Ministry of Education and Science of Ukraine NATIONAL UNIVERSITY OF KYIV-MOHYLA ACADEMY Department of Informatics of the Faculty of Informatics

SIMULATION OF THE DELAY PROPAGATION IN THE AIRPORT FLIGHT SCHEDULING PROCESS

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The content of the PM to the thesis:

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Contents

Abstract

This study explores how a congested airport can propagate delays to other airports through the flight networks. The thesis presents a simulation method developed to replicate the scheduling processes for arrivals and departures at a slot-controlled airport. The simulation adheres to a First Come First Served (FCFS) protocol while taking into account runway capacity limits, safety constraints, and turnaround time. Beyond the scope of this thesis, we compare the results from the simulation that follows ad hoc FCFS operations, with the results obtained from an optimization model specifically designed to evenly distribute peak-time flights over the day and reduce the total delay time.

Introduction

The high increase in demand in the aviation industry has resulted from most commercial airlines scheduling flights beyond the airport's capacity, causing congestion and under-resources at many airports [4]. These conditions have worsened the problem of flight delays, in particular, during major disruptions. Data from the US Bureau of Transportation Statistics suggests that around 22% of flights in the USA experienced delays during 2023. Among these, 31.30% were due to factors controlled by the airlines, 34.08% were the result of aircraft being late due to previous delays, and 24.10% were related to airport operations, including heavy traffic and air traffic control issues. [12].

Although airlines carefully plan their flight schedules, in practice deviations often occur due to airport capacity constraints and unforeseen events such as aircraft technical failures or extreme weather conditions, rescheduling of arrival and departure times, considering runway slot limitations and other resources to airports with a simplified schedule or full coordination. [10] A schedule-coordinated airport requires careful coordination to manage demands that far exceed its capacity, requiring adjustments to flight times to meet airline and passenger service expectations [5]. What may appear to be an optimal schedule from the point of view of airport management may not be in line with airlines' preferences and may result in increased operating costs for them. Changes in flight schedules due to airport restrictions at the tactical level mean that airlines must reorganize their operations according to the availability of slots at airports aligned with the schedule. Airlines operating in such controlled environments must provide slots that represent authorized access to airport facilities. [10] Optimization models were developed to represent decisions regarding the allocation of slots in schedule-coordinated airports, primarily aimed at reducing the discrepancies between the desired schedules of airlines and the actual schedules [8].

In my thesis, I describe the work on the simulation algorithm based on [9] (not yet accessible on the Internet), which became part of [10]. [10] presents an optimization model for flight rescheduling at a schedule-coordinated airport to reduce congestion and delays. A simulation algorithm was created specifically for [10] to validate the results of the optimization model and to evaluate its performance by comparing it to the delays that are typically encountered in ad hoc operational practices.

The practical importance of the developed simulation is in comparing the optimized results from the optimization model with ad hoc operational results (that are simulated results).

The goal of this thesis is to develop a simulation of delay propagation to mimic the real-time airport flight scheduling process. The simulation will follow a first-come, first-served protocol, adhering to runway capacity constraints, minimum safe separation intervals between consecutive flights, and turnaround time. This simulation aims to trace how the delay is propagated under congestion conditions when airport operations follow the FCFS framework both with and without adherence to safety constraints. The results will improve the understanding of the impact of security protocols on delay propagation during peak operational times.

Thus, the object of my study is the airport flight scheduling process, which encompasses the entire system by which flights are planned, managed and delays are handled.

The subject of my study is the simulation of delay propagation in this system, focusing on the mechanics and impacts of operational constraints and safety protocols on delay distribution.

The tasks of this study are:

- Develop a simulation algorithm that mimics the real-time scheduling and delay propagation processes of an airport.
- Implement the FCFS protocol within the simulation while respecting airport and safety constraints
- Analyze the propagation of delays both with and without strict safety constraints.

Several studies have explored aspects related to our work. For example, the researchers studied predictive modeling of delays due to airline operational decisions, and their research highlighted how tightly coupled airline resources can dramatically worsen the spread of delays if not properly managed. This is especially true in scenarios where weather causes the majority of delays, as detailed in a study demonstrating a model for predicting flight delays under non-standard operating conditions at the operations control center of a major US airline [2].

In addition, another study examines the relationship between airline scheduling decisions and the cascading effects of inflight delays. They constructed a propagation tree to represent all subsequent flights that could potentially be affected by the initial delay. [1].

In addition, our understanding of delay propagation in air traffic networks has improved after analyzing a study comparing US and European networks. The study uses 2 agent-based models to simulate and evaluate how delays spread due to scheduling failures or disruptions by analyzing the performance of different traffic management protocols in congestion control [3].

Our approach also integrates information from the Approximate Network Delays (AND) model, which illustrates the ripple effect of local congestion at airports, resulting in widespread network delays. This model iterates between queuing mechanisms and a delay propagation algorithm and offers a macroscopic view of how policy changes and operational strategies can influence overall system delays [7].

Despite the fact that my work includes key findings from the analyzed studies, the logic of the developed modeling algorithm is new and different from existing modeling methods, which emphasizes the scientific significance of this article.

The thesis consists of three sections:

- The first section explains the methodology, starting with data preparation and analysis where flight data is collected, cleaned, and initially analyzed to provide a basis for the simulation. Next, the fundamental elements of the modeling framework are described, including theoretical principles and operational constraints.
- The second section covers the design and operation of the simulation, explaining the mechanics of the algorithm with a detailed graphical diagram and providing an in-depth look at the technical architecture.
- The final section presents the results of the simulation and offers its analysis. It also includes a brief overview of the optimization model that the simulation was created for that illustrates how the simulation inputs and outputs integrate with and enhance the model.

