were handled using linear interpolation to ensure continuity and data integrity.

The original date format (MM/DD/YYYY) was converted to a datetime object for time series analysis. The data was then set as an index based on the datetime values and sorted accordingly, ensuring that the data was in chronological order for proper modeling. Temporal features such as the day of the week and time of day were extracted from the datetime index for training Long Short-Term Memory (LSTM) networks, allowing the models to account for potential patterns related to these aspects.

The data underwent feature scaling using the MinMaxScaler() method, which normalizes numerical features to a range of [0, 1]. This scaling is crucial for improving the performance and stability of the predictive models, particularly

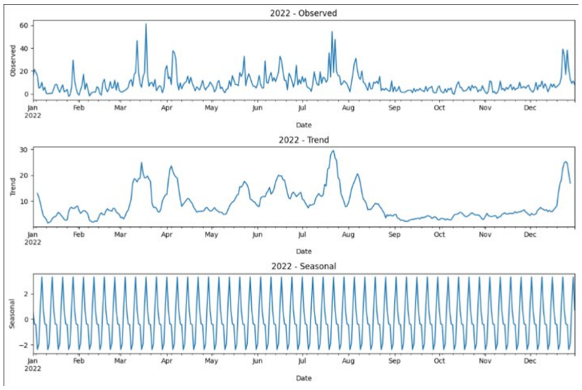

Fig. 1. Details of 2022 data

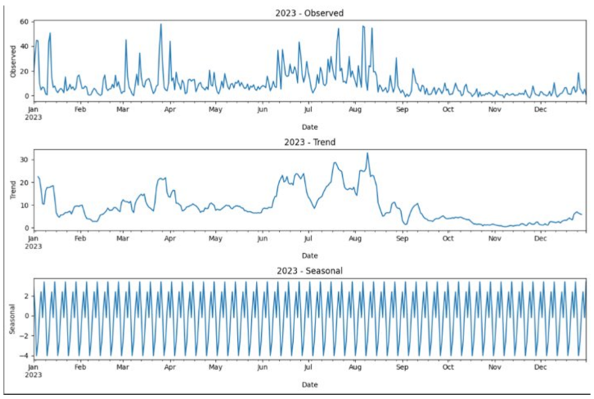

Fig. 2. Details of 2023 data

neural networks. Additionally, categorical features were label-encoded to convert them into numerical format, enabling the models to interpret categorical data effectively.

Additional preprocessing steps were carried out based on the specific requirements of each model, including SARIMA, LSTM, and Prophet. These included adjustments for handling time series data, such as removing trends or seasonal effects as needed. These preprocessing steps ensured the data was in the optimal format for the chosen predictive models, contributing to the accuracy and reliability of the forecasting results.

B. Exploratory Data Analysis

Exploratory data analysis (EDA) revealed that the flight delay data does not exhibit a significant long-term trend. However, there is clear seasonality present in the data, particularly observable around the time of holidays. These seasonal patterns align with periods of increased travel demand, suggesting that the data is influenced by holiday seasons and other peak travel times.

C. SARIMA

The Seasonal AutoRegressive Integrated Moving Average (SARIMA) model is a robust statistical approach for time series forecasting, especially when the data exhibits seasonal patterns. The analysis began with testing the stationarity of the time series using the Augmented Dickey-Fuller (ADF)

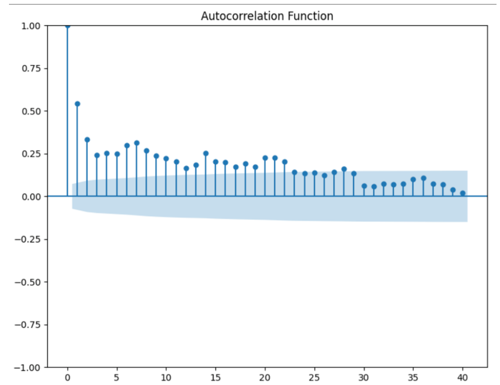

Fig. 3. ACF plot of data suggest stationarity

test. The test results indicated that the time series is likely stationary, as evidenced by a p-value of 0.002.

To assess the seasonality in the data, the Autocorrelation Function (ACF) plot was examined for daily lags across a span of 40 days. The plot revealed clear signs of seasonality, with spikes occurring approximately every seven days. This pattern aligns with the expected weekly cycle of air travel and underscores the presence of a seasonal component.

To identify the best-fit SARIMA model for the data, the auto_arima function was utilized. This function automatically determines the optimal parameters for the ARIMA model, considering both the seasonal and non-seasonal components. The use of auto_arima helps streamline the model selection process and ensures that the chosen model effectively captures the underlying patterns and seasonal variations in the data.

D. LSTM

Long Short-Term Memory (LSTM) networks are a type of recurrent neural network (RNN) designed to address the vanishing gradient problem common in traditional RNNs. LSTMs are effective in capturing complex temporal dynamics and external factors such as airport congestion and crew availability, allowing for more accurate forecasting of flight delays. This enables better resource management and contingency planning.

