The Behavioural Pattern of Airlines Regarding Slot Misuses

by

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I have imagined this moment a lot during the past six months, the moment where I write the last chapter. Not only six months of this project, but also two years of the master programme has been quite a ride. Hence, even though I am not an emotional person, I imagined it as an overwhelmingly emotional moment. But now, I only have two unexpected feelings; a feeling of relief that I finished another chapter of my life, gratitude to people who supported me for the last two years. And I liked to name a few people came to my mind.

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Executive Summary

The objective of managing airport capacity including the airport slot coordination is to maximise the efficient uses of airport infrastructure. While the slot allocation ensures to maximise of the utility of resources, a good slot allocation enhances global connectivity. The types of slot misuses can be categorised into nine types. They are; a) a flight operated without an allocated slot, b) a flight operated at a significantly different time from the allocated slot, c) a flight operated in a significantly different way to the allocated slot such as a different service type, aircraft subtype, aircraft capacity or origin and destination, d) an airline holds slots without the intention of operation, transfer, swap, e) an airline holds slots to deny capacity to another airline, f) an airline requests new slots without the intention of operation, g) an airline requests slots with the intention of gaining improved priority, h) a flight operated in curfew or another restricted operations period without an allocated slot in the corresponding period, i) no operations during an allocated slot. The failure of managing airport capacity leads to airport congestion. The Airport Coordination Netherlands - ACNL - monitors the conformity of airlines to the allocated slots in cooperation with the authorities. The ACNL discovered the non-conformity behaviour of slot usage in Schiphol Airport of the Netherlands. The number of the opened slot is limited, therefore, it needs to be utilised as much as it can without the backfire of plans. In this paper, only one type of misuses, operating at a significantly different time from the allocated slots, will be studied.

To answer the question, the main research question is formulated as following;

> *Can behavioural patterns of airport slot users in the Netherlands regarding operating in a significantly different time from the allocated slot be exposed with the data-driven approach and support the dialogue points between coordinator and airlines in the enforcement phase?*

The main research question will be answered by asking the following sub-questions,

> *SQ 1: What kinds of behavioural patterns can be detected from exploratory data analysis?*
>
> *SQ 2: What kinds of discovered behavioural patterns can be deemed as the intentional misuse of slots?*
>
> *SQ 3: What kinds of factors have a correlation to the discovered misuse case?*

The main research method is to conduct the exploratory data analysis with python.

To identify the knowledge gap, a literature review was selected with four topics. First, slot coordination and its recent research is searched to have a grasp of the concept and its importance. The slot coordination can be broke down into 5 procedure, slot allocation, slot monitoring, discussion, enforcement and sanction. These are aggregated into three sections, slot allocation, slot monitoring and discussion, enforcement and sanction to conduct the literature review.

The paper explained various components of the airport model scheme of departure and arrival from the literature. Based on the literature review, the paper suggests a model scheme of departure/arrival flights of AMS to reflect this research as much as it can. It is separated into two parts, departure and arrival, and focuses on each important component that will help to identify the correlation to misuses. Among components, the slack time is the difference between scheduled on-block time and scheduled off-block time, the preparation time is the difference between actual on-block time to scheduled off-block time. Two of them represent the time block to prepare an aircraft for greeting new passengers and to shift airline crews. The slack time and preparation time got emphasised as a potential key parameter as it reflects both the arrival and departure time of a certain aircraft.

As a research method, data analysis was used with exploratory data analysis, EDA. The data analysis goes through four steps - data collection, cleaning the dataset, making a regression model, and presenting it as

visuals. To supplement the dataset of ACNL, six external sources were used to collect more data.