All code described in the thesis can be found in the repository under the link: https://github.com/Anna-Kudiakova/flight_scheduling_system

Section 1: Background and Methodology

1.1 Data Preparation & Analysis

All data processing, analysis, and creation of the charts were carried out in the notebook ‘flight_scheduling.ipynb’. This file contains additional data analyses and data transformations that are not presented in the work because they were not developed for simulation purposes.

The data used to create and test my simulations was downloaded from the Bureau of Transportation Statistics website. [11] The Bureau of Transportation Statistics (BTS), a division of the US Department of Transportation (DOT), is the primary provider of statistics on commercial aviation, multimodal freight, and transportation economics. In my thesis, I was working with airline on-time statistics for arrivals and departures from/to the Hartsfield-Jackson Atlanta International Airport between January 1st and April 1st, 2023.

During this period, flights to and from Atlanta Airport were operated by 14 airlines. For each airline, two sets of data - one for arrivals and one for departures - were downloaded for the specified period. The dataset for arrivals includes the following columns: Carrier Code (Airline Code), Date, Flight Number, Tail Number (Aircraft Number), Origin Airport, Scheduled Arrival Time, Actual Arrival Time, Scheduled Elapsed Time (Minutes), Actual Elapsed Time (Minutes), Arrival Delay (Minutes), Wheels-on Time, Taxi-In time (Minutes), Delay Carrier (Minutes), Delay Weather (Minutes), Delay National Aviation System (Minutes), Delay Security (Minutes), Delay Late Aircraft Arrival (Minutes). The structure of the departure dataset is similar to the arrival structure but with logical differences, such as 'Destination Airport' instead of 'Origin Airport' and 'Taxi-Out Time' instead of 'Taxi-In Time.

After the files were collected, the data were organized and converted into data frames. After that, the data was filtered and transformed in many ways. Based on the processed data, the date with the highest total number of flights (arrivals plus departures) within the period was determined to be March 24, 2023, with 1,940 flights on one date. Below are the top 10 dates with most flights.

Date (YYYY-MM-DD)	Number of flights
2023-03-24	1940
2023-03-23	1936
2023-03-31	1935
2023-03-20	1934
2023-03-27	1932
2023-03-30	1929
2023-03-17	1918
2023-03-16	1914
2023-03-10	1913
2023-03-13	1906

Table. 1 Dates with the highest number of flights

The data from this date will be used for simulations. Additionally, I identified the most disrupted day in March as the date with the highest total delay. I calculated the total delay as the difference between the actual and scheduled arrival/departure times. March 26 was identified as the most disrupted day in March. Below are the top 10% of the most popular dates for the period that saw the most delays.

Date (YYYY-MM-DD)	Total Delay (minutes)	Number of Flights
2023-01-11	86682	1690
2023-03-26	83006	1892
2023-01-04	71266	1647
2023-03-25	68404	1663
2023-01-12	65486	1765
2023-03-03	58025	1860
2023-01-03	57123	1870
2023-01-03	56148	1698
2023-03-27	51581	1932

Table. 2 Dates with the highest total delay

To compare the dynamics of the distribution of flights during the day, I created a chart that shows the number of flights for each hour. I supplemented the results for the specified dates with the average number of flights per hour in March. Adding the average number of flights per hour provides a guide to more clearly visualize how actual traffic on selected dates deviates from typical traffic patterns. This chart is useful for research because it helps illustrate the impact of delays on overall airport traffic.

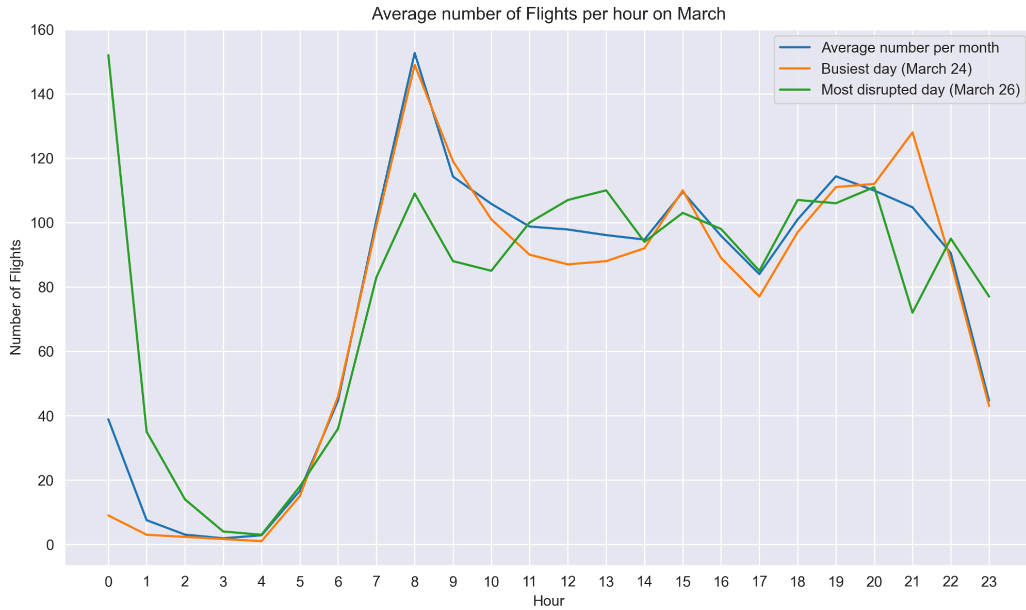

Fig. 1 Comparison of the No. of flights per h. on the busiest day, the most disrupted day, and the average on March

The chart compares the number of flights the average daily flights, the busiest day (24 March), and the day with the most disruptions (26 March). The average and busiest day lines coincide, indicating the typical volume of flights in March. In contrast, the most disrupted day shows clear variations compared to the other two lines. At certain times, particularly mid-morning and late evening, there are noticeable drops in the number of flights, accompanied by spikes, indicating attempts to cope with flight delays. This pattern shows how disruptions affect not only the immediate flight schedule but also the following hours as operations try to return to normal.

