Final Report

Brendan Marshall, Joseph Lim, Simha Kalimipalli

1. Executive Summary

1.1 Problem Overview

When unexpected variables such as extreme weather hit the Canadian aviation industry, the effects can be far reaching, impacting airports and passengers across countries due to the highly interconnected nature of the aviation industry. These delays can result from the direct physical impacts of weather, but are often caused by the actions taken in response to the weather conditions and the subsequent congestion at airports following the initial delay [1]. When quantifying this, weather accounts for up to 74% of all delays in the system with flight volume taking another 15%, often due to congestion effects[2]. The UN Sustainable Goal 11 (Sustainable Cities and Communities) affirms the need for better transportation, promoting "access to basic services, energy, housing, transportation and more" [3][4]. Aviation plays a crucial role in achieving these goals because it enables us to better support a distributed society, especially across an area as large as Canada. Air travel provides essential connections from smaller cities to regional hubs and facilitates cross-country travel between major population centers. Highlighting the significance of aviation, Canada ranks 19th in the world in passenger traffic, despite being only the 36th most populous country, indicating a strong reliance on and support for its aviation sector [5][6][7]. Currently, this industry accounts for 1.1% of Canada's GDP employing over 265,000 people while supporting hundreds of thousands more people through the industry's aviation support [8]. **As such, the overall problem this study aims to tackle is the social and economic impacts of storm events on the aviation industry in Canada.**

In Canada, winter storms, ice storms and hurricanes are the primary concerns to airplane operating patterns; In 2013, a thunderstorm over Toronto resulted in the cancellation of 79 flights when the runway was flooded, with delays spiraling to other airports as the overflow was slowly spread to nearby areas [9]. Later that year, over 200 flights were cancelled during the busy Christmas season in Toronto when an ice storm occurred, and these flights were not able to be reinstated due to the impact that it would have on the efficiency of the system [10]. According to the Canadian Climate Institute, due to the effects of climate change most regions in Canada will experience greater rainfall and an increase in severity of coastal storms year over year exacerbating the impacts on the airline industry [11]. When aircraft encounter these types of delays, holding patterns are frequently used, as they offer the most benefit to the airlines. However, this practice has been shown to increase stress on the airports that accommodate them [12]. These subsequent delays or cancellations commonly trigger a cascading series of delays within the broader North American airspace system, shown clearly by the landfall of Hurricane Milton in Florida which triggered delays and cancellations at Canadian airports far beyond the scope of the storm [13].

Through simulation of aircraft and airport responses to extreme weather scenarios we will help to inform the planning of procedures, policies, and technological adaptations to these storms, ultimately reducing their impact on society. Many previous attempts to improve airline response often fixate on the perspective of the company undergoing the study, usually a major airline, and fail to consider the impacts of other actors and tradeoffs between entities [14]. Such a simulation must take into account perspectives from various interested stakeholders including airport management, aircraft and the passengers of said aircraft, in order to ensure that no party is disadvantaged unfairly when providing insight into this problem.

1.2 Objectives

This study aims to provide NAV Canada and the associated air traffic controllers with a deeper understanding of the complex effects of extreme weather events in order to minimize the impact on the aviation industry. Through exploration of the impacts of factors such as financial incentives, cascading delays, selfish actors, and airplane sizings the simulation model will offer an effective strategy, or combination of strategies to improve delay response in Canada's airspace. The results of the agent-based simulation models may provide grounds for potential policy implementations to better control responses by the airlines in these events or the airports to better facilitate operations after a major delay. The simulation will also bring light to the most substantial factors in the delay process in order to help controllers understand and plan for the chaotic outcomes of a storm before the issues are able to compound.

Thus the first of our two considered parties will be major Canadian airlines such as Air Canada, WestJet, and Flair Airlines, working to minimize the time delays and lost flights that their own company suffers through minimizing individual flight impacts. These airlines operate and manage aircraft, employ pilots and crew, and are responsible for transporting passengers and cargo with a primary focus on brand reliability and profitable endeavors. The aircraft types these companies fly range from small regional planes to large international jets, each influencing air traffic management decisions and value to the company.

The second party will be the airports in Canada and associated air traffic controllers stationed there. While the overarching organization for these controllers is our stakeholder, the traffic controllers are the ones making the final decisions on the ground, allowing or disallowing landings and suggesting courses of action in disaster scenarios. The controllers focus on maximizing traffic flow at a national level while adhering to NAV Canada's guidelines [1]. They place less emphasis on specific aircraft brands or individual flight considerations, prioritizing the minimization of total system-wide impacts [2]. This approach often conflicts with the desires of each airline as oftentimes in order to maintain an efficient flow of aircraft, the controllers will cancel a flight departure or arrival in the event of adverse delay (caused by maintenance, weather etc).

1.3 Simulation workflow

Our workflow below shows the major implements of our model including the passenger model and the ghost plane model fed from the daily variation model and both feeding one of our two main agents. Alongside this, we also have our delay pseudo agent providing delays to the airplanes and airports to simulate the differences in delays that affect either one plane or the airport as a whole such as the recent crash at Toronto Pearson [21]. The maintenance model will also interact with the airplane agents, providing maintenance needs and ground-time quantities while receiving the flight details of the airplane in question. Finally the Airplane and Airport agents interact, with the airports controlling the behavior allowable by the airplanes constraining them as they act towards minimizing expenses while both agents work together to provide delay data to the delay cost model, measured in person delay hours calculated as the delay multiplied by the number of people affected.

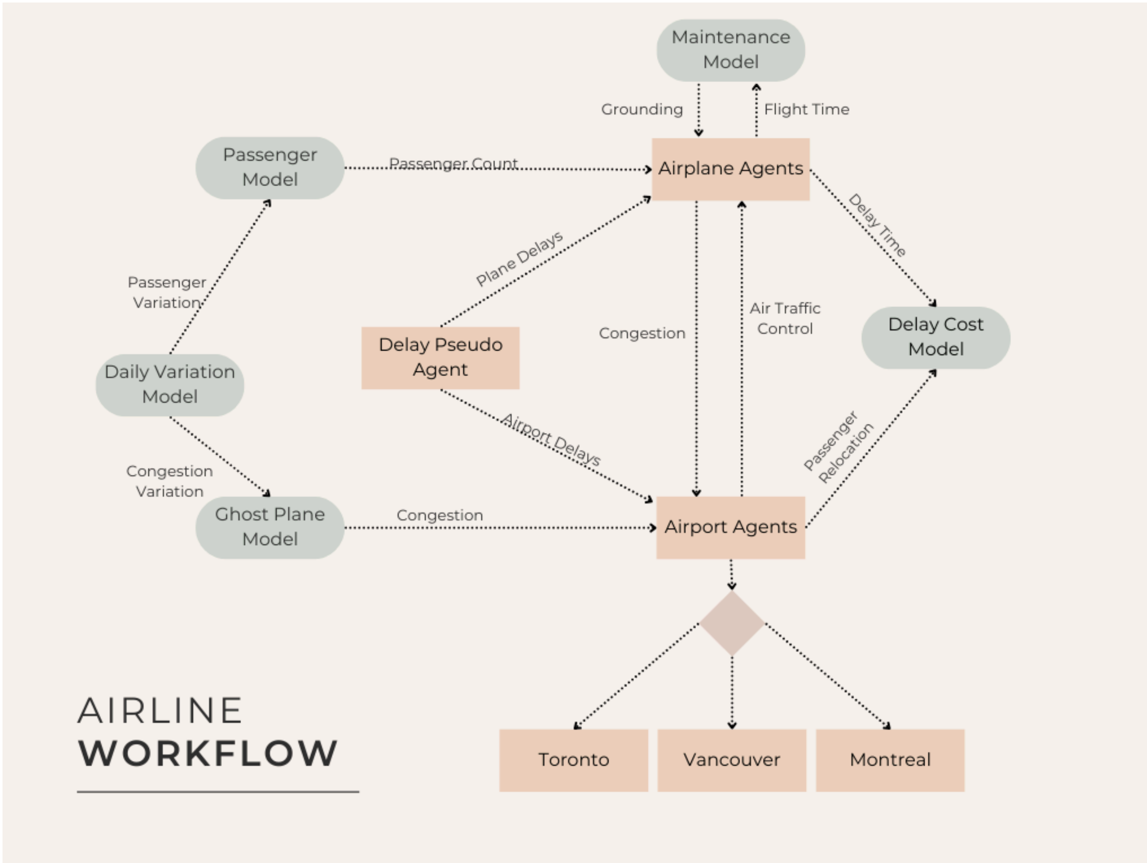

Figure 1: Workflow of Model System

1.4 Considered Scenarios

1.4.1 Baseline Scenario

We will first consider a "baseline scenario" with no procedure to minimize the delay. This is a good reference to quantify the effects of an intervention over the status quo state. Here the various functions for delay interventions would not be activated, and in order to run this base model we need information about the congestion levels at our three targeted airports alongside the number of flights from each airline moving between these destinations on an average day alongside the size of these flights and the infrastructure details of our major three airports.

1.4.2 Operation Management Scenarios

When considering methods of improving the air control space, our first set of methods will be based on options that can be undertaken through alterations in the policy decisions of NAVCAN that will enable them to change the behaviors of air traffic controllers without needing major capital investments as our other scenarios will entail. In these scenarios we will work to simulate the effects of traffic management forecasting, and ground delay programs to identify the potential value of each approach while considering the costs of training and changing procedure.

1.4.2 Capital Investment Scenarios

Our second set of methods will be based on options that require significant investment to implement and as such these can be tested in conjunction and independently from the above methods where needed while also expanding the scenarios that can be explored. To this end we will be comparing multiple possible investment options including increasing gate capacity, expanding the number of runways, and improving the build quality of the aircraft flying into the airports. While the aircraft build quality is directly out of the control of NAVCAN the information from these simulations can be used to inform regulation and incentive programs to aid the airlines in taking advantage of this benefit.

