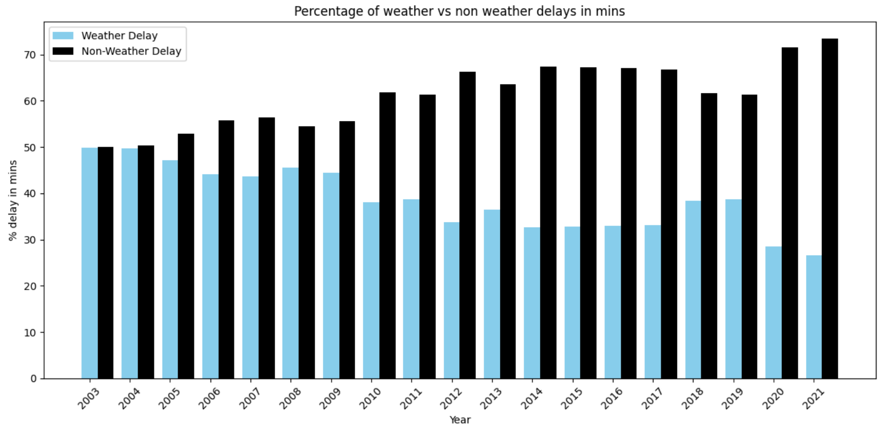
CSE 519: Project Final Paper
Understanding Flight Delays

Abstract

The objective of this paper is to explore the impact of various weather conditions on flight departure, taxi-out delays and then create a model that could predict the delays given the weather forecast. For this study, we use historical flight data and hourly weather data for 10 geographically distinct airports. We conducted an in-depth analysis of the correlations among weather metrics, departure delay, and taxi-out time. Given the substantial impact of taxi times on flight delays, we placed considerable emphasis on investigating patterns related to taxi-out durations. Subsequently, we identified the primary weather factors influencing delays at each location. Following this, we undertook exploratory analysis to ascertain the specific weather phenomena associated with each corresponding weather factor. In an effort to create a robust predictive model, we performed several data processing steps such as outlier removal, normalisation, encoding.



Introduction

Studying the causes of flight delays is of paramount importance for several reasons. Firstly, delays in air travel can result in cascading disruptions across the entire aviation system, affecting passengers, airlines, and airport operations. Understanding the underlying factors contributing to these delays allows for the development of effective strategies and interventions to mitigate their impact. Secondly, such studies provide valuable insights for aviation stakeholders, enabling them to optimise scheduling, allocate resources efficiently, and enhance overall operational resilience. Additionally, a comprehensive understanding of the causes of flight delays facilitates the formulation of targeted policies and procedures aimed at improving on-time performance and, consequently, passenger satisfaction. Ultimately, the pursuit of knowledge in this area contributes to the overall efficiency and reliability of air transportation systems, benefiting both industry stakeholders and the travelling public.

Flight delays can arise from a multitude of factors, encompassing both operational and environmental variables. Operational factors include air traffic congestion, technical issues, and scheduling conflicts, while environmental factors, notably weather conditions, play a pivotal role. Weather is a major contributor to flight delays, constituting a substantial portion, ranging between 30-50% of the total delay in minutes, as indicated by the aforementioned figure. Despite advancements in instrumentation and forecasting techniques since 2003, weather-related delays persist due to the inherent unpredictability and complexity of atmospheric conditions. Studying weather patterns and their impact on flight delays is crucial for developing proactive strategies to minimise disruptions. Insights gained from such studies empower aviation professionals to enhance preparedness, optimise flight schedules, and implement targeted measures to mitigate the impact of adverse weather, ultimately improving overall operational efficiency and passenger satisfaction.

Flight delays can stem from adverse weather conditions at the origin, en route, or destination airports, with the potential for a cascading effect if preceding flights experienced weather-related delays. Reports from Transtats and the National Aviation Service suggest that en route weather has minimal impact on delays, given aircraft resilience and the ability to reroute. However, delays during takeoffs and landings due to weather are more substantial. Therefore, our focus will be on analysing airport weather data at the time of departure to discern patterns in flight delays.