To get a more detailed picture that would be useful for analysis before starting work on the simulations, I also created charts showing the number of arrivals and departures for every 15-minute interval (simulation is based on

15-minute intervals) on the busiest day, the most disrupted day, and the average for March.

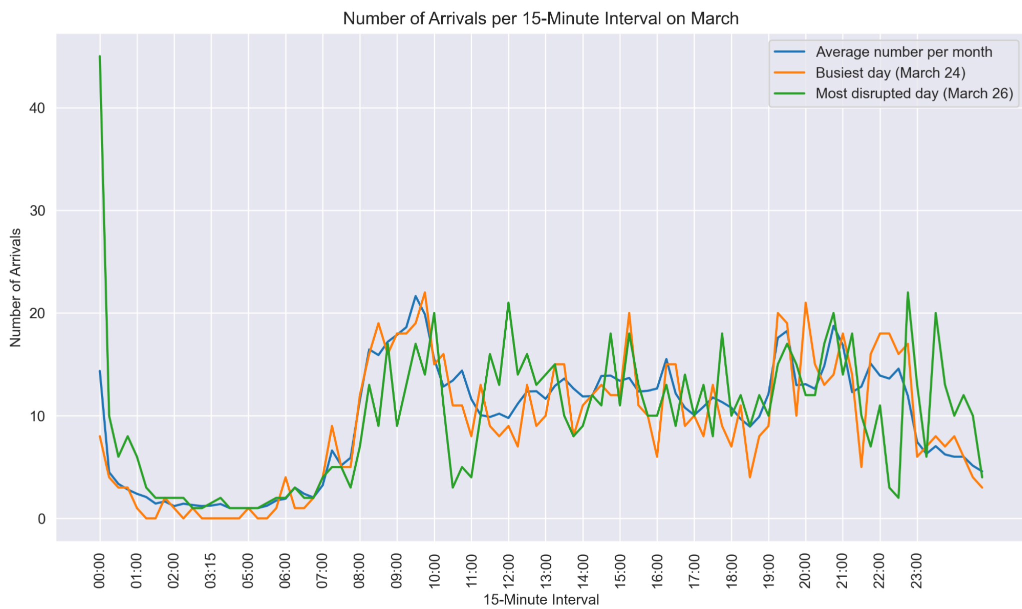

Fig. 2 Comparison of the no. of arrivals per 15-min. interval on the busiest day, the most disrupted day, and the average on March

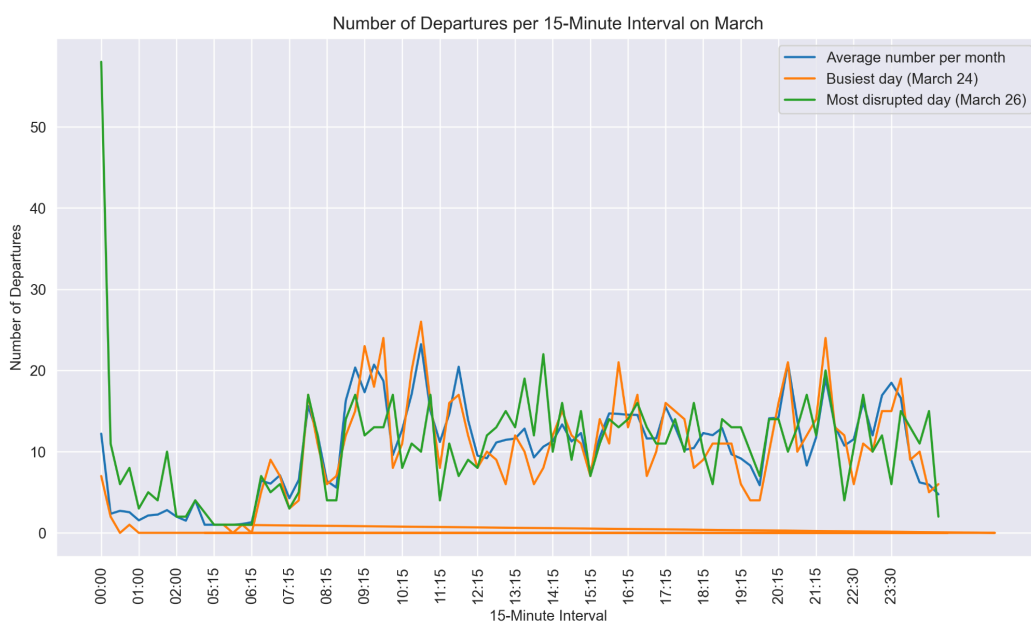

Fig. 3 Comparison of the No. of departures per 15-min. interval on the busiest day, the most disrupted day, and the average on March

The chart illustrates the number of arrivals per 15-minute interval for March 2023, showing differences between the average, busiest, and most disrupted days. The average traffic is relatively stable, while the busiest and most disrupted days have more peaks and troughs that indicate flight fluctuations.