1.5 Key Findings and Recommendations

We will first discuss the null results and why certain explored methods for improving the system resulted in low to zero benefits. Firstly, when considering the impacts of adding more runways to the airport, a fairly common solution for problems of this type, we see an unintuitive result where the total amount of experienced delay ends up rising 5% contrary to expectations. While the effect of this change was positive for most of the simulation, the addition of more lanes and thus more traffic resulted in a larger magnitude of delays when severe events did occur. For example, while in the default model we could expect planes to take a holding pattern 50% more often than in the expanded runway simulation, when a major delay in the simulation occurred only 2-5 planes would be thrown out of schedule while with the traffic patterns in the expanded runway scenario 7-10 could be delayed. These impacts then propagated relative to their scale and resulted in the larger delay over the whole system. The next low impact change to be identified is the impacts of adding traffic demand forecasting to the capabilities of the airports. While this did have a small amount of positive impact it was far below expected in both Toronto and Vancouver airports with only the Montreal airport benefiting from this change. This resulted in a 7% improvement, supporting the value of adding this system to the Montreal airport. This is not a solution we recommend for implementation through NAVCAN however as the benefits are not similar at a national level. The final low impact factor of note is the addition of more bridges and increase in the speed of tarmac operations. While there was once again some positive impact, the time saved from improving these measures was below the amount that would be needed to prevent propagation of delays. This is due to the small total time that this process already takes as even if a 30 minute process can be halved in the most optimistic cases this would still not be substantial enough to prevent propagation as storm delays are often much larger scale.

With all of these scenarios investigated we can now focus on the two major changes that have shown significant merit starting with the implementation of ground delay procedures. Ground delay procedures work to delay aircraft when major delay is identified elsewhere in the system, preemptively stopping conflicts before they happen and smoothing out the curve. This change was able to reduce the total system delay by 20%, however this system also created an additional 650 cancelled passengers over the simulation. As such deciding on the level of impact acceptable in cancellations to prevent delay propagation will be crucial when working to implement this method as the consideration of delay against cancellation impacts is complex in airline scheduling. One advantage of the type of cancellation caused by ground delay however is the large advance notice as in this scenario cancellations can often be performed with upwards of six to twelve hour notice helping avoid situations where customers have to turn away while waiting at the gate or otherwise are at the airport.

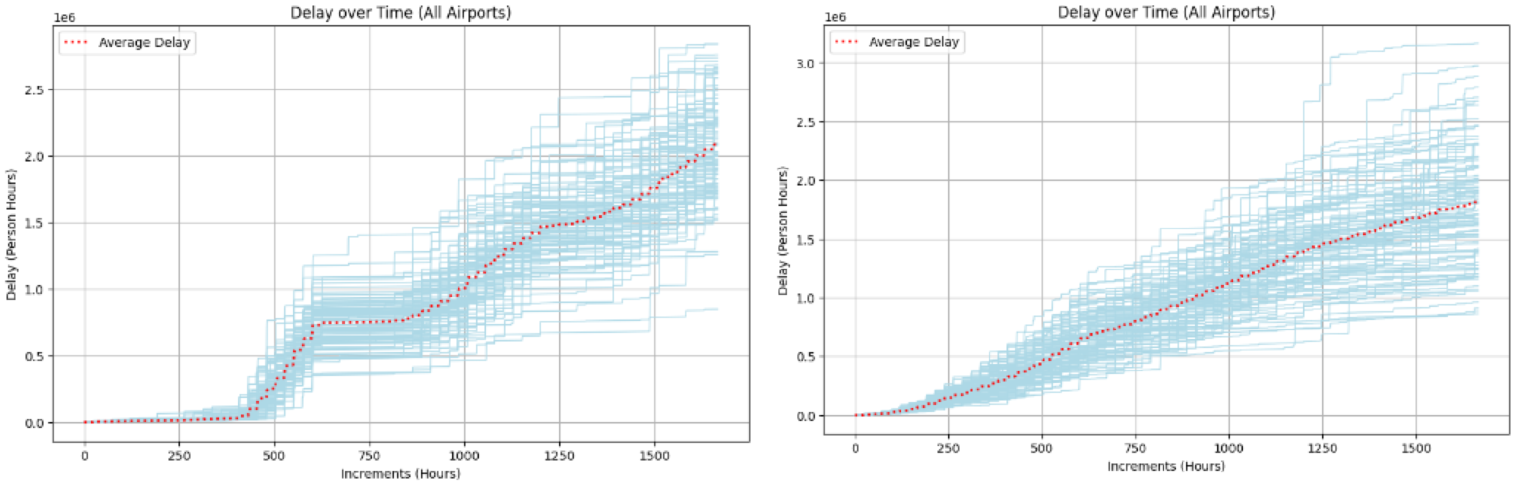

Figure 2: Delay Comparison of Baseline (Left) and Ground Delay (Right)

Here we use a passenger delay hours metric utilizing the passenger count of each flight to weight delay by the number of affected passengers. As an example due to a total number of 70 days simulated and an average of 92 flights per day with 80 passengers each the final delay pictured above in the baseline of 220,000 person hours can be seen as an average of 220,000 / 80 / 70 / 90 or 0.43 hours of delay per flight or about 26 minutes of delay per flight, while the ground delay reduces this value to 21 minutes on average or 180,000 minutes overall.

Much more substantially the improvements to airplane maintenance and build quality simulation showed improvements even beyond this at a level of an 80% reduction in delay. This improvement primarily came from an extreme reduction in the ability of delays to propagate as with maintenance being required less often and repair speed being much higher when a delay did run into maintenance time it was less impactful and in many scenarios the maintenance was able to be delayed through the next flight in order to avoid propagation. Similarly through faster maintenance extreme weather events could be mitigated as repairs from those events could be undertaken more quickly. This is an incredible boon could it be implemented, however, as the cost of upgrading all aircraft in domestic canadian flights would be incredibly prohibitive this solution is likely best implemented at a lower level through improvement of maintenance facilities at airports with a lower but still substantial impact. Another consideration here is that with maintenance being shortened significantly should the industry consensus be to subtract this improvement from expected operation times the benefits from a consumer perspective could be lost and the system could become even more fragile to delay.

From our findings therefore we suggest that NAVCAN work to implement a new policy that would support ground delay procedure adoption should it seek a solution that is able to be implemented for lower cost while benefiting both parties equally. This solution while increasing cancellations substantially offers a uniquely fair improvement that benefits both the airlines and airports equally while evenly spreading the burden of cancellation. Should this level of delay reduction be unsatisfactory however, we suggest that NAVCAN implements systems of grants for airports to help improve the maintenance facilities located thereupon such that the propagation across these required checkups is minimized and airlines are not pressured into rushing checkups and risking unsafe flights in support of a higher satisfaction from the passengers. Finally, our most substantial finding and recommendation is that NAVCAN shares the potential detriment of increasing runway capacity as a solution to delay problems as the implementation of new runways can slow operations for years and the expense of the solution was not found to be sufficient for its level of improvement.

2. Technical Appendix

2.1 Methodology

2.1.1 Input Data Descriptions

When working to gather data for our model our primary sources for agent information and the attributes and behaviors assigned to the airports were the webpages of the airports themselves [24][25][26] and the guidance provided by NAVCAN on specific operating procedures [17]. This is one of the major simplifications we had to make for the design of our model as while data on the specific operating procedure of each airport would have been preferable for our needs, as each likely has different priorities and values it hopes to uphold through its management, each keeps its exact procedure confidential and as such we work on the assumption that the airports follow the policy of NAVCAN properly and exactly [17]. This assumption likely homogenizes the delay between the differing airports more than would be expected should we have used the exact behaviors of the airports, however as our primary stakeholder is NAVCAN and the primary concern is for general canadian airspace efficiency this should not affect our ability to identify the impact of varying decisions on overall delay and as such our model remains useful despite this assumption [22]. Following this, we then went to the Airplane company websites for the most significant brands in Canada for flights between our chosen airports and used that data to collect the proportion of flights between our chosen airports that are undertaken by each brand and what the fleet of each brand contained in order to identify the size, passenger capacity and maintenance statistics of each model to allow for sampling of the models based on the true statistics and distributions of the planes on those routes[28][29][30]. Following this, we then had to identify more exact timings for the planes when undergoing the needed maintenance and the landing checks and tarmac procedure. To do this we used information from Qantas airlines that worked to summarize the behavior of the various companies and models as this data is not directly made available to the public[10]. To this end we had to make some simplifications with regards to the data as not all models owned in our modelling were given data to work with on this end. In order to remedy this issue we then had to identify models with similar statistics and copy over the maintenance data, as while this may result in some minor discrepancies the differences in maintenance time between similar models the maintenance is generally similar in the models for which data is available within size categories so we support the validity of this assumption in our model. Finally, we had to gather information on the delay volumes and probabilities for our model. When defining the methods of circling and delayed landing we once again followed the NAVCAN guidelines with the weather and ground delay data being provided from a series of similar studies that produced similar delay models in [14][15][16]. In order to improve this data further we then combined the data with airport level data on the volume of delay these causes created and through this synthesis created a new distribution following the probabilities from the reference papers with the impact assessment from the airports.

2.1.1.2 Input Analysis

One of the most major inputs we had to create and develop was that of the daily variation of our congestion and passenger delay over the course of the day in our simulations. To this end the Google Maps capacity API forms an important input for creating the Passenger_Percentage and congestion variables. Google business has the % of max capacity information for various locations including the three main airports we focus on for this study. From this data we captured hourly capacity information and placed it in a CSV using methodology from [18] and [20] for processing the data, creating a system of split time series that holds the variation over the expected congestion. Specifically we summed up all the cumulative capacity percentages over the 24 hours, assuming that this summed value time (a constant) is proportional to the daily number of passengers using the airport on that day. We then divided daily count by the summed total capacity percent to get a multiplicative constant. We then multiplied the hourly capacity percentage values by this multiplicative constant to get the approximate total number of passengers across all flights in any given hour. This method proved comprehensive when compared to simpler modelling but allows for variation that fully daily models lack as allowing for techniques such as forecasting and ground delay to be modelled effectively as they can target the daily peak times.