The architecture of the LSTM model consists of multiple layers:

- Layer 1: This layer captures temporal dependencies across the entire sequence, which is crucial for understanding context in sequence data. It contains 128 units and is configured to return sequences, allowing the layer to output a sequence of predictions to the next layer. A dropout layer is incorporated with a dropout rate of 20
- Layer 2: The second layer processes and condenses the information from the sequence into a single vector that summarizes the entire sequence. This layer contains 128 units and is set to return only the last time step's output (Return Sequences set to False). This single output provides a concise representation of the sequence data for the subsequent layers. A dropout layer with a rate of 20

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_2 (LSTM)               (None, 100, 128)          69632

 dropout_2 (Dropout)         (None, 100, 128)          0

 lstm_3 (LSTM)               (None, 128)               131584

 dropout_3 (Dropout)         (None, 128)               0

 dense_1 (Dense)             (None, 1)                 129

=================================================================
Total params: 201345 (786.50 KB)
Trainable params: 201345 (786.50 KB)
Non-trainable params: 0 (0.00 Byte)
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Fig. 4. Summary of LSTM architecture

- Dense Layer: The final dense layer produces the tangible prediction from the processed data. This layer translates the LSTM outputs into the final forecast, serving as the model's prediction for flight delays.

The structure of the LSTM model is designed to balance the trade-offs between capturing temporal dependencies and preventing overfitting, resulting in robust and accurate delay predictions.

E. Facebook's Prophet Model

Prophet is a forecasting model that requires minimal data preprocessing, making it a convenient choice for predicting flight delays. To ensure compatibility with Prophet, columns in the dataset were renamed to 'ds' and 'y.' The 'ds' column represents date and time, while the 'y' column contains the metric to forecast, which in this case is the departure delay.

Prophet is designed to automatically detect and model seasonal patterns, making it particularly well-suited for datasets with daily observations. This ability to capture seasonality is beneficial for predicting flight delays as it accounts for variations in delay patterns throughout the week and over different times of the year.

To optimize the model, explicit holidays were defined and set with an upper and lower window (number of days before and after the holiday to consider). This helps the model account for the impact of holidays on travel patterns and delays. Additionally, the "changepoint_prior_scale" parameter was tuned, allowing for increased sensitivity to changes in trend when the scale is adjusted. This parameter helps the model better adapt to shifts in trend and provides more accurate forecasts.

By leveraging these tuning techniques, Prophet can effectively model the complexities of flight delay data and generate reliable forecasts for improved operational planning and resource management.

III. Results and Evaluations

In this section, the performance of each predictive model—SARIMA, LSTM, and Prophet—will be evaluated in detail. The evaluation focuses on the models' ability to accurately forecast flight delays for Delta Airlines flights departing from Hartsfield-Jackson Atlanta International Airport.

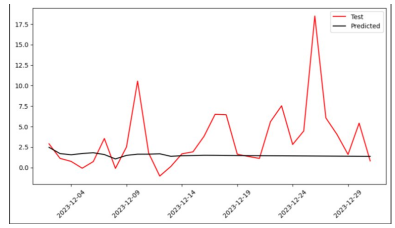

Fig. 5. Prediction Plot by SARIMA Model

For each model, there will be a table of errors that outlines the mean absolute error (MAE) and root mean square error (RMSE) achieved during model testing. These error metrics provide insight into the models' predictive accuracy and reliability.

In addition to the tables of errors, prediction graphs will be presented for each model. These graphs visualize the models' predicted flight delays against the actual observed delays, offering a clear illustration of the models' accuracy and their ability to capture patterns in the data.

A. SARIMA

The Seasonal AutoRegressive Integrated Moving Average (SARIMA) model was implemented to forecast the average daily delay of each day, aggregating data across all flights for that day. This approach was expected to capture specific patterns in the data, particularly related to holiday seasons. However, the model struggled to effectively identify and predict delays around holiday periods, even though such periods are critical for understanding and anticipating flight delay patterns.

The SARIMA parameters were determined using the auto_arima function, resulting in the configuration (4,0,1),(0,0,1)[12]. Despite this optimization, the model's performance was limited in its ability to account for the specific seasonal patterns associated with holiday travel.

TABLE I
SARIMA errors

	Mean Absolute Error (MAE)	**Root Mean Square (RMSE)**
Training Data	4.96	7.99
Testing Data	2.64	4.31

B. LSTM

The Long Short-Term Memory (LSTM) network was designed to forecast delays on a per-flight-day basis. This approach potentially indicates patterns such as multiple flights being delayed together or the influence of a particular flight's delay on the average daily delay.