In our simulation algorithm, we work with the data on the busiest day, not the most disrupted day. The main goal is to investigate how a congested airport propagates delays through flight rescheduling in subsequent flights, which is more evident on days with higher traffic volumes. On the other hand, the most disrupted days can be affected by adverse weather conditions or internal problems with airport operations, which are the main causes of delays, rather than the number of flights themselves. Such reasons for delay are not the subject of this study.

A separate data frame was created to account for the turnaround time required for ground operation services (detailed in the next section). This data frame groups all flights by tail number, allowing further analysis of sequential arrivals and departures in the simulation. Using this data, we can combine consecutive flights to ensure that each scheduled departure takes place after the aircraft's minimum readiness time after its arrival.

In total, after careful filtering, we gathered statistics for 881 arrivals, 873 departures, and 739 connecting flights at Atlanta Airport on March 24.

1.2 Foundational Elements of the Simulation Algorithm

An algorithm to simulate the arrival and departure processes was developed to simulate the arrival and departure processes at a congested airport, following a first come, first served (FCFS) protocol while maintaining runway capacity restrictions. Capacity in this context refers to the allowable number of arrival or departure slots that can be safely allocated to flights in each 15-minute interval during the day. Operational safety is defined here as the minimum safe separation time required between successive landings or takeoffs. [9].

The simulation takes into account the arrival delays that might be shifted to later time slots and how these delays can affect connected departure flights via shared airline resources (such as aircraft, crew members, or passenger connections). In our analysis, we track flight connections only by aircraft numbers due to the lack of other data on connections. We assume constant taxi time, constant turnaround times, and no capacity constraints on ground operating resources. [9]

In our simulation, we concentrate on 2 important elements: the number of parallel runways assigned to either arrivals or departures and the minimum safe separation time between sequential flights. Our study investigates the operational capacity of Atlanta Airport (ATL), which has 5 parallel runways, that allow the simultaneous landing and takeoff of multiple aircraft on several spatially separated runways located in the same direction. Typically, ATL designates 3 of these runways for arrivals and 2 for departures. We assume that each runway at ATL is exclusively for inbound or outbound flights, not both. Such a setting significantly increases the safety and efficiency of air traffic management.[9]

The most important safety measure in our analysis is the minimum safe separation time between aircraft, which is vital to prevent in-flight collisions, , providing sufficient space between aircraft to avoid the aerodynamic effects of colliding with each other. For our purposes, we have assumed a minimum safe separation time of 3 minutes for arrivals and 2 minutes for departures.[9]

Furthermore, the simulation considers the process of the ground operation, covering tasks such as fueling, de-icing, cleaning, feeding, loading, and unloading. Currently, it is assumed that there are no capacity limitations on these ground services, but this factor is planned to be taken into account in future work. [9]

Additionally, an average minimum turnaround time of 35 minutes is included in the simulation.

Section 2: Simulation Design and Operation

2.1 Simulation Mechanics and Dynamics

Figure 1 illustrates the flowchart of the simulation algorithm. The algorithm is used to model the arrival and departure scheduling processes, taking into account the connection of arrival and departure flights for each tail number. To simulate arrivals in one day, all flights over a 24-hour period are grouped into 15-minute intervals. After that, each flight from these intervals is assigned one by one to the least busy runway, considering the required minimum safe separation time. [9]

Suppose all runways reach their capacity during a specific time interval. In this case, the relevant flight and any subsequent flights are rescheduled for the next 15-minute period, or even further, if the next slot is also full. Since each runway operates independently, transitions to the next slot could have already taken place on other runways. Therefore, it is important to also take into account the load on other runways in subsequent slots, when shifting a flight to a new slot, to ensure a balanced distribution of flights on all runways. [9]

If there are no other flights scheduled for a particular slot on the runway, the minimum time of departure from the last flight scheduled for the previous slot on that runway must also be considered. If this minimum departure time is not met, the flight must be rescheduled for a later time slot. [9]

When a flight is scheduled for a certain interval, the value of the delay is determined. This value is calculated as the difference between the rescheduled time of the flight after the resource is allocated and its scheduled time.

In summary, our modeling relies on three main processes:

1. Sequentially iterating through flights from the start to the end of the day
2. Evenly distributing flights across runways within each 15-minute interval
3. Calculating delays, which are defined as the difference between the originally scheduled time and the actual time assigned after the runway is allocated.

We treat parallel runways as independent queues where flights are distributed evenly, based on the minimum safe separation time and the division of the day into separate intervals to simplify calculations. [9]

The departure simulation works in a similar way. However, before assigning flights to runways, we first ensure that there minimum ready time for ground operations is met after the aircraft has landed. If a flight arrives late and there isn't enough time between its arrival and the next departure, this will result in a delayed departure. To achieve this, we track the flights associated with each tail number to manage sequential arrivals and departures. It is very important to mention the departure simulation depends on the rescheduled arrival times derived from the arrival simulation. Thus, we must first complete the arrival simulation to get the updated times, which will then be used to run the departure simulation. We maintain a minimum turnaround time of 35 minutes for each connected pair of arrival and departure flights operated by a specific aircraft. [9]

After taking into account the ground operation time, we calculate the delay as the difference between the scheduled and actual times. After that, the updated flight schedule moves to the next phase, the assignment of runways, which reflects the methodology used in the simulation of the arrival process. In the departure simulation, the total propagated delay time is calculated by summing the delays after ground operation services with the delays resulting from the runway allocation. [9]

Figure 4 has been created to provide a detailed illustration of all the necessary steps to simulate realistic airport operations.