To determine the percentage of passengers on planes, we use a procedure where we summed up all the cumulative capacity percentages over the 24 hours. We assumed that this summed value time (a constant) is proportional to the daily number of passengers as in literature planes are found to often have very high full capacity factors in terms of passenger count keeping this volume close to the ideal number. We then divided the daily count by the summed total capacity percent to get a multiplicative constant. We multiplied the hourly capacity percentage values by this multiplicative constant similar to the above to get the approximate total number of passengers across all flights in any given hour. This method has some minor issues when it comes to the exact timing of the passengers over the day as the data we are working with was only up to hourly granularity however due to the timesteps in our simulation being close to the hourly mark the discrete nature of this approximation is likely to be of only minor affect in our final results. While this variable keeps track of our passengers in the model our congestion variable represents plane congestion. In the absence of high quality publicly available datasets regarding airplane congestion, we will use the daily_variation_model described above as the basis for this setup. As Travel Canada recommends travellers to come to the airport at least an hour in advance of the flight taking off, the congestion would be proportional to the daily variation shifted 1 hour allowing us to map this data onto our model effectively [27]. The congestion is then treated using UTC and shifted to handle how data is kept vs how our model handles time over our simulations ensuring that we keep valid time over the various airports.

We then focus on the 4 key elements in our delay pseudo agent: weather delay, maintenance, ground procedures and congestion. Congestion was previously explained in the above section, hence we will focus on the other factors. Firstly, weather delay is something that is difficult to model due to the 4000 km+ expanse between Vancouver and Toronto/Montreal and the fact that weather patterns are often difficult to predict in advance and to simulate for our needs. Hence, we looked at research into ground delay programs due to weather. This is when planes are delayed at the origin airport due to bad weather anywhere along the airplane journey. From NASA's research, we have a probability of each type of weather occurring alongside an average delay due to each type of weather in minutes from historical data. These weather categories fall into 7 types of weather: Wind, Low Ceilings, Low Visibility, Rain, Snow and Thunderstorms, and fog with other types of delay weather accounting for less than 1% of impacts. We used this to build the weather delay component of the delay pseudo agent through creating a two step probabilistic process where initially the flight will determine if weather is affecting it and if so what type followed by a sampling from a delay distribution in order to identify the magnitude of the delay[33][35]. Additionally, from the Federal Aviation Authority (FAA)'s flight delays and cancellations dataset, we understood that the FAA considers two categories of delay due to weather (less serious and more serious). We were able to combine this data with the previous NASA data in order to validate and ensure that the assumptions used were defensible and would allow for effective simulation. This weather delay data was available in the highest quality for several airports in the USA: Namely SFO (San Francisco), and ORD (Chicago) and we support that despite the data coming from outside our scope of simulation that the data is relevant to our needs as in other working studies it has been shown that the impacts of weather delay across the north american region as a whole can be effectively simulated using this data [35]. In order to ensure viability even beyond this however, we performed a weather trend comparison of the airports. We were able to match the American airports with the Canadian cities with the most similar climate. We found that Vancouver (YVR) was most similar to SFO, due to the oceanic climate with mild yearly temperatures and lack of snow impacts. Toronto and Montreal were instead most similar to ORD, due to high winter and summer temperature swings (snowy winter) and hot summer with thunderstorms [36].

For ground procedures delay there are four tasks that an airplane performs at gate that are along the critical path for a plane departing: deboarding, cabin cleaning, catering, and boarding. Normally there is up to a 3 minute buffer allocated due the time associated with transport and setting up the equipment such as catering, cleaning trucks and gate bridges. This is a key point of delay for ground procedures as should this buffer be exceeded there is often no allocation for delay and the next tasks overstay their availability. These effects will then cascade, making the absolute time of the total procedure (absolute_task_starting_time) longer. We then take the length of the total process (from start of ground procedures to the the end of the last procedure), captured by absolute_task_starting_time and subtract this value by 41 minutes (which is the time the procedures are assumed to take) to get the net delay on the aircraft [37][38]. The ground procedures simulation was adapted from industry guides for single aisle aircraft with all of the airplanes operating as single aisle aircraft in our simulation [37][38]. This has some effects on the maintenance of larger planes as we lack the allocation for longer catering and cleaning preparations however as these are the lesser of the time delays in this process the difference is largely negligible compared to the maintenance period included that we scale with aircraft model and size.

As such for maintenance, we have flags for aircraft which indicate whether they need maintenance alongside internal maintenance requirement details to calculate the time and gaps between maintenance periods taken from available maintenance databases [28][29][30]. Aircraft that need maintenance then remain parked at the airport for a certain period of time (maintenance_time). We modelled two types of maintenance and used a recent article from Qantas Airlines to validate our maintenance values including line maintenance which takes 12 hours and must be done every week and A-check taking 50 to 70 hours once every 400 to 600 flight hours [10]. Other types of maintenance do exist for aircraft however due to their larger flight hour gaps we exclude them from this situation as they occur only a few times per year or once over a period of many years a time length that is outside our simulated ranges.

2.1.2 Model Descriptions

2.1.2.1 Airplane Attributes

Airplane Agent		
Attributes [units]	**Data source/Assumption**	**Input Model/Notes**
Initializations (various)	It is worth mentioning that we 0/false initialize several attributes. This is because we require some value to	Example (s): needs_maintenance = False

	create an object or to start a function but this is overwritten once the simulation starts as many values are set in every loop and as such are not worth initializing at a value.	last_maintenance_time = 0 delay = 0 cancelled_passengers = 0
Origin [string]	One of the three airports in our simulation (Toronto, Montreal, Vancouver)	Origin and destination cannot be the same
Destination [string]	One of the three airports in our simulation (Toronto, Montreal, Vancouver)	Origin and destination cannot be the same
Random_arrival_time [int, minutes]	Uniformly sampled from 0 to 1441.	This samples a random value representing a random minute in the day. 0 is the starting minute and 1441 is the last (24*60+1 minute)
Goal_arrival_time [int, minutes]	Initially as equal to random_arrival_time	When setting the new values with the below behaviors we assume expected flight times from the aviation databases referenced below
Arrival_time [int, minutes]	Equal to random_arrival_time + a random number from 0 to 100	We wanted the initialize airplane agents to not land at the sample time hence we had a 100 minute buffer number. This number was randomly selected but doesn't not affect the simulation past the initialization.
Departure_time [int, minutes]	Actual departure time (in terms of minutes after the simulation has started)	Not focusing on exact date tracking for the simulation as we do not use seasonal surge effects in our model
Goal_departure_time [int, minutes]	Initial departure time (in terms of minutes after the simulation has started)	The goal is fixed based on below behaviors and is used to reference the time delayed
Airplane Brands [string]	["Air Canada", "West Jet", "Porter", "Flair"] Brands that fly these routes from [1] [2] [3] [5].	Focusing on the airlines with the most presence due to the existing monopoly on the routes
BRAND_WEIGHTS [float, percentage]	[0.67, 0.1, 0.2, 0.03]	We used flight aggregator data and manually summed the total

	% of total flights from each brand respectively Raw data from flight aggregator data but processing was needed [1] [2] [3].	flights across the destinations in the tables we divide the number of flights from a given brand over this number
Status [string]	One of [unallocated, flying, arriving, departing, blocked, cancelled, stalled, maintaining, landed] We follow the states outlined in key simulation papers. [12]	Used to route the agent to varying submodels and behaviors while limiting computation
Needs_maintenance [boolean]	False if the airplane doesn't need maintenance. True if the airplane needs maintenance.	This attribute triggers the change in the status of the planes and starts the maintenance model
Last_maintenance_time [int, minutes]	Number of Minutes since last maintenance time. Starts at 0, increases throughout simulation and rest to 0 when maintenance occurs.	Dependent on the various maintenance attributes like Time_between_mandatory_maintenance, maintenance_time, needs_maintenance etc
Delay [int, minutes]	Initialized at 0, accumulates over time from the delay pseudo agent counts upwards (monotonic increasing) as delay cannot be undone after customers have been made late	This is the delay per plane agent (as opposed to airport delay which is for the delay for the whole airport)
Fullness [float, percentage]	Relative fullness of the plane to be tracked as a percentage for each flight following [1] [2] [3].	We currently assume that the fullness of a plane is gaussian as the flight from airlines are distributed evenly through the day (even night flights have decent fullness according to flight planners) [1] [2] [3]
Cancelled_passengers [int, count]	Initialized at 0. Over time the number of cancelled airplanes gets higher similar to the delay variable.	The capacity of the airplane is multiplied by the plane fullness to get the total number of passengers which is added to the cancelled_passengers attribute.
Max_capacity [int, count]	The maximum capacity of each of the planes that the airline has (in terms of maximum number of passengers). We look at planes actually flown by the 4 airlines on direct flights between the 3 airports [1][2][3][28][29][30][31].	Data is using fleet data from various websites owned by the brands in question and read from a CSV for loading the model.

Maintenance_time [int, minutes]	We modelled two type of maintenance and used a recent article from Qantas Airlines for reference maintenance values: **Line Maintenance** which takes 12 hours ie 720 minutes [10] **A-check** takes 50 to 70 hours [10] (ie 3000 to 4200 minutes).	Frequency is used to determine what type of maintenance to do when
Time_between_mandatory_maintenance [int, minutes]	We modelled two type of maintenance and used used a recent article from Qantas Airlines for values: **Line Maintenance** is done once a week [10] **A-check** Done once every 400 to 600 flight hours [10]	Same as above
Cleaning_time [int, minutes]	We arrived at an average of 27 minutes for a single-aisle aircraft (All of the planes are of this type) [11]	The variation is explained separately through the delay model with this acting as a base time
Threshold_time [int, minutes]	The time in minutes after which an airplane's status is changed from delayed to cancelled. The usage of this parameter is detailed in similar models [18] but values are not given for our circumstance.	We have selected a value of 120 minutes from [18] as we have not found a consensus of the threshold time for airlines. The model is able to set this for each airline individually should we be able to find an internal cancellation procedure for each individually.
NUMBER_OF_AIRPLANES = 54 [int, count]	Based on research from a flight tracking API website there are 92 total flights per day (summing all flights between destinations [1] [2] [3].	This is arrived by summing the flights from (Toronto to Montreal, Vancouver to Montreal, Toronto to Vancouver, Montreal to Toronto, Montreal to Vancouver,Vancouver to Toronto) = 92 flights/day Overall at the speed our planes choose new routes we need to simulate 54 total in order to

		match the figures found in flight data and align with the 92 flights per day figure.