Dataset

We relied upon Transtats(Department of Transportation Statistics) to get the flight schedules. This source hosts the flight data in 5 categories - departures, arrivals, air borne, cancellations and diversions. We downloaded data for 10 different airports(discussed later) and top 4-5 airlines covering more than 90% flights from each airport. We have taken 10 years of historical data from Jan, 2013 to Dec, 2022. The method we used to choose the 10 airports was based on their popularity/busyness and geographical location. Airlines report their delay causes in 5 categories - NAS, air carrier, security, extreme weather and late aircraft delays. And so, the columns we have in our departure flight data are date, airline code, flight number, tail number, scheduled departure time, actual departure time, taxi-out time, wheels time, delay in mins, NAS delay in mins, security delays in mins, air carrier in mins, extreme weather delay in mins, late arrival aircraft delay in mins. All 5 categories of delays add up to total delay in mins. “Extreme weather” column only denotes the delay that was unavoidable and the total delay in minutes from this account to less than 1%. Often bad weather just requires some adaptability and different strategies deployed by NAS which goes into “NAS delay”. NAS reports that ~50% delay in mins by them were due to weather.

Now that we have flight departure data, corresponding weather data needs to be appended to it. NAS(National Aviation Service) depends upon METAR(Meteorological Aerodrome Report) data to understand weather conditions and deploy strategies. MESONET archives have historical METAR data from various networks across the USA. We collected past 10 years of data for all 10 of our airport locations. These METAR data records hold information about temperature, dew point, precipitation, visibility, wind speed & direction, and WX weather codes. WX codes tell us about ongoing weather phenomena and its intensity.

Data preprocessing

1. As the data originated from 2 different sources for each location, there was more than 5gb of data. Our first step was to filter the non-delay flight records. As per TRANSTATS, a scheduled flight is marked as a delay only when the actual departure time is more than 15 mins from scheduled departure time. We deemed this filtering to be essential as the correlation between weather factors and on time flights is very minimal and is likely to cause a lot of noise during analysis. However, we decided to keep these on-time records while designing the model.

2. In both datasets(flight & metar), date and time are provided in string format, so created a new column with ‘time_stamp’ object. As the flight schedules are provided in local times and METAR data in UTC. We had to carefully change the flight timings to UTC keeping their time zone in mind. Then we performed a join on scheduled departure time and metar time. This join performs a nearest match on the time_stamps. As the metar data is provided hourly, The maximum error difference between matched time_stamps(flight and metar) would be 30 mins.

3. The METAR data provides WX codes describing the ongoing weather phenomenon. It proves valuable while analysing geographical regions and their weather conditions, so we had to preprocess it appropriately. It is provided as a string of codes separated by spaces(ex: -RA +BR TS). During exploratory analysis, we maintain it as an array of strings(ex: [‘-RA’,’+BR’,’TS’]). We also one hot encoded the top 5 most occurring wx_codes for our model at the end of this paper. We chose the top 5 wx_codes after conducting some exploratory analysis which described in the later sections.

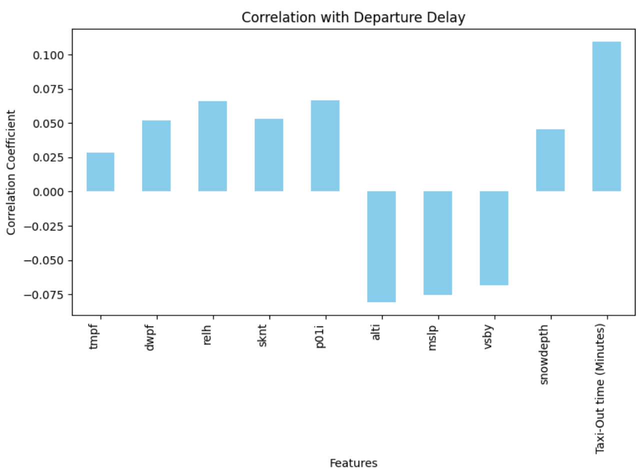
4. For the data preparation phase of prediction, we incorporated the discarded data(delay<15 mins) so as to provide more data for the model to train on. We also used additional data preparation techniques like outlier/anomaly removal, scaling of data, encoding. For the outlier removal, we removed the rows for which any of the columns had value outside the 5th and 95th percentile range. We used MinMax Scaling too which transformed numerical values into the range [0,1]. For Encoding we used OneHotEncoder to transform categorical variables like Airport Name to continuous variables. We also created some extra features like fraction_of_year, fraction_of date to take into account the effect of date and time respectively.