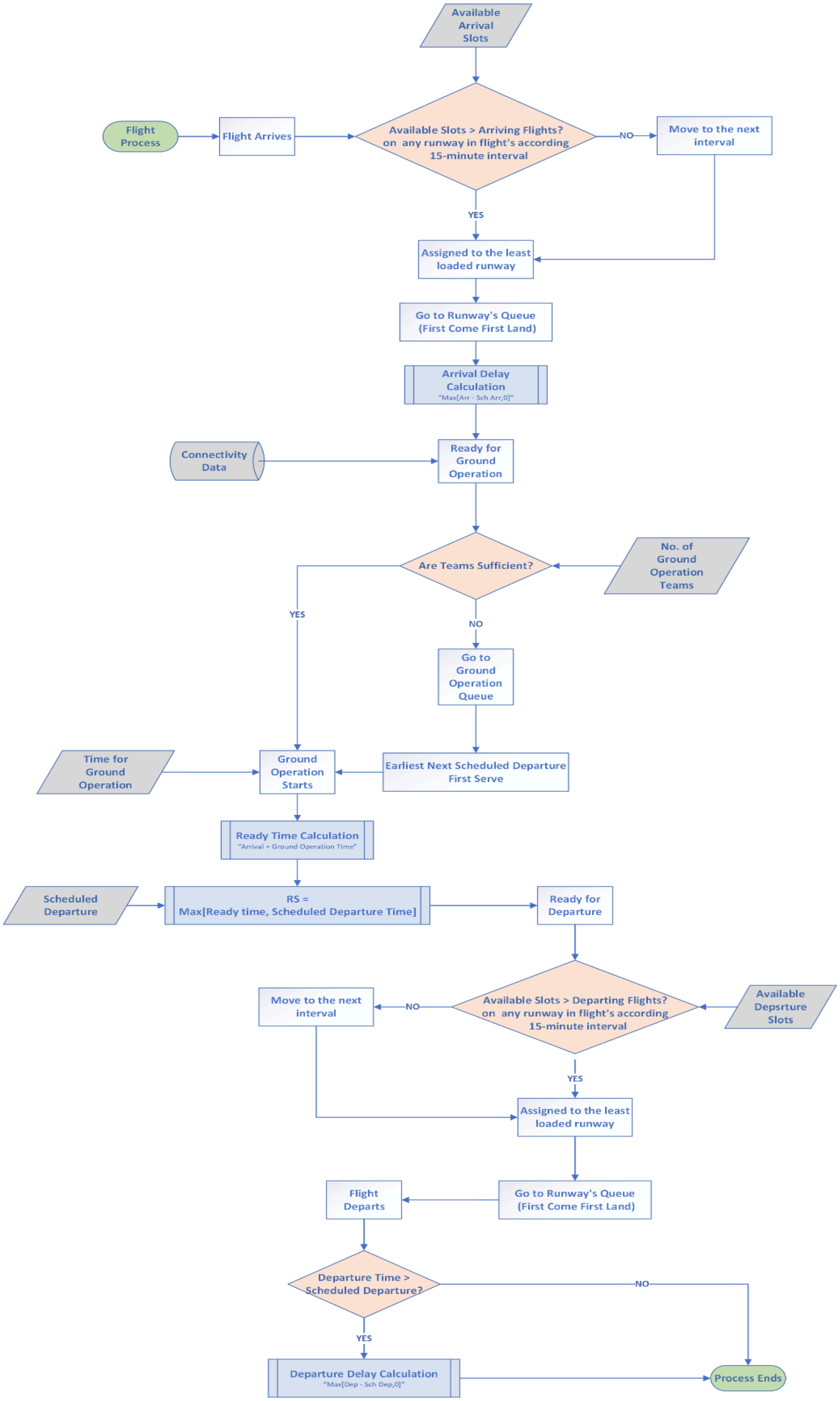

Fig. 4 Flowchart of the simulation model of airport operations.

Please note that the chart contains a resource for the ground operation team and a corresponding step to verify that at least one group is available. If it is not available, it goes to the ground operations queue. However, as noted earlier, we currently assume there are no capacity limitations on ground operations due to limited data on the connections. If capacity limitations are integrated in the future, the total departure delay will increase depending on the constraints of ground operation services.

2.2 Simulation architecture and key components

The simulations for arrivals and departures are implemented in two separate Python scripts: simulation_arrivals.py and simulation_departures.py.

The implementation includes defining a 'Flight' class, that represents the important details of each flight, including flight number, scheduled arrival time, and tail number. Each flight instance also tracks any delays during rescheduling.

'Runway' class controls the flight schedule on a particular runway. Each runway instance maintains a dictionary of time intervals, each containing flights scheduled within those periods. Functions in this class allow you to add flights to slots, calculate total delays, and retrieve the number of flights in any given time slot.

The simulation algorithm follows the next steps :

1. Data Preparation

Filters and sorts the data set for the busiest day. This additional data filtering guarantees accurate sorting. Primary processing takes place in the 'flight_scheduling.ipynb' file.

2. Flight assignment and rescheduling

The mechanism of the algorithm was described in the previous section. Refer to the code for deeper details.

3. Reporting

Main performance metrics, such as the total delay time, the number of delayed flights in every 15-minute interval, the time of the delay of each flight, and the flight with the maximum delay etc., are calculated and logged. Simulation results are output to the console and stored in CSV, providing a detailed record of simulation results.