2.1.2.3 General Attributes

General attributes		
Attributes [units]	**Data source/Assumption**	**Input Model/Notes**
INCREMENT [int, minutes]	30 (minutes) Most flight data comes in intervals of 15 minutes. For example, a flight is considered “On Time” if it has departed or arrived within 15 minutes of the schedule. However due to computational limitations we encountered we had to change it to 30 minutes [6].	An additional reason for this change is the 30 minute interval fits better with the airspace clearance rules [17] and the timing of delay.
START TIME = 0 END_TIME = 50000 [int, minutes]	We want to initial the simulation click at t = 0 and end it at t = 100000 minutes ~70 days. We wanted to model around two months of data and chose 100,000 as a round approximation of that timeframe.	Data is likely to even out for longer time periods due to our lack of seasonality and as such 70 days covers the variation in the model results effectively.
DELAY_IMPACT	Weighting the delay of the system based on human impact of delay following the values in [22]	Assumptions here are simple using aggregation of large scale data.
Attributes for ground_service function contained in data dictionary. (see below)	See below	
task_name [string,categorical]	These are adapted from industry guides for single aisle aircraft (all of the airplanes are single aisle aircraft in our simulation) [37][38].	Four tasks that an airplane does at a gate that are along the critical path for a plane departing namely, Deboarding, Cabin cleaning, Catering, and Boarding.
task_length:[int,minutes]	This is also adapted from industry guides for single aisle aircraft [37][38].	Length of the aforementioned four tasks (, Deboarding, Cabin cleaning, Catering, and Boarding).

buffer_before [int,minutes]	This is also adapted from industry guides for single aisle aircraft [37][38].	The buffer in minutes before one of the four tasks starts. Normally there is up to a 3 minute [0,3 minutes] buffer due the time associated with transport moving and setting up the equipment such as catering, cleaning trucks and gate bridges. This is a key point of delay for ground procedures.
buffer_after [int,minutes]	This is a key point of delay for ground procedure and is similarly adapted from industry guides for single aisle aircraft [37][38].	The buffer in minutes after one of the four ends starts. Normally there is up to a 3 minutes buffer due the time associated with transport moving and taking down the equipment such as catering, cleaning trucks and gate bridges.
next_task_starting_time [int,minutes]	Adapted from industry guides for single aisle aircraft [37][38].	The time after the start of a certain task that the next task starts. Delays in the previous task will cascade making the absolute time(absolute_task_starting_time) longer.
Absolute_task_starting _time [int, minutes]	Modelled including findings of propagation studies propagated by buffer_before , buffer_after And next_task_starting_time [14][15]	The actual task starting time from the start of ground procedures.
Probability of weather event occurring [int, minutes]	Taken from NASA data and FAA flight delays dataset. [32][33][34][35]	Probability considered includes varied options for different types of weather as detailed above.
Minutes [int, minutes]	This is from the interval observed by NASA for data collection [35].	The cumulative number of minutes that planes were delayed due to the various weather causes.
Aircraft_numbers [int, count]	This is from the interval observed by NASA for data collection [35].	The cumulative number of planes that were delayed due to the various weather causes.
Delay_per_plane [int, minutes]	This figure works to accumulate the delay from the system and compare it to existing data about base delay.	The cumulative number of minutes that planes were delayed over cumulative number of planes that were delayed due to the various weather causes.

2.1.2.3 Airport Attributes

Airport Agent		
Attributes [units]	**Data source/Assumption**	**Input Model/Notes**
NUMBER_OF_AIRPORTS = 3 [int, count]	We have selected three airports as per our last Milestone (Toronto, Montreal, Vancouver)	Chosen due to high traffic and control being entirely owned by NAVCAN
Location [string]	Location of the selected airport (Toronto, Montreal, Vancouver)	Used primarily for if statements and reference
DIST_OTHER_AIRPORTS (various) distance_to_other_airports [int, distance in km] Ex TORONTO_DIST_OTHER_AIRPORTS MONTREAL_DIST_OTHER_AIRPORTS VANCOUVER_DIST_OTHER_AIRPORTS	Collected data about the distance from airport (ie TORONTO for TORONTO_DIST_OTHER_AIRPORTS) to other airports From the Google Maps measuring tool [4]	This data is used for average flight requirements and for choosing the nearest airport when needed.
Daily_variation_model [float, hourly % capacity variation of airport]	Though technically not an attribute, it forms an important input for creating the Passenger_percentage and congestion variables. Google business has the % of max capacity information for various locations including the 3 main airports.	We captured hourly capacity information and placed it in a CSV using methodology from [18] and [20] for processing the data.
Passenger_percentage [int, count]	We use a procedure where we summed up all the cumulative capacity percentages over the 24 hours. We assumed that this summed value time (a constant) is proportional to the daily number of passengers (ie the contant1). We then divided daily count by the summed total capacity percent to get a multiplicative constant We multiplied the hourly capacity percentage values by this multiplicative constant to get the approximate total number of passengers across all flights in any given hour.	This is fairly comprehensive when compared to simpler modelling but allows for more variation that our first model lacked

Congestion [float, percentage]	This represents plane congestion. In the absence of high quality publicly available datasets regarding airplane congestion, we will use the daily_variation_model described above. As Travel Canada recommends travellers to come to the airport at least an hour in advance of the flight taking off, the congestion would be proportional to the daily variation shifted 1 hour which the assumption used [27].	Congestion is treated using UTC and shifted to handle how data is kept vs how our model handles time over our simulations.
Delay [int, minutes]	Initialized at 0, accumulates over time from the delay pseudo agent. The delay pseudo agent is currently dependent on the maintenance model.	Penalty term
Buffer_time [int, minutes]	Buffer time between planes for a given airport. Initialized to 0. One of the attributes that the departure time/goal departure time is based on is the airport buffer time.	To be used to implement airport strategies involving intentional separation for less overlap, currently unused in our scenarios so far.
Delay_end_time [int, minutes]	Minute in simulation when delay ends. [21] [22] Data for setting this value is from incident reports of the recent crash and NAVCAN procedure.	A time set from sampling of the airport delay pdf representing plane crashes, flooding or similar.
airspace_capacity [int, count]	From Pearson airport's blog, we know that they have 50 air traffic controllers. From NAVCAN's Air Navigation and Operational Basics guide, we divided this figure by 5 to get an airspace capacity of 10. This has to be the same at all of the airports as suggested by the NAVCAN regulation [13] [17].	While airports could set higher or lower values per member of staff this data is confidential so NAVCAN suggestions are assumed to be followed exactly. Variation will be explored in the future.
Airspace [int, count]	Airspace is initially a copy of the above value but is changed to max of airspace_capacity times (1 - the level of congestion minus the number of departing airplanes (please see behaviours).	Represents active airspace remaining
Runway_capacity [int, count]	Runway_capacity refers to the number of runways an airport has. This was sourced from airport handbooks [24] [25] [26].	Not separated into classes of runway anymore due to many models in airline fleets being grey on what runway was required
runway_space [int, count]	Runway _space is initially a copy of this value but is changed to the max of 0 and runway_capacity times one minus the level of airport congestion minus	The same alterations as above were made

	num_of_departing_airplanes - num_of_landed_airplanes This is based on NAVCAN runway rules [17].	
PASSENGER_COUNT_CONSTANT (for get_passenger_count) [int, count]	This is the number of daily passengers an airport receives. Yearly data for 2023 was found through research and divided by 365 to get daily passenger count for the whole airport [7] [8] [9]	The seasonal variation is once again absent here but from the reference simulations in delay the propagation is more important to our simulation and if needed we can run a rush season simulation [22]
CONSTANT_2 (for get_congestion_amount [int, count]	Set to 1 for all airport agents (so that the congestion amount is a percentage)	Used to set scenarios like above where congestion is seasonally heightened.

2.1.3 Agent Behaviors

2.1.3.1 Airplane Behaviors

Airplane Agent		
Behaviours	**Data source /Assumption**	**Input model (equation)**
Leave for Destination	Planes need to Leave Airports	If the departure_time >= Time status = 'departing'
Identify Maintenance Need	[15]. We used the delay maintenance identification model from the seminal "MODELING AND SIMULATION ANALYSIS OF AIRCRAFT MAINTENANCE OPERATIONS" paper	(arrival_time >time_between_mandatory_maintenance +last_maintenance_time) and (status == 'landed') Airplane_status = "maintaining"
Perform Maintenance	[15] For this behavior we also followed the	goal_departure_time += maintenance_time departure_time += maintenance_time + delay

	information from above	`last_maintenance_time = TIME` `airplane.status = "landed"`

Choose New Destination	When modelling few flight locations uniform logic has been shown to be effective from “A connectivity-based methodology for new air route identification” [16]	`available_destinations = [d for d in DESTINATIONS if d != self.origin]`
		`self.destination = rng.choice(available_destinations)`
		
		`avg_time_to_airport = flight_times_df[(flight_times_df['start_destination'] == airplane.origin) & (flight_times_df['end_destination'] == airplane.destination)]['avg_time'].iloc[0]`
		`current_arrival_time = airplane.arrival_time`
		`airplane.arrival_time = current_arrival_time + avg_time_to_airport + delay`
		`airplane.goal_arrival_time = current_arrival_time + avg_time_to_airport`
		`airplane.departure_time = current_arrival_time + airplane.cleaning_time + current_airport.buffer_time + delay`
		`airplane.goal_departure_time = current_arrival_time + airplane.cleaning_time + current_airport.buffer_time`