The case study was conducted with five airports - BCN, LHR, PRG for short-distance flights and JFK, SIN for the long-distance flights. In the Josep Tarradellas Barcelona-El Prat Airport (Barcelona Airport, BCN), Vueling Airlines had the most frequent delay, from the linear regression, the preparation time and the departure delay had a correlation. The median value of slack time for Vueling Airlines was only 45 minutes which was evidently not enough to turn around the flights. For Heathrow Airport, similar behaviour can be found on British Airways. British Airways had 45 minutes of slack time and about 35 minutes of marginal time between actual flight time and scheduled travel time. Even though the marginal time was big enough to cover the entire flight time, taxi time at both airport, as well as some of the departure delays at LHR, the average departure delay time at LHR were over 30 minutes. Similar behaviour was observed at Václav Havel Airport Prague (PRG) with Czech Airlines. For Czech Airlines, the correlation between departure delays at AMS and departure delays at the origin airport (PRG) was found. Three airlines which had the frequent delay are the airlines that do not have an AMS as a hub airport but have the corresponding airport as a hub.

For the long-distance flights, or referred to as intercontinental flights, because of the nature of long travel time and a bigger aircraft, the slack time or preparation time did not affect the delays in general. However, the actual flight time affected by the jetstream, and it often made an aircraft arrived earlier than scheduled. Depending on the season or the type of aircraft, flight time varied. Intercontinental flights had a considerably bigger travel time than actual flight time, which made a constant early arrival.

From these case study and literature review, the term 'misuses' had been categorised into several parts. The one-time misuse is an event occurred due to unexpected event to the airport or airline, such as deteriorating weather condition, technical problems of an airport or air traffic control, or even a strike of airline crews. These behaviours are hard to correct by enforcing policies.

Another part is a structural problem. The policy aims to correct the misuses from this category. In a structural problem, there are three sub-categories, issues caused by airlines, issues caused by the aircraft and airport crowdedness. The issues caused by airlines were often the case of short-distance flight. The narrow slack time was not enough time to prepare an aircraft or recover time from previous arrival delay and it led to the departure delays. The ACNL can negotiate or enforce the policy of having a larger slack time. In the pursuit of expanding a slack time, ACNL can link an issue originated from airlines and an issue from airport crowdedness. For example in the case of LHR, the problem of LHR can be explained in two ways. An airline should have set a bigger slack time to compensate for their departure delay. Or since the delay was caused by an origin airport, LHR, an airport crowdedness should be decreased. By having a larger slack time, the airport congestion from flight delays would be decreased and it will lead to lower airport crowdedness. Issues caused by the aircraft can be seen in the case of long-distance flights, in which the flight time varied by the jet stream and affected as an early arrival. However, it is risky to reduce the scheduled travel time.

The research can be extended to continue the monitoring and address the other types of slot misuses. By following the current process of case studies, other airports of interest can be analysed with newly acquired datasets. Four additional types of slot misuses that occurred during the tactical phase can be addressed in the current framework with additional data collection. Operating in curfew or restricted operations can be addressed by restricting the time range of analysis as the curfew time. A flight operated in different time slots than scheduled can be narrowed to the flights operated during the curfew. The misuses of operating in significantly different ways to the allocated slot can be examined with the additional passenger data and mismatched types of aircraft. The misuses of operating without allocated slots and no operation in allocated slots and can be analysed with a current dataset by comparing the coordinated and operated flights.

This study can help to address the other four types of misuses that happened during the strategic level by pinpointing the airlines that have shown the most nonconformity behaviour. The slot coordinators can have an extensive investigation on operators that requested new slots to examine the intention or possible misuses. However, slot coordinators need to pay attention not to make a premature judgement of airlines from one-time misuses or occasional misuses.

This research faced some challenges and has five limitations. First, there was a challenge to collect data and verify them. If one wants to extend the research into different airports, the size of data will be rapidly increased and will meet the same challenge. One of the structural problems, airport crowdedness was not addressed yet with the current dataset and scope of research. The analysis of the airport crowdedness is deemed to help to track the root causes of airport congestion. The current research is focused on one airport level, Schiphol airport, but not one airline level. To find the intention or track the root cause of delays on airlines' side, analysis on one specific airline can be made. The involvement of air traffic control was not included in this study. As the ATC has authority on the runways, intervention from ATC will be worth researching. Finally, the dialogue at the strategic level should be included as the research ruled out the decision-making process of airlines during the slot allocation procedure.