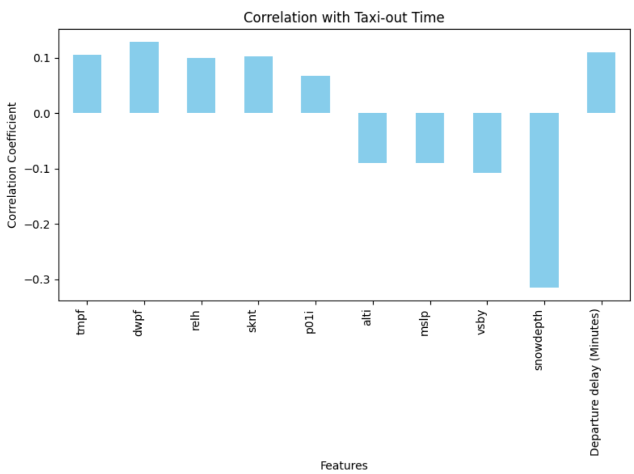
Below table specifies all the features begin used for the prediction model without normalisation & Outlier Removal-

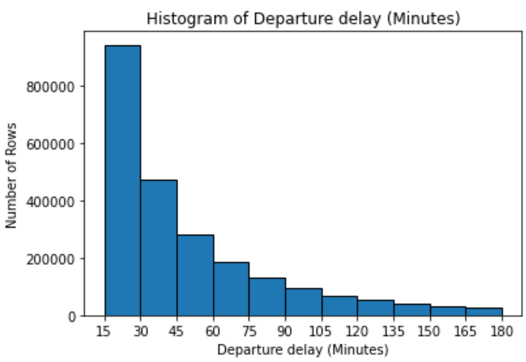
flight data	**range & units**	**weather data**	**range & units**
Departure time	00:01 to 23:59(HH::MM)	Relative humidity	0 to 100(Percentage)
Departure Delay	-123 to 187(Mins)	precipitation	0 to 0.02(Inches)
Taxi-out Time	0 to 69(Mins)	wind speed	0 to 42(Knots)
Date	2013-01-01 - 2023-08-31	temperature	-23.1 to 109.0(Kelvin)
Station	string encoded	Dew point	-32 to 84(Fahrenheit)
		Atmospheric pressure	0 to 1047.4(millibar)
		visibility	0 to 15(Miles)
		Snow depth	1 to 21(Inch)

Exploratory Analysis

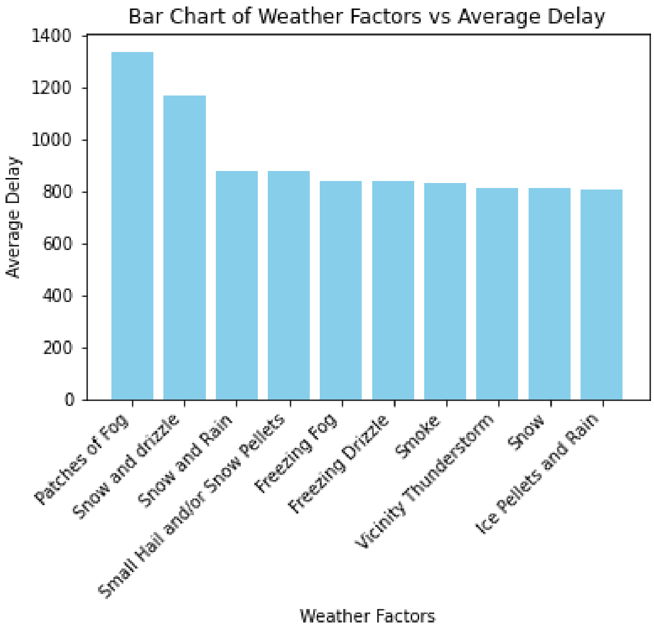
To understand which weather factors highly correlate with departure delays, we calculated the Pearson correlations of delay with several weather factors such as temperature, dew point, humidity, wind speed, pressure, snow depth, cloud coverage altitude, taxi-out time. We don't see very high correlations as departure delay has several other contributing factors such as weather at destination airport and en route weather. We also see that departure delay and taxi-out times are correlated, this is intuitive as taxi-out times increase when the surface weather is bad and special protocols have been deployed for safer taxiing. In the later parts, we analyse how different weather factors affect taxi-out time. In the below plots, it is shown that weather factors have more correlation with taxi-out time than they do with departure delay.