The report for arrivals is structured as follows:

‘’’

Stage # 1 : simulate runway allocation and calculate total delay

Separation time between arrivals : 3 min, 3 Arrival Runways

flights in interval(0, 15): 0 + 0 delayed

interval starts : 00:00:00; interval ends : 00:15:00

flights in interval(15, 30): 4 + 0 delayed

interval starts : 00:15:00; interval ends : 00:30:00

Flight # 1335.0. Tail # N875DN Delay: 0 min. Scheduled time : 00:18. Actual time : 00:18. Runway # 0. Interval: 00:15 - 00:30

…

flights in interval(450, 465): 22 + 5 delayed

interval starts : 07:30:00; interval ends : 07:45:00

Flight # 2661.0. Tail # N926DZ Delay: 5 min. Scheduled time : 07:30. Actual time : 07:35. Runway # 2. Interval: 07:30 - 07:45

Flight # 1008.0. Tail # N6710E Delay: 7 min. Scheduled time : 07:31. Actual time : 07:38. Runway # 0. Interval: 07:30 - 07:45

…

Total delay: 7862.0 min, Number of delayed flights: 591/881, Max delay : 45 min, Scheduled time of flight with max delay: 09:50

‘’’

The report for departures follows a similar format but includes an additional log detailing the ground operation stage, including any delays associated with connecting flights.

‘’’

Stage # 1 : simulate ground operation and calculate delay due to connecting flights for each aircraft

Tail # N106DN; Flight # 1314; Org Dep time: 14:19:00; Org Arr time: 14:06:00; Simulated Arr time: 14:06:00; Min ready time: 14:41:00; Delay: 0 days 00:22:00

Tail # N107DN; Flight # 499; Org Dep time: 13:17:00; Org Arr time: 12:55:00; Simulated Arr time: 12:57:00; Min ready time: 13:32:00; Delay: 0 days 00:15:00

…

Total delay across all flights due to connecting flights: 0 days 17:36:00, Number of delayed departures: 88/873

Stage # 2: simulate runway allocation and calculate the total delay

…

[same as arrival report]

‘’’

4. Data Visualization

Finally, a plot is created that visualizes the number of rescheduled flights per 15-minute interval, providing a graphical representation of the rescheduling pattern over the day. This visualization helps to better understand the distribution and impact of rescheduling on airport operational capacity and their subsequent matching with actual and scheduled flights.

Section 3: Results and Model Overview

3.1 Simulation Results with Discussions

Charts were developed to compare the amount of actual, scheduled, and simulated flights, separately arrivals and departures, during every 15-minute time interval.

To estimate the accuracy of the simulation model, we ran the algorithm with 20 arrivals/departures capacity per 15-minute interval, setting 2.25 minutes separation time for arrivals and 1.5 minutes for departures. The results, that are presented in Figures 5 and 6, show that the simulated data closely matches the actual arrivals and departures. Whereas our simulation algorithm imposes runway capacity restrictions to guarantee safer operations, the actual data reflect ad hoc operations using a first-come, first-served (FCFS) approach.

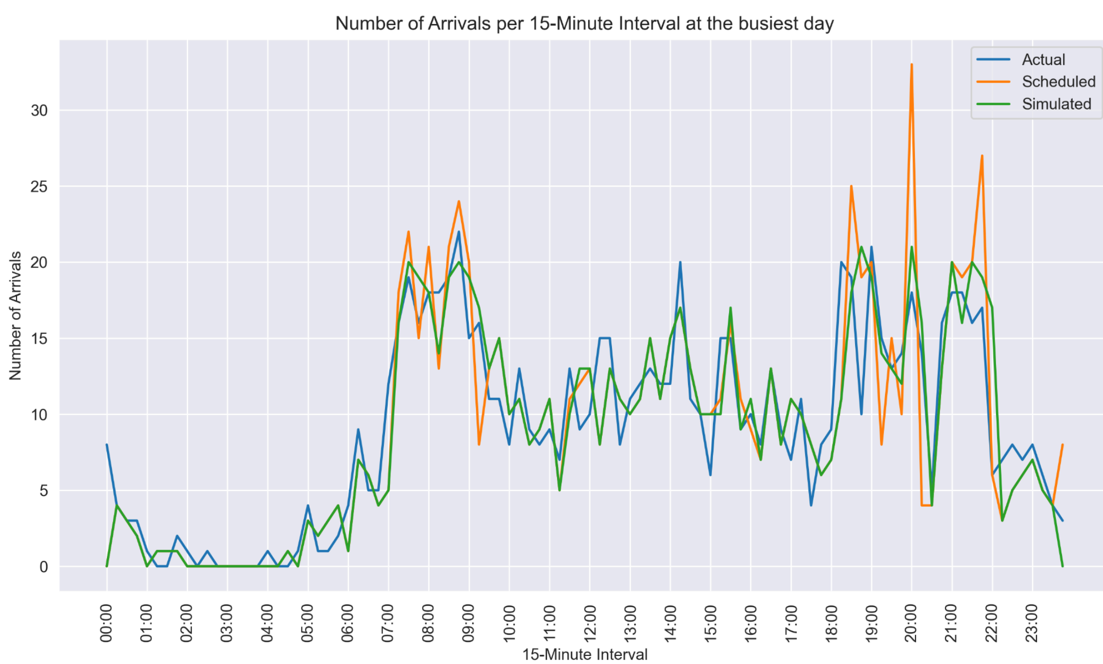

Fig. 5 Simulation results for arrivals, showing a max. capacity of 20 flights every 15 min.