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1 Introduction

According to the airport industry connectivity report by Airport Council International (2020), Amsterdam Schiphol Airport ranked as the number one airport that has the direct connectivity despite COVID-19 drastically undermining the air connectivity. The direct connectivity represents the availability of the direct air services considering both the number of destinations and frequency of flights to the same destination (Airport Council International, n.d.). Even before the global pandemic hit the aviation industry, Schiphol airport acted as an important hub airport in the world, Schiphol airport ranked in second place at the global hub connectivity in 2016 (Airport Council International, 2016). A hub connectivity is the key metric to measure whether the airport is small or big (Airport Council International, n.d.), and the Schiphol airport serves an important role in the air connectivity.

With an increasing importance of Schiphol airport, Zuidberg (2018) reported through SEO Amsterdam economics that there is capacity scarcity in Schiphol airport, especially during the morning peak (07:50 - 10:39) and evening peak (18:20 - 21:39). The report also suggested that the capacity demand at 2023 will be increased until the inbound peak capacity would be insufficient to accommodate the demand. Airport capacity is the maximum number of flights operated during the fixed time interval (Gilbo, 1993) with a certain condition of an airport. Failing to operate a designed airport capacity can cause airport congestion. It is regarded as 'congested' when airports operate simultaneously close to or over their peak capacity (EUROCONTROL, 2018). The airport congestion brings delays of flights; a side-effect for the utilising full efficiency of the airport.

Airport congestion can occur in both highly utilised or under-utilised airports (Wang et al., 2002). A heavily utilised airport would have more flights with a higher possibility of mechanical problems, passenger delays and ground delays, and at-gate delays can occur in an under-utilised airport. It proves that airport capacity, airport congestion and at-gate delays are closely related to each other.

In a collaboration of the Airports Council International (ACI), the International Air Transport Association (IATA) and the Worldwide Airport Coordinators Group (WWACG), the world wide airport slot guidelines are published to inform the regulatory authorities about policies, principles and processes of airport slot allocation. Airports Council International (2020) defines airport coordination as the means of managing airport capacity to maximise the efficient uses of airport infrastructure. The slot coordination ensures slots are allocated in an open, fair, transparent manner at congested airports and will lead to improving global connectivity and convenience for consumers. An airport slot sets a specific date and time for aircraft to arrive or depart at a coordinated airport.

To coordinate the available slots of an airport and operate accordingly, five procedures are implemented with the coordination committee. The coordination committee advises on matters relating slot allocation and its monitoring, and in the case of the Netherlands, the Airport Coordination Netherlands - ACNL - is entrusted by law. The first procedure is the slot allocation process. According to the working procedure slot allocation of Airport Coordination Netherlands (2018), ACNL will issue the slot historic list and an agreed historics deadline. After the initial submission from airlines, initial allocation by ACNL has to be done followed by the reallocation of slots. Exchanges and transfers are possible with a notification and confirmation of the coordinator.

Although the airport slot allocation enables it to reach the full capacity potential of the airport, it will work under a precondition that the airlines would conform to the designated slots. Otherwise, it will only contribute to airport congestion and decrease efficiency. It leads to the next procedure, the monitoring of slot allocation. The objective of slot monitoring is to ensure that flights are operated in accordance with allocation, scarce capacity is not wasted and to prevent the misuse of slots.

WASG defined the misuse of slots as 8 types. These are; a) a flight operated without an allocated slot, b) a flight operated at a significantly different time from the allocated slot, c) a flight operated in a significantly different way to the allocated slot such as a different service type, aircraft subtype, aircraft capacity or origin and destination, d) an airline holds slots without intention of operation, transfer, swap, e) an airline holds slots to deny capacity to another airline, f) an airline requests new slots without intention of operation, g) an airline requests slots with the intention of gaining improved priority, h) a flight operated in curfew or another restricted operations period without an allocated slot in corresponding period.