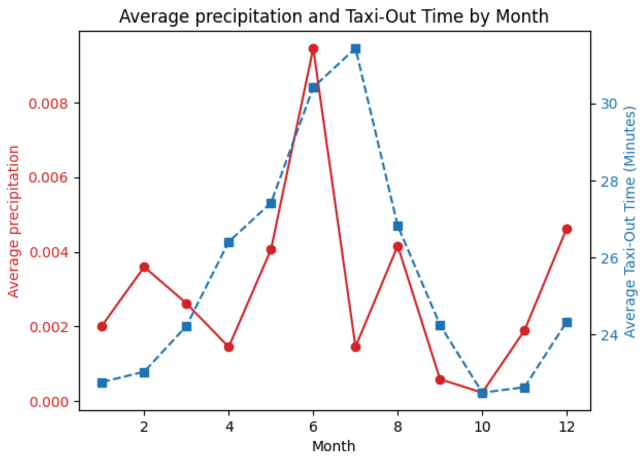


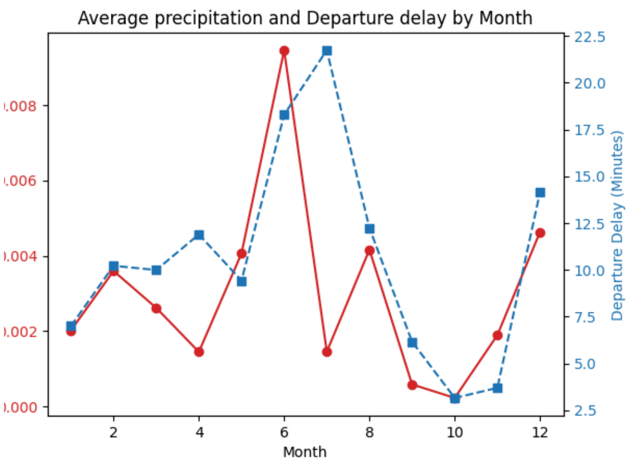
Our flight data consisted of many anomalies such as departure delay lasting more than a day or flights departing many hours before the scheduled time. Such records were as part of the outlier removal process. As flights that depart within 15 mins after the scheduled time are said to be on time. We look at the distribution of delays in 15 min bins. We observed that more than 90% of delays are less than 90 mins.



To enhance our comprehension of weather anomalies and their impact on aviation, we conducted an analysis to identify the weather phenomena associated with the highest average flight delays, specifically those exceeding 14 hours. Our observations revealed that adverse conditions characterised by cold and wet elements, such as snow, freezing fog, ice pellets, and rain, exhibit a propensity to induce prolonged delays. This can be attributed to their disruptive effects on airport runways. In contrast, dry phenomena like heavy winds have a tendency to dissipate swiftly, resulting in minimal operational hindrance and necessitating no extensive cleanup measures.

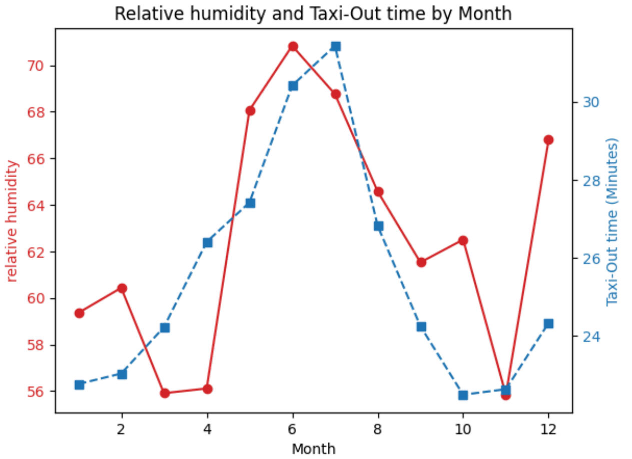
Analysing weather factors with departure delay and taxi-out times