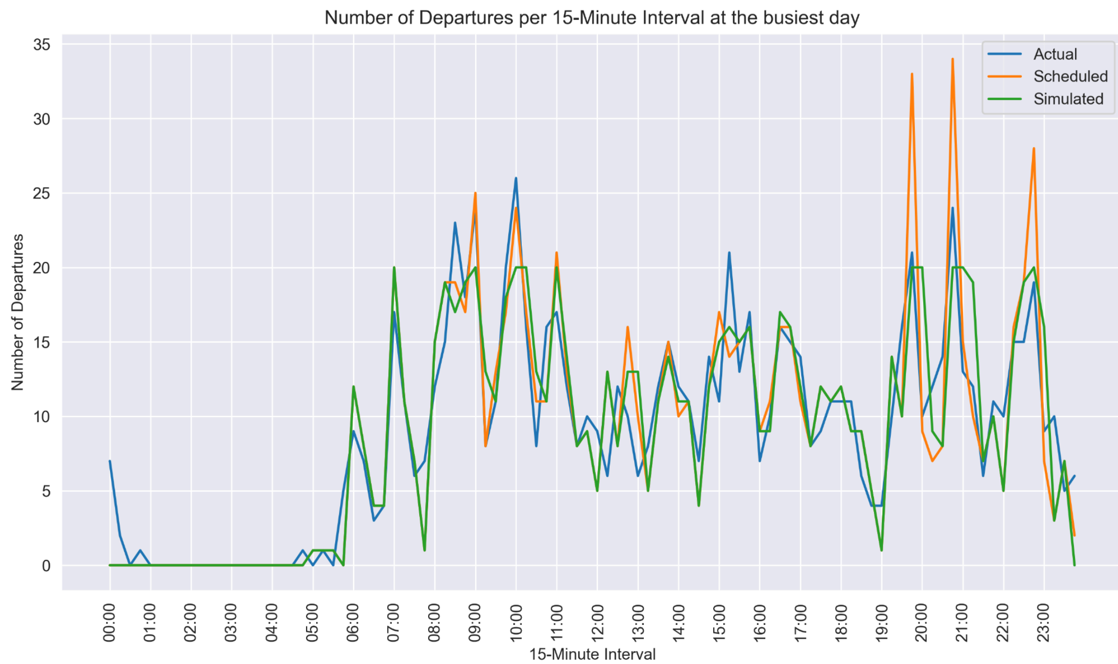

Fig. 6 Simulation results for departures, showing a max. capacity of 20 flights every 15 min.

After model validation, the algorithm was run with a set capacity of 15 flights per 15-minute interval for both arrivals and departures, respecting 3-minute separation time for arrivals and 2 minutes for departures. The results are illustrated in Figures 7 and 8, where several slots clearly demonstrate that the number of flights is limited to 15. Meeting these capacity constraints is very likely to increase the total number of delays.

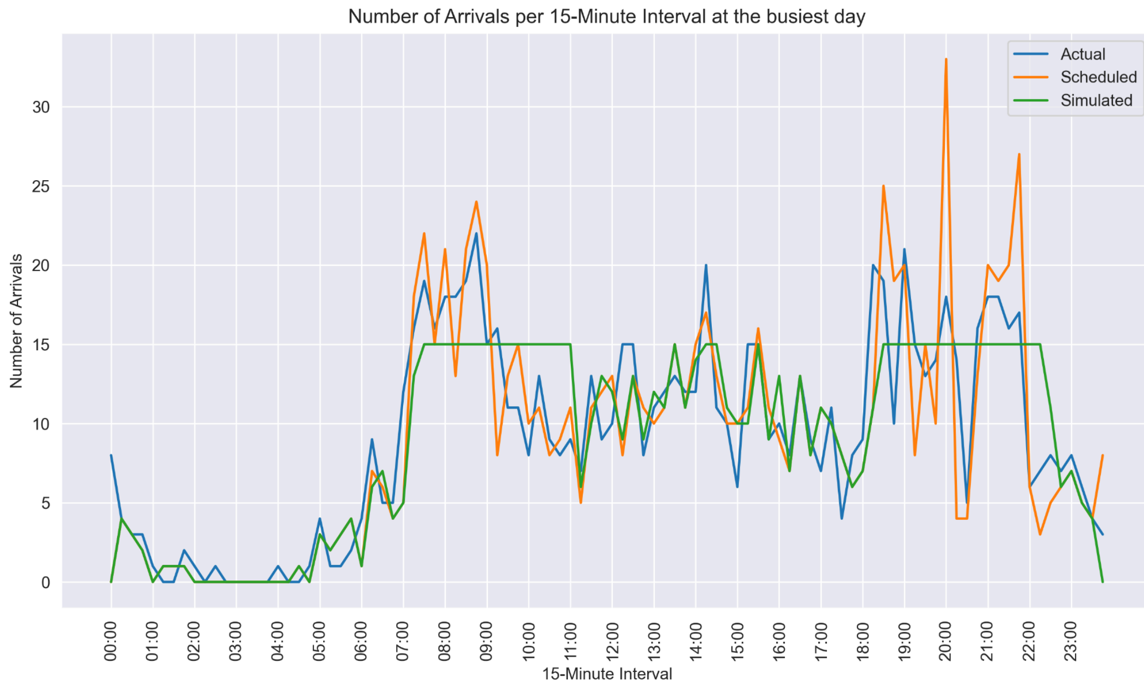

Fig. 7 Simulation for arrivals with a safe operation capacity of 15 flights per 15-min interval