Land at Airport	Airplanes will attempt to land at their destination	`elif (TIME > airplane.arrival_time):` `airplane.status = "arriving"`

Circle Airport	Airplanes when delayed will attempt to land at the destination airport after the delay unless instructed otherwise	`elif airplane.status == "stalled":`
		`airplane.arrival_time += INCREMENT`
		`delay_sum += INCREMENT`
		`airplane.status = "arriving"`

Cancel Future Flights	Here we choose to model the cancellation using time based thresholding following “Modelling airline flight cancellation decisions” This approach while simplistic has	`elif airplane.arrival_time - airplane.goal_arrival_time > airplane.threshold_time:` `airplane.status = "cancelled"`

	been shown to be effective for modelling as long as brand behaviors are separated [14]	

When considering our airplane agent the first and most critical behavior to consider is its ability to takeoff from the airport. To this end the plane attempts to leave by setting a new status of "departing" after its departure time has been reached. The plane will still need to pass clearance from the airport agent and this does not guarantee an exit immediately, as if airspace is full or another event has shut down the airport the departure will not be approved. The departure time will be set considering maintenance and other factors in the choice of new destination behavior following the logic from [15]. One of these factors is the maintenance of the airplane, one of our more complex models in our simulation. To this end what the formula in the above table aims to achieve is that the plane model will ensure that its next flight does not go past its allowable flight hours without maintenance and as such if it would exceed this value, set individually for models and airlines, it would land and perform the maintenance before departing. An additional check is added for the landed status in order to prevent in-flight planes from diverting for maintenance should a need arise as in [15] the model considers the behavior of airlines to complete routes above performing rapid repair. This is then updated in the perform maintenance behavior where the airplane updates its departure and goal departure times to align with its maintenance schedule while considering the delay from the delay model possible through schedule overruns in the maintenance of the aircraft detailed further below. The select destination behavior is simple as the planes in our model represent only planes operating nationally in Canada between the three chosen airports and as such the options for flight paths are limited. To this end we allow a random selection in order to simulate fluctuations in flight density to a destination while keeping the average distribution even a simplification shown to be effective in [16]. Alongside this selection comes the more complex behavior of having to define a new route and goal times for departure and arrival. To this end we first reference the expected flight time using available data on the subject taking into account the origin or where the plane is coming from and the destination to calculate a baseline expected flight time taken from airline attributes in the previous part. Following this, we reference the buffer time mandated by the airport and the time it takes to clean the model of plane being flown by its brand together to calculate the time expected for departure from the strip. Both the departure and arrival are then updated with a random delay subject to the delay model below before being set to finalize the route. The plane will then avoid being queried until landing to minimize computational cost of the simulation. This leaves some simplification as delays in flight are being determined at one point as opposed to constantly; however, as the end result of delay in flight is identical as we do not handle plane behaviors on route we choose this approach to ensure fast execution of the realizations. Similar approaches have been used in [14] with findings showing minimal accuracy losses and large computational savings. When considering the cancellation of future flights requiring this plane: If the time a flight is projected to reach the airport exceeds a maximum threshold beyond the goal time dependent on each airline the flight will be cancelled and the plane will be set to a new route or maintenance after its next stop also following the methodology in [14].

2.1.3.2 Airport Behaviors

Airport Agent

Behaviours	**Data source /Assumption**	**Input model (equation)**
Catalogue Airplanes	Airports have information about airplanes in their airspace as is required to maintain safe operation	**departing_airplanes_list = [airplane for airplane in airplanes if airplane.origin == airport.location and airplane.status == "departing"]** **landed_airplanes_list = [airplane for airplane in airplanes if airplane.origin == airport.location and airplane.status == "landed"]** **arriving_airplanes_list = [airplane for airplane in relevant_airplanes_list if airplane.status == "arriving"]** **num_of_landed_airplanes = len(landed_airplanes_list)** **num_of_departing_airplanes = len(departing_airplanes_list)** **num_of_arriving_airplanes = len(arriving_airplanes_list)**

Delay Departures	[17] The methodology for delay is taken from NAVCAN regulatory papers on reducing accidents in low airspace	if (num_of_departing_airplanes > airport.airspace):
		available_spots = num_of_departing_airplanes - airport.airspace
		chosen_airplanes_to_depart = departing_airplanes_list[num_of_departing_airplanes:]
		for airplane in chosen_airplanes_to_depart:
		airplane.status = "flying"
		airplane.fullness = airport.passenger_percentage

Restrict Arrivals	[17] This behavior is documented in the same paper with similar rules	limiting_space = min(airport.airspace,airport.runway_space)
		if (num_of_arriving_airplanes > limiting_space):
		for arriving_airplanes in arriving_airplanes_list[limiting_space:]:
		arriving_airplanes.status = "stalled"

Redirect Planes	In the event of airport failure the planes need new destinations to land	if airport.delay_end_time - TIME > airport.redirect_threshold:
		for airplane in relevant_airplanes_list:
		airplane.status = "blocked"

Model Passengers	[18] When modelling how	Firstly we take the average passenger count for each airport over the course of the day and store it as the num_daily_passenegrs in the class for each airport.

	passengers use the aircraft we follow “Simulation modeling of passengers flow at airport terminals to reduce delay and enhance level of service” while using data from google analytics to split the data sub daily. [20]	Following this we then read in the google analytics data as a list and take TIME % 1440 to get the time in minutes of the current day. Then we take index = int((TIME % 1440) / 60) to be the hour of the day between 0 and 23 and then take the num_daily_passenegrs * daily_variation[index] to calculate the proportion of passengers at this point in time at the airport. The nuance behind how the daily_variation is calculated is detailed above in attributes.

When working with the airport agents the behaviors are simpler than for the airplanes. Firstly the airport catalogs the planes that are either currently at the airport by finding planes that originate from this airport (a state set upon landing) and are currently landed, a combination that in our simulation ensures the plane is still at this airport. Similarly, the planes arriving are found from arriving planes with a destination of this airport, and departing planes from the origin and departing status. Once the planes are cataloged, the model can identify if the runway space or airspace will prevent arrivals or departures and, using a priority system, allow planes to arrive or depart based on arrival order and how much space is available. For the departures, the assignment of the passengers also takes place where the values from the passenger model are used to fill a proportion of the flight leaving the airport. Additionally, should the airport be shut down for too long a period of time the airport will begin redirecting planes away similar to behaviors in the recent Toronto Pearson crash to other destinations with availability [21]. This threshold is very similar between airports in Canada due to regulation [19], however we keep the thresholds independent to airports to leave open the ability to explore its effects more in future tests. Finally, the airport also assigns passengers by sampling from a distribution of passenger variation dependent on the current time of day, taken from existing volume data to allow for different airports to have varied peak times and variance in expected passenger flow. The data behind this is taken from google's location density trends combined with the flights and passengers per day data from the airports webpages in order to subdivide the passengers across the day, this data is blocky due to how the data is presented so we additionally have to smooth the data before moving forwards by interpolating linearly to remove some of the non-continuous nature of our data.

2.1.3.3 Delay Behaviors

Delay Pseudo Agent		
Behaviours	**Data source/Assumption**	**Input model (equation)**
Delay Airport Landings	[20] This behavior was informed using information from both NAVCAN procedure and the recent shutdown at toronto due to its recent and well documented nature. The method for sampling is taken from the below using the data from the NAVCAN and recent for modelling the PDF once the failure triggers. [21]	If rng < chance_of_failure: Delay_Time = sample(airport_pdf_delay) Airport_delay_end_time = TIME + Delay_Time
Delay Airplane Flight	[22] For this model we are utilizing an approach found in "Flight delay propagation modeling: Data, Methods, and Future opportunities" to model airplane flight delays based on an amalgamation of all possible flight delay motivations simplifying the data to a time function.	If rng < chance_of_failure_weather: Delay_Time = sample(airplane_weather_delay) arrival_time = TIME + Delay_Time else: sample(airplane_route_variation) [can be -ve] arrival_time = TIME + Delay_Time
Delay Airplane Ground Procedure	[23] For this model we use similar simplifications as above however with additional details from "Airline-driven ground delay programs: A benefits assessment" where we focus on how predictions of ground programs affect the perceived delays.	If rng < chance_of_ground_delay: Delay_Time = sample(airplane_ground_delay) arrival_time = TIME + Delay_Time

When working to delay landings at an airport we primarily focus on sources of delay that would cause major interruptions such as plane crashes or massive storms in order to leave the effects that affect a subset of the planes to be handled by the airplane class. As such, we take our collected delay values considering the range of frequencies and the chance of a delay occurring and create a probability of a major event occurring before then running a normal distribution to capture the variance of the issue's severity. A normal distribution capped at zero is chosen here as the center of the distribution is quite far from zero as if an issue occurs at an airport level it is likely to take multiple hours to resolve and as such the chance of the normal sampling a very low value is highly unlikely. Additionally, from existing historical data [21] we have found that major delays tend to take similar amounts of time with minor variation and in other models of service delays normal assumptions have been shown to work well[22]. Alongside this each airplane when leaving for flight is subjected to the airplane flight delay model, this is being modelled using a normal as well but for a differing reason to the previous. In this case the ability of a normal vs a lognormal to present negative values is important to us as while most of the time an airplane will be late or on time due to favorable winds or other conditions the possibility of an airplane being early and acting to help prevent delay compounding is a behavior we value in our simulation. Finally we set delays for the maintenance of the aircraft, this will be modelled using a lognormal following other research [23] as most ground procedures tend to run very few minutes overtime while occasionally the odds of the model having major issues are possible and the maintenance finishing early is negligible and very unlikely due to the needs of boarding time communication [23].