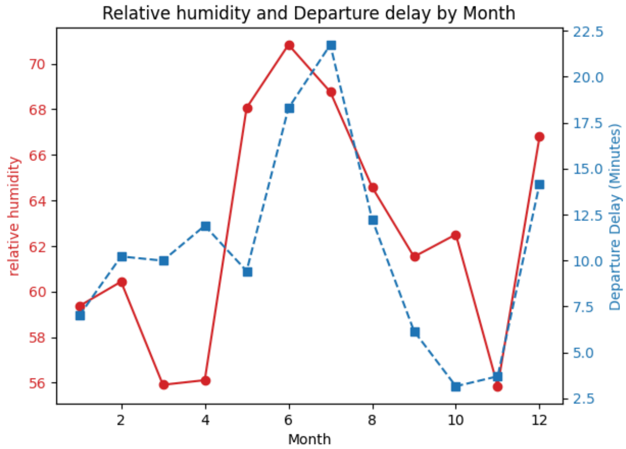




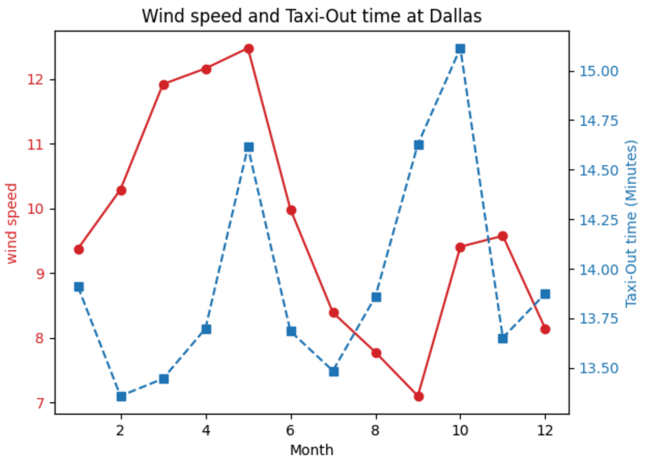
The presented data illustrates the precipitation trends observed at JFK Airport over the years, indicating peak levels during June and July, with a subsequent rise in December. Concurrently, taxi-out time and departure delays exhibit a similar temporal pattern. Both metrics gradually escalate from January to July, experience a decline until November, and exhibit a marginal increase in December. This discernible correlation underscores the potential significance of precipitation as a substantial contributing factor in our predictive model.

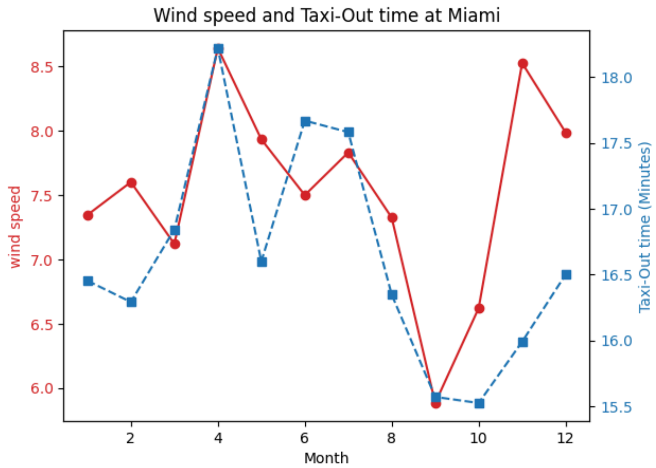
In the context of background research, it is well-established that relative humidity significantly influences taxi-out time. This phenomenon is not exclusive to JFK but is widely observed across various airports. Elevated humidity levels contribute to increased drag and diminished engine performance, consequently extending takeoff times. Furthermore, when humidity combines with precipitation, it gives rise to adverse weather conditions such as snow and fog, exacerbating visibility issues in the aviation environment.