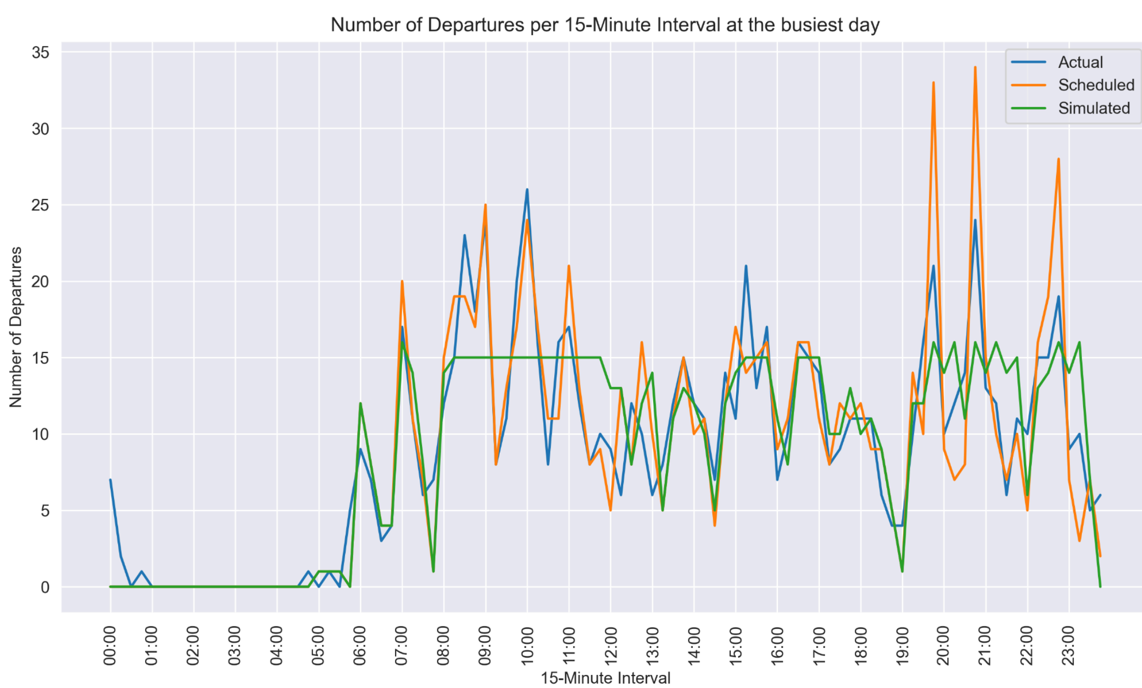

Fig. 8 Simulation for departures with a safe operation capacity of 15 flights per 15-min interval

Table 3 presents the final simulation results. The data show that a capacity limit of 20 flights per slot significantly reduced the total delay and maximum delay time per flight, even though the total number of delayed flights increased. This increase can be explained by the clear observance of the minimum separation time between flights; even the minimum delay of 25 seconds required to meet the 2.25-minute departure time requirement is considered a delay that contributes to more flight delays.

Reducing capacity to 15 resulted in a dramatic increase in both total delay time and the number of delayed flights, confirming that reducing airport capacity increases delays. However, the maximum delay experienced by any flight in the simulation remains lower than that observed in real operations. This discrepancy arises because our simulations only consider operational delays, such as during slot control or ground operations, whereas in real life unpredictable factors such as weather conditions can result in significantly longer delays.

	Arrival Total Delay			Departure Total Delay		
Delay Statistics	Actual	Simulated (capacity = 15)	Simulated (capacity =20)	Actual	Simulated (capacity = 15)	Simulated (capacity =20)
Total delay times	6279	7862	1506.25	8001	7917	2778.5
Max. delay of flight	196	45	15	199	31	12
No. of delayed flights	285	591	399	341	678	519

Table 3: Comparative analysis of actual versus simulated delay times (measured in minutes)

Results demonstrate that while actual airport operations achieve lower overall delays, they may achieve this at the expense of peak-hour security standards. In contrast, our simulation, which strictly adheres to safety protocols, produces higher total delays but shows lower maximum delays for each individual flight.

3.2 Brief Overview of the Optimization Model

The optimization model modifies the approach described in [10]. It integrates the limitation of the runway capacity constraints into the mixed-integer linear programming formulation. The main goal of the developed model is to minimize the total displacement of all flights, taking into account both delays and earlier departures. It applies constraints to guarantee that all flights are scheduled, manages displacements from original times, enforces turnaround times, and maintains runway capacity limits.

The model shows great potential to reduce delays and congestion by moderately adjusting to flight schedules. Calculated analyses indicate that total potential delays could be reduced by 52.6% for arrivals and 61% for departures compared to previously simulated delay times. Achieving this involves moving flights one hour later or 15 minutes earlier, without canceling any flights or disrupting connections at ATL. It is important to note that such adjustments can be planned a lot before the operational day and should not be considered delays.[7]

After that, the simulation algorithm was run again using the optimized schedule to estimate the potential delays due to the optimal planning. The results showed a large reduction in both the total and maximum delay times due to airport capacity constraints, with reductions of 75% and 80% for arrivals, and 80% and 84% for departures, respectively.

In this section, a short overview of the optimization model and the generated results are described. If you are interested in knowing more about model variables, operations, and a detailed discussion of the results, refer to the full article [10].

Conclusions

In conclusion, I developed a simulation that models the propagation of delays in the flight scheduling process at an airport. The study has shown how delays grow under operational and safety constraints by simulating real-time ad hoc operations under a first come first served protocol. The simulation serves as a tool to evaluate the performance of an optimization model by comparing the optimized results with those obtained from the simulation.

The simulation was run with different capacity values. The results show that while actual airport operations typically achieve lower total delays, this performance may be due to airport violations of safety standards during peak hours. Our simulations, which strictly follow security protocols, and thus, maintain safe airport operations, result in higher total delays but show lower maximum delays for each flight. It highlights the necessary balance between operational efficiency and safety compliance.

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