2.1.4 Key modelling assumptions

When setting up our models we rely on a few key assumptions in order to ensure that our model can meet the computational and informational limitations we have when working to design our systems. To this end our model relies on three key assumptions to simplify our operations while working within our data limitations. These being the assumption of predictable external traffic, the assumption of selfish actions, and the assumption of equal management. Firstly, in order to be able to evaluate our simulations with an expectable amount of agents for the airplanes and under a unified set of rules for air traffic control we have assumed that flights external to Canada and the major airports we are focusing on can be abstracted to a unified level of congestion due to the averaging behavior of large populations. To implement this we take the amount of flights in each of our major airports over the course of the day and compare those values hourly to the amount of flights we expect over a single day and the number of those flights that are domestic in order to create a daily varying proportion of runwayspace and airspace that we expect to be taken up by planes we do not have the computer to simulate. This has some issues in terms of losing the effects of delays very external to the system adding delay to the airports we focus on however, as the number of flights that behave externally reaches an incredibly large number the behavior of those planes can become closer and closer to an average expected behavior and can be modelled accurately excluding extreme events.

Secondly, a major assumption we make is the assumption of selfish actions. For this assumption we make it so that when working to decide when and how to land an aircraft the airplanes will always seek to prioritize their own or their brand's delay over all other planes. This behavior results in planes often simply trying to land as quickly as possible giving very little concern for the size of other planes and the effects this landing would have on others and simplifies the operation of the airplane model due to a lack of available information. While it would be preferable to work with a large amount of detailed behaviors the behaviors of each individual piloting a plane depend both on policy that is not accessible to us instead being internal to each airline, alongside training from the airline, and the mental state and decision making of each individual pilot in relation to the former two points. As such, we model this decision making selfishly under the assumption that pilots are incentivised to not make mistakes as individuals in their time working for airlines as found in [14].

Finally, when making our airport landing decision models we needed to define sets of logic that the airports can use to determine how to solve conflicts between landing and departing aircraft as well as how to police their own airspace. In order to do this we first had to gather information on these behaviors however as most operations are internal and based on information not made public our modelling for this behavior was based on publicly available NAVCAN guidelines for air traffic control that while they may be close to the real behavior likely miss some nuance of the operations that will occur in a real system. One of the major assumptions that arises from this is the fact that the airport will never prioritize one brand over another, something that in actuality is likely to occur due to agreements with companies and biases that, while substantial, lack sufficient data for modelling. Additionally, another assumption on this behavior that is worth noting is the prioritization of landing flights over departing flights in the system we have developed. While the fact that landing a plane in flight is more efficient than releasing a grounded plane is clear and referenced in NAVCAN documentation, the behavior of the model is very rigid on this stance, never allowing a grounded plane to leave over a flying plane to arrive [17]. This should be close to the behavior in operation but nonetheless is an assumption we are making that has implications on how delay propagates especially when the airspace is limited but the groundspace is large.

2.1.5 Limitations

When implementing our model our primarily limitations come from our enacted scope, our implementation of simplified behaviors, and our level of model specificity. Firstly when working with our scope we are primarily limited in our reliance on the three airports we have chosen for our modelling. In a more fleshed out simulation we would like to expand to many more airports in Canada for our analysis in order to more accurately capture the changing and cascading effects of the delay in this system. We support that despite our simplifications this model is effective for learning how differing solutions can benefit NAVCAN as while a full simulation of a larger proportion of flights would be closer to fully accurate than our simulation there will always be a level of abstraction that other situations and studies have been able to prove to be effective and similar to the actual effects found in the real world [14][15][16].

Similarly, alongside the limitations in scope of simulation our simulation was also limited by the simplifications we had to make to the behaviors that our agents will undertake. In the real world there is a large degree of effects that change how airports will choose to allow in airplanes for example with some having deals with airlines or internal preferences for size or lateness or first come first served that are not documented and published and as such are not fully implemented in our model. As our model instead assumes that the airports are following the behavior recommended by NAVCAN many parts of the simulation lack some nuance that exists in imperfect operation brought through bias and under the table deals between airlines and airports. Similarly our modelling delay lacks some information about the perception of delays and all of the steps that stakeholders can take to make passengers feel less disgruntled even if the problem never actually gets better. We defend that an understanding of the objective delay impacts is still very helpful as even if effects can be masked and reconstrued to reduce the negative public opinion of the delays through an objective reduction in delay these techniques acting to remove a percentage of backlash will still overall result in a system that improves the interested parties experience.

Finally, we are limited by the specificity of our model as when making our model and going through airlines and makes and models of their fleets some of the data that would be relevant to the fleet we are simulating was either unavailable or too complex to add to the modelling for our computational efficiency. For example when working to model the airline maintenance we worked to model it based on company and federal guidelines and regulations as opposed to on a per plane basis. While this can be effective on aggregate our model failed to consider that specific plane makes and models and specific planes in operation can require exceptionally more maintenance due to previous failures or aging that was not taken into account here. We defend our choices however as planes tend to cycle and change in ownership and needs over time and as such the relative change in delay that our model is able to identify is much more important than the minute levels of delay affected by one plane or model of plane being more susceptible to maintenance issues.

2.2 Results

2.2.1 Baseline Scenario

In order to define the effects that will be compared for the proposed changes below we first need to investigate the behavior of the system under regular conditions where the changes have yet to be implemented. To this end we use a passenger delay hours metric whereupon the number of passengers is used to weight the delay of a flight in order to account for the consequences of delaying larger and smaller planes affecting differing numbers of people. This leads to the metric being not as intuitive at a glance so for simplification here due to a total number of 70 days simulated and an average of 92 flights per day with 80 passengers each the final delay pictured below of 220,000 person hours can be seen as an average of 220,000 / 80 / 70 / 90 or 0.43 hours of delay per flight or about 26 minutes of delay per flight. This leaves much room to be improved and as most of the flights in the simulation are on time or very close represents a subsection of flights performing very poorly with delays upwards of five hours in the more extreme cases. Additionally pictured below is cancellation data that while fairly constant in most of our below scenarios is important to understand when working with the ground delay procedures model tested in section 2.2.2.2.