Unlike precipitation and relative humidity, we found out that other factors such as temperature, atmospheric pressure, dew point don't influence taxi-out times as much and therefore we don't see any patterns when plotted over an year. It is important to note that there are region specific factors such as snow and heavy winds. Airports in the northern regions such Chicago, Denver, Seattle, JFK face a bump in taxi-out times during winter due to snow/icing on the runway which requires additional maintenance. Upon studying wind speeds and taxi-out times, we observed that they don't hold much similarity in the northern regions. But in regions where thunderstorms and hurricanes are common, we see high similarity. Below plots show the pattern between wind speed and taxi-out at Dallas Fort Worth and Miami International.

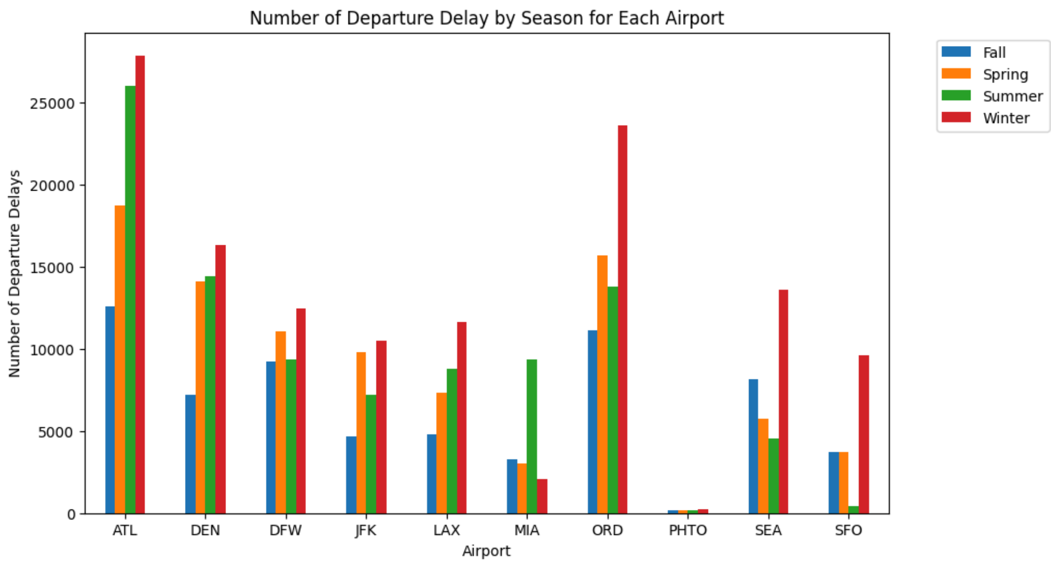




Analysing weather codes at different regions

As discussed earlier in the data preprocessing section, wx_codes reveal a wealth of information about the ongoing weather phenomenon. We have done a detailed study on the different wx-codes that occur at various airports and the different seasonal delays. This analysis aimed to unravel patterns and correlations between specific weather phenomena and seasonal delays. Below is a graph showing seasons that incur the most delays due to weather. The months are categorised into various seasons as follows: 1. Winter: December, January, February, March 2. Summer: July, August 3. Fall: September, October, November 4. Spring: April, May, June.

To complement the graphical representation, a table detailing the most frequently encountered wx-codes is provided. This table offers a granular insight into the specific weather phenomena contributing to delays. By correlating wx-codes with seasonal patterns, we gain a comprehensive understanding of the diverse weather challenges faced by airports across different geographical locations. The word 'delay' in the conclusion encompasses departure delay > 15 minutes at the origin airport only.