The LSTM model used a time step of 60, providing a detailed analysis of the temporal dependencies in the data. While LSTM is known for its effectiveness in large datasets, the lack of compute resources and time to train on the full dataset limited its performance. As a result, the model missed

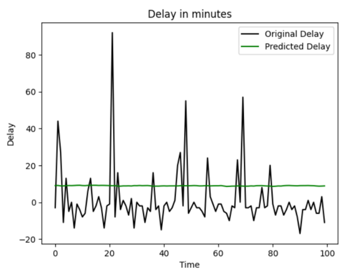

Fig. 6. Prediction Plot of LSTM model

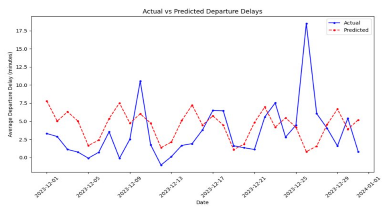

Fig. 7. Vanilla Prophet Model Prediction Plot

the seasonal aspects of holiday periods, which is crucial for accurate delay predictions.

TABLE II
LSTM ERRORS

	MAE	RMSE
Training Data	17.69	38.53
Testing Data	13.0	26.78

C. Facebook's Prophet Model

The tuned Prophet model provided the most promising results among the three models, particularly due to its ability to handle seasonal patterns effectively. Prophet was trained to forecast the average daily delay for each day and incorporated explicit definitions of holidays, enabling the model to adapt to seasonal variations and holiday patterns.

By accommodating holiday effects, Prophet managed to achieve higher accuracy and better predictions compared to SARIMA and LSTM. This superior performance highlights the importance of explicitly incorporating holiday patterns into the model to capture the unique challenges and behaviors associated with these periods.

TABLE III
FACEBOOK'S PROPHET MODEL ERRORS

	Vanilla Prophet Model	
	MAE	**RMSE**
Training Data	6.18	9.28
Testing Data	3.26	4.54
	Tuned Prophet Model	
	MAE	**RMSE**
Training Data	6.05	9.12
Testing Data	249	3.42

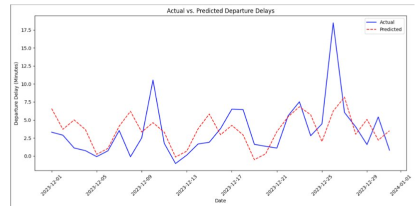

Fig. 8. Tuned Prophet Model Prediction Plot

IV. CONCLUSIONS

The research focused on forecasting flight delays for Delta Airlines flights departing from Hartsfield-Jackson Atlanta International Airport using three predictive analytics models: SARIMA, LSTM, and Prophet. Among the models, the tuned Prophet model emerged as the best performer, achieving a minimal mean absolute error (MAE) of 2.49 and a root mean square error (RMSE) of 3.42. These results demonstrate the high accuracy and reliability of the Prophet model in predicting flight delays.

The average daily delay across the entire dataset was 9.42 minutes. The minimal MAE achieved by the Prophet model indicates that its predictions are close to the actual observed delays, which is crucial for effective operational planning, customer service, and communication within the airline industry. A lower MAE allows airlines to better assess the reliability of their delay predictions, ultimately leading to more efficient resource management and improved passenger experiences.

The RMSE of 3.42 achieved by the Prophet model is also a strong indicator of its effectiveness in minimizing large errors. Accurate prediction of delay times is critical for avoiding operational bottlenecks, reducing excessive costs, and mitigating severe customer dissatisfaction. The model's performance in this regard highlights its potential for application in real-world scenarios.

Overall, the tuned Prophet model provides a robust and accurate approach for forecasting flight delays, offering Delta Airlines a valuable tool for optimizing operations and improving strategic planning. Future work may involve exploring additional factors and features to further enhance the model's performance and applicability across different scenarios within the airline industry.

A. Real World Impact

The research and its findings hold significant real-world implications for Delta Airlines and the broader airline industry.

1) By delivering high prediction accuracy, the tuned Prophet model can effectively forecast flight delays, allowing for more precise operational planning and enhanced decision-making.
2) The model's ability to identify patterns and root causes of delays provides valuable insights into potential areas for improvement. This information can be used to optimize resources, such as crew scheduling, maintenance planning, and gate assignments, resulting in a smoother and more efficient operation.

3) Refined customer communication is another key benefit. Accurate delay predictions enable the airline to proactively inform passengers of potential delays, offering alternatives and reducing uncertainty. This transparency can lead to improved customer satisfaction and loyalty.
4) Cost reduction is a natural outcome of better resource management and minimized delays. By avoiding unnecessary delays and maximizing efficiency, the airline can achieve significant savings in operational costs.
5) Enhanced customer service is another advantage. With more precise delay forecasts, the airline can tailor its customer service approach, such as offering rebooking options and amenities to affected passengers, leading to a more positive travel experience.
6) Strategic advantages include the ability to respond quickly to changing conditions and opportunities within the industry. The model's high accuracy and adaptability can give Delta Airlines a competitive edge in terms of scheduling flexibility and resource allocation.
7) Finally, the broader application scope of the tuned Prophet model means it could be extended to other airlines and transport sectors, contributing to industry-wide improvements in operational efficiency and customer satisfaction. Overall, the research offers a pathway for Delta Airlines to achieve strategic goals while enhancing its reputation and customer service quality.

REFERENCES

[1] Dataset Source Link: https://www.transtats.bts.gov/ontime/Departures.aspx