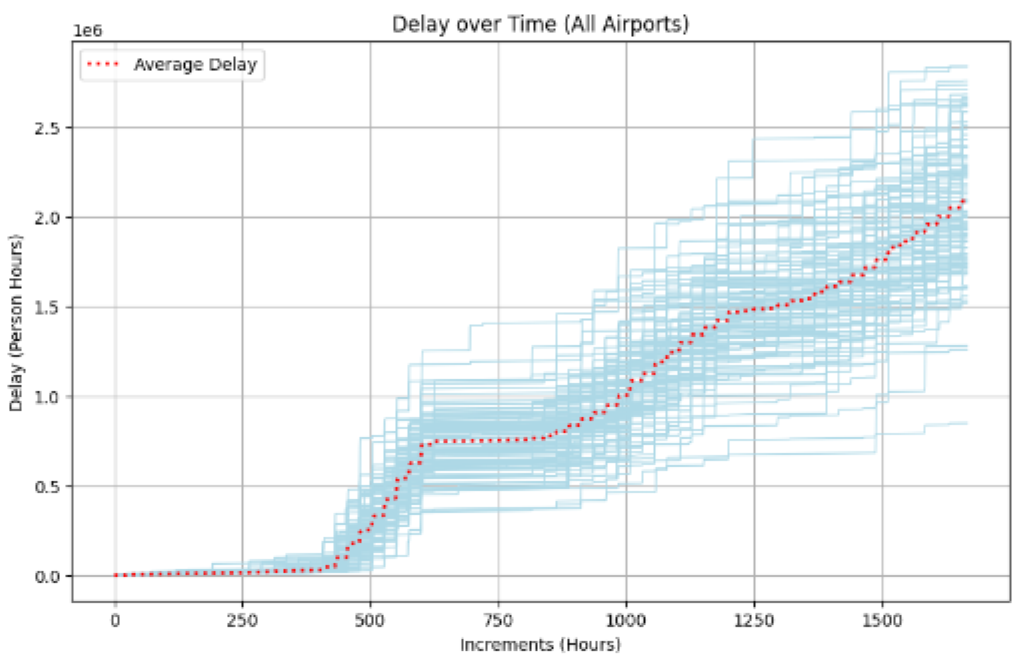

Figure 3: Baseline System Delay

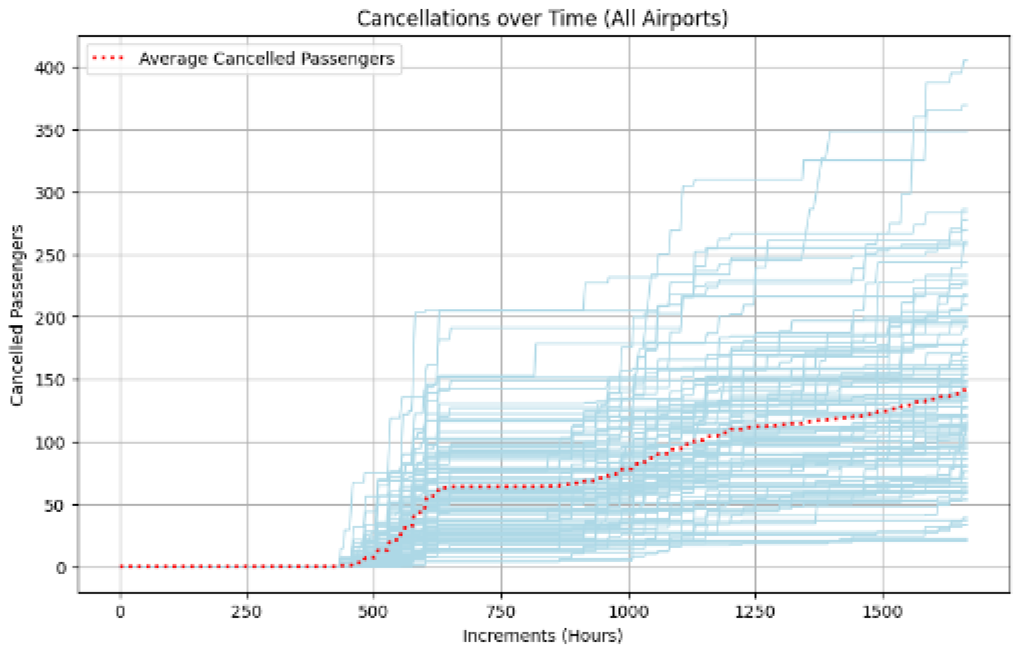

Figure 4: Baseline Airplane Cancellation

2.2.2 Operation Management Scenarios

2.2.2.1 Implementing Traffic management forecasting

Demand management procedures are often used by airports to reduce delays. They consist of several major parts: The first of these is the ability to forecast future airport demand in 15 minute intervals. Information from this forecasting model is then used to identify periods when extra baggage handlers/security personnel are needed in advance to ensure that staffing is optimal. Secondly, flight distribution algorithms are used to forecast high demand times and move departure/arrival times (with the cooperation of airlines) to ensure aircraft spacing is manageable by the airports. In order to implement the methods in this model we will be using information on the efficiency effects from London Gatwick airport as it has previously applied these methods and has found it has forecasted demand faster and more accurately leading to fewer delays [3]. To do this we will be altering the decision making function of the airports to make decisions about the incoming planes by increasing the operation information factor to allow the airports to make more optimum decisions. Alongside this, we will be reducing the buffer period of the airports following the process at Gatwick and reducing the uncertainty in the ghost plane model to represent a more informed airport environment. This all culminates in simulation in a series of effects that serve to help prevent overloading at a singular moment and reduce the impacts of back to back to back landings. While this has a generally positive albeit small effect on the delay structure overall most of the airports considered see no benefit from this procedure. This delay is additionally not well spread and when investigating the causes of this reduction we find that while the procedure has little to no benefit in toronto and vancouver it is a majorly helpful set of procedure in montreal reducing local delay by 7% something that is quite substantial for the low cost of implementation and is a consideration in montreal.

2.2.2.2 Ground Delay Program

Our second implementation of a control process would be a Ground Delay Program. This is a reactive procedure, applied after an adverse delay-causing event occurs. Here planes are instructed by air traffic controllers to not depart the origin airport until a) sufficient aircraft are cancelled due to the aforementioned event to lower volume or b) the Ground Delay Program is declared over due to length. Events such as bad weather, excess volume, or a runway closure can cause a Ground Delay Program to be initiated [4]. This process will be implemented by decreasing the cancellation threshold and through increasing the threshold needed in available airspace for planes to be allowed to depart, in order to ensure in uncommonly high congestion environments the planes outgoing will be kept grounded. In order to change these variables by the correct amounts we will need data about the process from NAVCAN in multiple scenarios in order to tune these variables appropriately. When implementing this scenario we immediately identify a large-scale improvement where for the low cost of implementation with the total passenger delay time dropping by almost 20% overall. This was also associated with an additional 650 passengers experiencing flight cancellations however so deciding on the level of impact acceptable in cancellations to prevent delay propagation will be crucial when working to implement this method. This change can be seen primarily through its smoothing effect on the delay curve over time where due to the procedure preventing a large amount of backup issues the delay can progress smoothly as weather events occur and avoid negative impacts from delay propagation that result in large spikes in delay events.

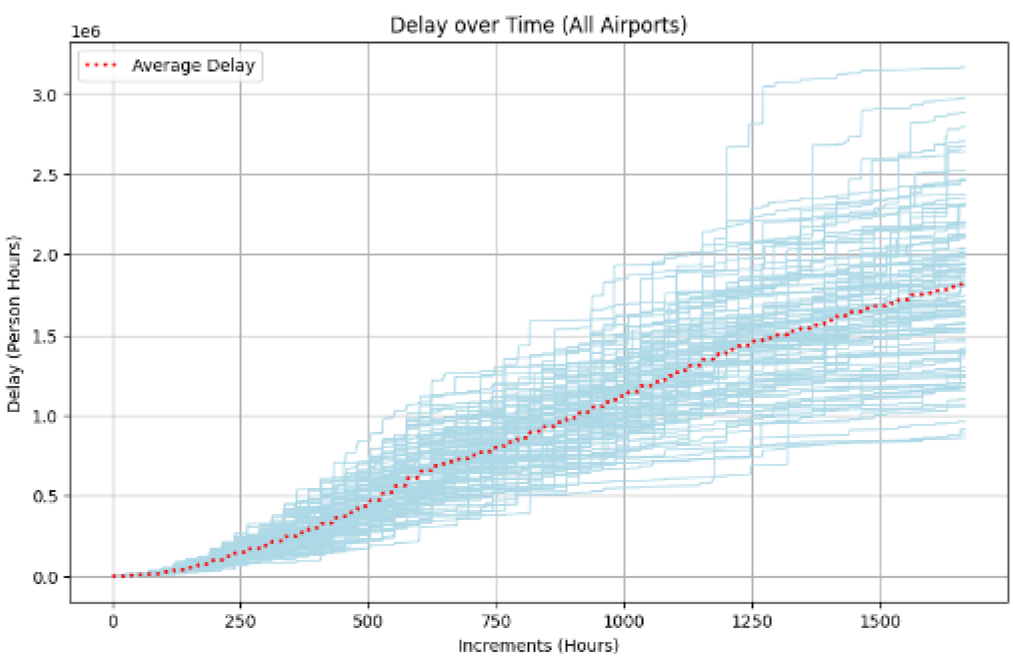

Figure 5: Delay Impact of Ground Delay Programs

2.2.3 Capital Investment Scenarios

2.2.3.1 Increasing bridging (gate) capacity at the airport

Our first option for investment would be increasing the number of gates at the airports in our simulation. Currently for most airports, smaller planes might have to stop on the tarmac and have a bus service to connect passengers with the main airport. For larger planes, one bridge may not offer enough capacity. In this scenario, there would be a more liberal use of bridges. For example, larger aircraft might have multiple bridges (for example one at front and one at back) to expedite boarding/deboarding the plane. To do this we will decrease the time between landing and departure at the airports to simulate the more efficient loading procedures. In order to ensure our data is tuned appropriately we will need data from before and after renovations of Pearson and our other target airports as they have previously increased the amount of gates for expansions and we will use this data to model the time difference of these effects [5][6][7]. This change has a surprisingly little effect on the total operation of our simulation and while the effects are quite positive they are understated compared to the major sources of delay. When investigating the cause of these results we identified that while the impact of the faster bridging was substantial for each airplane the effects never met the scale required to make up for major delays leading up to those events and as such while the bridging was much more efficient the effects of bridging remained minimal and did not prove worthy to implement on a delay scale.

2.2.3.2 Expanding the runways and number of control operators

Our second scenario for investment involves increasing the number of runways for both small and large aircraft while also increasing the number of staff performing air control to compensate for the added complexity. This would require information on the costs and the correct ratio of controllers to new runways and would be implemented by increasing the capacity variables of the airport in all factors, working to reduce the delay for the airplanes that would otherwise have to circle waiting for space on the tarmac [5][6][7]. This is one of the effects in our simulation with some of the most unintuitive results in our testing as from our modelled data there is actually a minor increase in the total delay accrued by our model. This is because as the number of available runways increases the number of planes attempting a simultaneous operation in the airport increases alongside it. This generally reduces the number of delays that occur over the course of the simulation however as each delay is now affecting a much larger number of grounded planes simultaneously when these less likely events occur they are much more impactful on the total efficiency of the system than they would be otherwise raising delay by 5% overall.

2.2.3.3 Improving build quality of aircraft

Our final scenario for large investment involves improving the build quality of the aircraft. As a major reason for propagating delays is the time of flight exceeding the need for maintenance on the aircraft the increase of the time between maintenance would work to widen the buffer of delay allowable before it propagates through maintenance reducing how far delay continues to extend after the initial event. In order to identify how much to increase the maintenance time, we performed research to identify the difference in maintenance needs between various models of aircraft to identify what a reasonable improvement would be in this scenario [5][6][7]. Of all of the changes that we have proposed this one has the most major impact overall, however it also represents the largest cost to implement as requiring new aircraft and maintenance procedure is not only a massive undertaking but relies on spending out of the control of NAVCAN. With all of the fleets of every major airline redone and improved to reach the expected maintenance improvements in [6] we see the total system delay drop to only 20% of the system delay that was originally present. This delay may represent a change that is too major however, as if this becomes the new normal for expectations and the new airline planning operations begin planning for even tighter windows of maintenance we are likely to increase the variance of the delay substantially as the delays on these now much tighter windows fail to reduce in scale as the total time for maintenance is reduced. As such while this represents a major change and flattens the impacts of delay substantially, we do not support this option as significantly viable as the costs would be too immense.

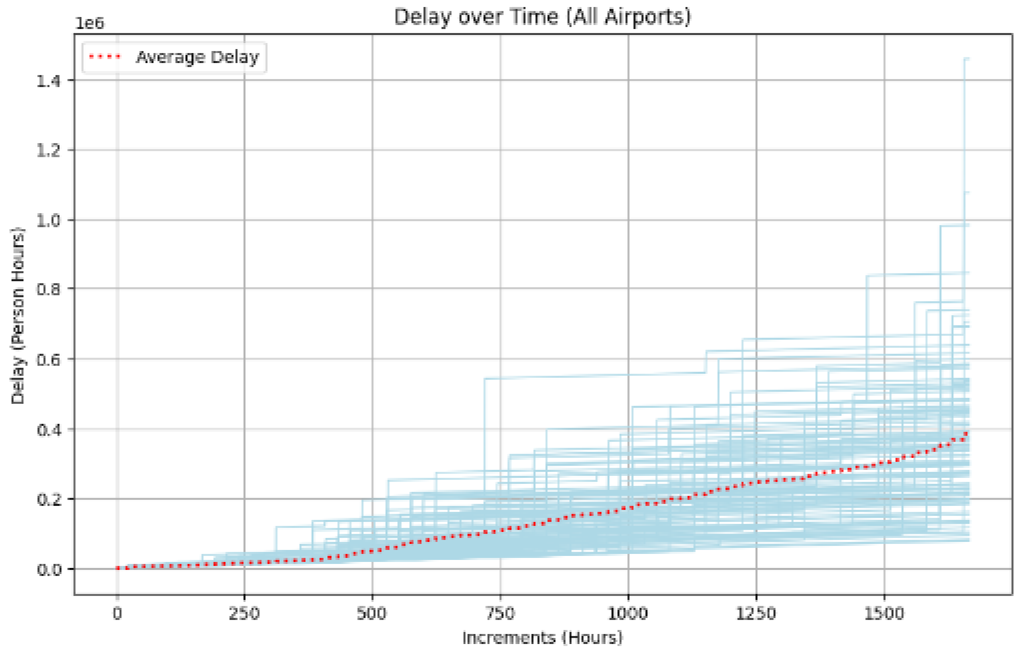

Figure 6: Delay with Fleet Renewal and Maintenance Improvements

2.5 References

[1] “How long does a flight from Montreal (YUL) to Vancouver (YVR) take?,” schedules - FlightsFrom.com, https://www.flightsfrom.com/YUL-YVR (accessed Mar. 14, 2025).