Airport	Top Delay Months	Major causes of Delay	Geographical reason
Chicago O'Hare (ORD)	December, January, June	Mist, Mild Snow, Mild Rain, Haze	The cold winter months bring heavy snowfall, leading to increased delays as the airport copes with snow removal and de-icing processes. Mist and rain further contribute to reduced visibility and operational challenges.
Denver (DEN)	May, December, November	Mist, Mild Snow, Mild Rain, Haze, Thunderstorm, Vicinity Thunderstorm	Experiences most delays during winter when weather phenomena like snow fall, freezing rain, ice fog and chinook winds which are known to cause thunderstorms are prevalent..
Los Angeles (LAX)	December, January, February	Mist, Haze, Mild Rain, Rain, Fog, Patchy Fog	Los Angeles, California, has a Mediterranean climate, characterised by mild, wet winters.. Experiences most delays during winter when conditions like precipitation, visibility issues (due to fog and low clouds) are prevalent.
New York JFK (JFK)	December, January, February, July	Mist, Mild Rain, Mild Snow, Rain, Mild Drizzle	The cold winter months in New York bring challenges related to snowfall and freezing conditions. Mist, rain, and drizzle further impact visibility, while fog adds to operational challenges.
Seattle-Tacoma (SEA)	November, December, January	Light Rain, Mist, Haze, Mild Snow, Fog, Rain, Smoke	Seattle is known for its wet conditions with high humidity throughout the year.
San Francisco (SFO)	December, January, February	Light Rain, Mist, Rain, Haze, Smoke, Heavy Rain	San Francisco is known for its unique microclimate experiencing moderate temperature fluctuations with cool and foggy weather in winter
Hawaii (ITO)	January, February, March	Mist, Mild Snow, Mild Rain, Haze, Thunderstorm, Vicinity Thunderstorm	Hawaii is known to have a tropical climate and mild temperature throughout the year with little to none adverse conditions.
Dallas/Fort Worth (DFW)	December, January	Mist, Light Rain, Light Drizzle, Rain, Thunderstorm, Thunderstorm with Rain	Dallas is known for frequent thunderstorms throughout the year but elevates during winter causing heavy rains.

Atlanta (ATL)	January, February, July, August	Mist, Light Rain, Light Drizzle, Rain, Light Thunderstorm with Rain, Thunderstorm	July, August months create favourable conditions for the development of thunderstorms,leading to delays. And While winter in Atlanta is relatively mild, the increased mist, rain, and drizzle contributes to reduced visibility and delay
Miami (MIA)	June, July, August	Light Rain, Mist, Thunderstorm, Light and Heavy Thunderstorm with Rain,	The tropical climate in Miami during summer and closeness to the Atlantic Ocean leads to increased thunderstorm activity, impacting airport operations.

Models for predicting departure delay and taxi-out times

Our exploratory analysis has shown us that surface weather metrics at the origin airport are a better predictor for flight taxi-out times. The airports in our study are quite popular and extremely busy. They tend to have multiple runways, each receiving and letting out flights every few minutes. Therefore, the planes in these locations spend several minutes moving across the airport from their terminal to take-off point and waiting in queues.

Weather factors during this time often play a crucial role in determining the speed with which the planes can taxi. Whereas departure delay can be caused due to several factors such as security, carrier, NAS, weather en route and at destination, etc. So, we use our features to predict not just departure delays but also taxi-out times. Our intuition is that having an estimate of expected taxi-out time will show us how departure delay may change.

At first we used only the weather features (temperature, precipitation, dew point, humidity, wind speed, pressure, visibility, snow depth) for prediction. We first tried a linear model and then a non-linear model. Our reason for using non-linear models such as Random Forest Regressor is that weather conditions often exhibit nonlinear interactions, and Random Forest Regressor excels in modelling intricate patterns. Its feature importance analysis helps identify key weather factors impacting delays, and the model's robustness to outliers and scalability make it well-suited for handling diverse and large-scale weather datasets.

This didn’t make an accurate enough model. Analysis of different weather factors at every region has shown that there are a specific subset of factors at every location that heavily influence the taxiing and departure delay. For example, wind speed and direction play a bigger role in southern locations. Whereas northern locations respond more to dew point, snow depth. All locations are affected by relative humidity and precipitation.

As we have 10 years worth of data leading to ~1 million records per location. We decided to create a model for each location separately and see if the accuracy increases. This shows us that when the data for locations was merged the model performed worse because there was no feature to keep track of location. So, we decided to perform one hot encoding upon the origin airport. This has improved the accuracy significantly. Below table the Root mean squared error and mean absolute error in predicting taxi-out times and departure delay for all the 10 locations. We also show the values of the model after final encoding.