[2] “How long does a flight from Toronto (YYZ) to Vancouver (YVR) take?,” schedules - FlightsFrom.com, https://www.flightsfrom.com/YYZ-YVR (accessed Mar. 14, 2025).

[3] “How long does a flight from Toronto (YYZ) to Montreal (Yul) take?,” schedules - FlightsFrom.com, https://www.flightsfrom.com/YYZ-YUL (accessed Mar. 14, 2025).

[4] Google Flights, https://www.google.com/travel/flights (accessed Mar. 14, 2025).

[5] Google Flights, https://www.google.com/travel/flights (accessed Mar. 14, 2025).

[6] “On-time performance for Global Airlines: OTP Flight Data: OAG,” oag_white, https://www.oag.com/on-time-performance-data (accessed Mar. 14, 2025).

[7] G. T. A. Authority, “GTAA reports 2023 annual results,” Cision Canada, https://www.newswire.ca/news-releases/gtaa-reports-2023-annual-results-878884597.html (accessed Mar. 14, 2025).

[8] Admtl.com, https://www.admtl.com/en-CA/corporate/medias/publications (accessed Mar. 14, 2025).

[9] Facts and stats | YVR, https://www.yvr.ca/en/about-yvr/facts-and-stats (accessed Mar. 15, 2025).

[10] “The A, C and D of aircraft maintenance,” Qantas News Room, https://www.qantasnewsroom.com.au/roo-tales/the-a-c-and-d-of-aircraft-maintenance/ (accessed Mar. 14, 2025).

[11] Turnaround gantt-chart for a typical single aisle aircraft, https://www.researchgate.net/figure/Turnaround-Gantt-chart-for-a-typical-single-aisle-aircraft-Source-inspired-and-adapted_fig3_367317346 (accessed Mar. 15, 2025).

[12] D. Grether, S. Fürbas, and K. Nagel, “Agent-based Modelling and Simulation of Air Transport Technology,” *Procedia Computer Science*, vol. 19, pp. 821–828, 2013, doi: https://doi.org/10.1016/j.procs.2013.06.109.

[13] “Air Traffic Control and Flight Paths 101,” Pearson Airport, https://www.torontopearson.com/en/whats-happening/stories/flight-paths?form=MG0AV3 (accessed Mar. 14, 2025).

[14] M. Clarke and M. Hansen, “Modelling airline flight cancellation decisions,” Transportation Research Part E: Logistics and Transportation Review, https://www.sciencedirect.com/science/article/pii/S1366554513001129 (accessed Mar. 14, 2025).

[15] “A connectivity-based methodology for new Air Route Identification,” Transportation Research Part A: Policy and Practice, https://www.sciencedirect.com/science/article/pii/S0965856423001350 (accessed Mar. 14, 2025).

[16] F. Abdulmalek and M. Savsar, “Modeling and simulation analysis of Aircraft Maintenance Operations,” International Journal of Industrial Engineering: Theory, Applications and Practice, https://journals.sfu.ca/ijietap/index.php/ijie/article/view/5923 (accessed Mar. 14, 2025).

[17] “Nav Canada Air Navigation and Operational Basics,” NAV CANADA, https://www.navcanada.ca/en/air-traffic/airspace-reviews/air-navigation-and-operational-basics-.aspx (accessed Mar. 14, 2025).

[18] S. Kalakou et al., “Simulation modeling of passengers flow at airport terminals to reduce delay and enhance level of service,” Case Studies on Transport Policy, https://www.sciencedirect.com/science/article/pii/S2213624X24001676 (accessed Mar. 14, 2025).

[19] “About popular times, Wait Times & Visit Duration Data,” Google Business Profile Help, https://support.google.com/business/answer/6263531?hl=en (accessed Mar. 14, 2025).

[20] G. Rodrigues, “Here’s the latest on the Delta Plane Crash at Toronto Pearson Airport,” Global News, https://globalnews.ca/news/11022908/toronto-pearson-airport-plane-crash-delta-airlines/#:~:text=All%20passengers%20and%20crew%20were,released%20and%20two%20remain%20hospitalized. (accessed Mar. 14, 2025).

[21] “Nav Canada Service notices,” NAV CANADA, https://www.navcanada.ca/en/flight-planning/service-notices.aspx (accessed Mar. 14, 2025).

[22] AbdelghanyK.F. et al., “Flight delay propagation modeling: Data, methods, and future opportunities,” Transportation Research Part E: Logistics and Transportation Review, https://www.sciencedirect.com/science/article/pii/S1366554524001169 (accessed Mar. 14, 2025).

[23] J. F. Bard et al., “Airline-driven ground delay programs: A benefits assessment,” Transportation Research Part C: Emerging Technologies, https://www.sciencedirect.com/science/article/pii/S0968090X18302195 (accessed Mar. 14, 2025).

[24] Master plan, https://cdn.torontopearson.com/-/media/project/pearson/content/corporate/our-future/pdfs/gtaa-master-plan.pdf?rev=fe7a67440061412da99af754dbac1e9f&hash=1D38BDF0F5522FA3733FA1F23F3355B0 (accessed Mar. 15, 2025).

[25] Admtl.com, https://www.admtl.com/en-CA/community/soundscape-management/understanding-soundscape/yul-runways-designation#:~:text=Additionally%2C%20when%20two%20runways%20are,well%20as%2006L%20and%2024R (accessed Mar. 14, 2025).

[26] Fact sheet vancouver international airport (YVR), https://www.yvr.ca/-/media/yvr/documents/facts-sheets/2019/2019_yvr-fact-sheet_en.pdf (accessed Mar. 15, 2025).

[27] G. A. Canada, “Pre-boarding checklist,” Travel.gc.ca, https://travel.gc.ca/air/pre-boarding-checklist (accessed Mar. 14, 2025).

[28] Air Canada, “Air Canada - Our Fleet,” *www.aircanada.com*, 2024. https://www.aircanada.com/ca/en/aco/home/fly/onboard/fleet.html#/

[29] “Our aircraft | WestJet official site,” *www.westjet.com*. https://www.westjet.com/en-ca/aircraft

[30] “Flair Airlines - Our Fleet,” *flyflair.com*. https://flyflair.com/our-fleet

[31] *Flyporter.com*, 2023. https://www.flyporter.com/en-ca/about-porter/our-fleet

[32]“ Types of Delay - ASPMHelp,” *aspm.faa.gov*. https://aspm.faa.gov/aspmhelp/index/Types_of_Delay.html

[33] T. Canada, “Passenger performance,” *Transport Canada*, Jul. 07, 2023. https://tc.canada.ca/en/corporate-services/transparency/corporate-management-reporting/transportation-canada-annual-reports/transportation-canada-2023/passenger-performance (accessed Apr. 02, 2025).

[34] Bureau of Transportation Statistics, “Understanding the Reporting of Causes of Flight Delays and Cancellations | Bureau of Transportation Statistics,” *www.bts.gov*, Jan. 10, 2022. https://www.bts.gov/topics/airlines-and-airports/understanding-reporting-causes-flight-delays-and-cancellations

[35] Y. Wang and D. Kulkarni, “Modeling Weather Impact on Ground Delay Programs,” *SAE International Journal of Aerospace*, vol. 4, no. 2, pp. 1207–1215, Oct. 2011, doi: https://doi.org/10.4271/2011-01-2680.

[36] “Compare the Climate and Weather at Toronto Pearson International Airport, Montréal-Pierre Elliott Trudeau International Airport, Vancouver International Airport, Chicago O’Hare International Airport, Logan International Airport, and San Francisco International Airport - Weather Spark,” *Weatherspark.com*, 2025. https://weatherspark.com/compare/y/146971~147207~145203~146513~147265~145212/Comparison-of-the-Average-Weather-at-Toronto-Pearson-International-Airport-Montr%C3%A9al-Pierre-Elliott-Trudeau-International-Airport-Vancouver-International-Airport-Chicago-O (accessed Apr. 02, 2025).

[37] F. G. Hutter and A. Pfennig, “Reduction in Ground Times in Passenger Air Transport: A First Approach to Evaluate Mechanisms and Challenges,” *Applied sciences*, vol. 13, no. 3, pp. 1380–1380, Jan. 2023, doi: https://doi.org/10.3390/app13031380.

[38] A. S. Antonio, A. A. Juan, L. Calvet, P. Fonseca i Casas, and D. Guimarans, “Using simulation to estimate critical paths and survival functions in aircraft turnaround processes,” *2017 Winter Simulation Conference (WSC)*, Dec. 2017, doi: https://doi.org/10.1109/wsc.2017.8248055.

[39] “Diversion | SKYbrary Aviation Safety,” *skybrary.aero*. https://skybrary.aero/articles/diversion

[40] “U.S. and Canada’s best and worst Airlines and Airports based on flight delays and cancellations - BestBrokers.com,” *BestBrokers.com - Best Brokers for Trading Online*, Mar. 07, 2024. https://www.bestbrokers.com/2024/03/07/u-s-and-canadas-best-and-worst-airlines-and-airports-based-on-flight-delays-and-cancellations/