Table: RMSE, MAE for Taxi-out time and Departure delay for each airport

Location	Linear Regression(Baseline Model)		Non Linear Model(Random Forest Regressor)	
	Taxi-out time (RMSE, MAE)	Departure delay (RMSE, MAE)	Taxi-out time (RMSE, MAE)	Departure delay (RMSE, MAE)
JFK	12.46, 9.00	33.5, 20.12	9.68, 6.50	32.48, 18.47
ORD	8.74, 6.17	29.17, 18.49	7.76, 5.37	27.87, 16.69
DFW	6.84, 4.73	29.64, 18.75	6.11, 4.22	27.89, 17.86

ATL	6.44, 4.61	27.91, 14.63	5.58, 3.98	25.39,12.70
SEA	7.44, 5.42	18.80, 11.56	6.53, 4.69	18.96, 11.44
SFO	8.38, 6.02	29.72, 17.33	7.45, 5.37	29.46, 16.80
LAX	7.49, 5.47	23.55, 14.70	7.15, 5.20	23.44, 14.14
MIA	7.97, 5.5	26.68, 17.18	7.31, 5.03	26.44, 16.23
DEN	6.96, 4.66	30.01, 18.23	5.95, 3.94	28.01, 15.94
ITO	2.29, 1.51	10.32, 6.57	2.63, 1.85	10.96, 7.20
Overall	7.51, 5.30	32.29, 17.69	6,59, 4.59	31.09, 16.30

Conclusion

There are different weather factors that dictate delays at each geographical location. Airports follow protocols when leading up to an extreme weather event. Depending on the nature of the event and its impacts, airports will take different actions. To answer this question, Are airlines better prepared for extreme climates (time of the year) than unexpected weather phenomena like blizzards? We analysed the delays caused due to different wx-codes and found that some phenomena can be dealt with and some can't. Things like thunderstorms, hurricanes, blizzards, and anything that causes visibility issues cannot be avoided if they aren't mild. If the extreme climate causes visibility issues then they are bound to cause delays, on the other hand if the extreme climate just includes low temperatures then airports are prepared to deal with it.

Future Directions

1. Multifunctional Nature of Departure Delays:
Our research underscores the complexity of predicting departure delays. Relying solely on weather data proves insufficient due to the multifaceted influences on departure times. Factors such as airline infrastructure, air traffic conditions, and decisions made by air traffic control (ATC) play pivotal roles in determining departure delays.

2. Comprehensive Weather Considerations:
Beyond the origin airport's weather, accurate prediction of weather-related flight delays necessitates a broader scope. Contextualizing weather conditions in en route air spaces and the destination airport is crucial for a more precise assessment of potential delays.

3. Taxi-Out Time Determinants:
The duration of taxi-out times is intricately tied to various factors. These include the specific protocols implemented by each airport, the layout of the airport, as well as aircraft-specific attributes such as size, weight, and the availability of specific instruments on board.

4. Influence of Taxi-In Times:
To comprehensively gauge taxi-out times, it's imperative to consider the arriving flight's taxi-in times. Analysing data from the 'arrival' database provided by Transtats allows us to understand the interconnected relationship between arrival and departure times.

5. Cascading Effects of Delayed Aircraft:
Delays in earlier flights can set off a chain reaction with far-reaching consequences. Subsequent flights may experience delays due to the ripple effect of earlier disruptions. Furthermore, a delayed flight can have ramifications at its destination airport if it fails to make up for lost time during travel, leading to potential disruptions in scheduling and operations. Understanding and mitigating these cascading effects is crucial for a more robust departure delay prediction model.

References

[1]“FAQ: Weather Delay | Federal Aviation Administration.” Faa.gov, 2013, www.faa.gov/nextgen/programs/weather/faq.

[2]“National Oceanic and Atmospheric Administration.” www.noaa.gov, noaa.gov/.

[3]OpenWeatherMap.org. “Current Weather and Forecast OpenWeatherMap.” Openweathermap.org, 2012, openweathermap.org/.

[4]“OST_R | BTS | Transtats.” www.transtats.bts.gov, www.transtats.bts.gov/.

[5]Sternberg, Alice, et al. A Review on Flight Delay Prediction. https://arxiv.org/abs/1703.06118. Accessed 25 Oct. 2023.

[6]Team, D. T. N. “How Bad Is Too Bad? Weather That Affects Flights.” DTN, 26 Feb. 2021, www.dtn.com/how-bad-is-too-bad-weather-that-affects-flights/.

[7]https://www.sciencedirect.com/science/article/pii/S2772415822000050#sec3