Slot monitoring for the Dutch airport is done by ACNL, ACNL focuses on inconsistencies of slot uses in three categories (ACNL, n.d.), unplanned night movements at Amsterdam Airport Schiphol, NORECS (a flight operated without allocated slots), NOOPS (a flight did not operated with allocated slots).

Throughout two procedures of slot coordination, slot allocation and monitoring, the procedures can be divided into four phases; seasonal allocation, ad-hoc allocation, pre-operation and post-operation. The nine types of slot misuses are happening during these four phases. The eight types are defined by WASG as stated above, ACNL added one more type of misuse which is not operating flights for which a slot was allocated. Requesting new slots with the intention of gaining improved priority or undermining other operators can be happened in the seasonal allocation phase. Holding slots without intention of operating or transfers, and with the purpose of denying capacity to other operators can occur in the ad-hoc allocation phase. In the pre-operation phase, operating a flights in a significantly different way wihout the prior confirmation of the coordinator can happen. At last, operating in a curfew time, in a significantly different time slot, operating without slots and not operating in an allocated slot can be monitored in the post-operation phase.

After the monitoring, the discussion takes place within the ACNL. In this procedure, ACNL would discuss whether the detected misuses were intentional or what kinds of misuses can be enforced by the further regulations. Some of the misuses can be justified as defined by Environment and Inspectorate (n.d.) such as expected or unavoidable technical failures, strikes, ATC measures and severe weather conditions. In addition, a dialogue between coordinator and airline can be initiated to identify the slot performance issues. If the airline can provide an appropriate and sufficient explanation of the possible misuses, the coordinator would keep monitoring the situation.

With the results of monitoring and discussion, the enforcement procedure takes place. Enforcement is especially effective when the dialogue between airlines and coordinator was not successful. It includes the loss of historic rights and/or a lower priority for the new slots in the next season. The enforcement in the Netherlands is authorised by ILT, the Human Environment and Transport Inspectorate of the Ministry of Infrastructure and Water Management. As a final procedure, ILT can impose a sanction such as financial burden to the particular airline or operator that showed constant misuses behaviour that cannot be corrected by the enforcement. ACNL has an authority of withdrawing slots, lower the priority of airlines during the slot allocation process. In a repetitive loop of these five procedures, ACNL ensures the optimal use of airport capacity of coordinated Dutch airports.

Furthermore, the IATA held a slot conference twice a year to provide a forum to airlines, airports, and coordinators. The recent slot conference was held virtually in June 2021 due to COVID-19 pandemic with inormative discussion. The subjects of slot conference does not confine the subject at the slot allocation, but it also provides the broad program of slot monitoring and regulations. However, the discussion may not be dealt with pooling operations or division of markets, any commercial arrangement.

The ACNL discovered the non-conformity behaviour of slot usage from departing/arriving flights in Dutch coordinated airports. A series of slot misuses could hinder the schedule and potentially violate the slot regulation. Considering the number of available slots is limited and low as aforementioned, allocated slots need to be utilised as much as they can. Therefore, the extensive slot monitoring and to complementing the existing enforcement are recommended (Buchli et al., 2019). To achieve it, detecting misuses through the behavioural patterns is urged to provide the discussion points with airlines to improve the slot performance.

WASG suggests at the post-operation analysis, the monitoring can be done by data comparison. Considering the datasets that ACNL owns, among the eight types of misuses that are defined by WASG as stated earlier, the type b and c are deemed suitable to analyse with a data analysis. However, this research will only take a focus on the type b misuse due to the scope of the research. The research will be beneficial to the two procedures of slot coordination, monitoring and discussion. The data entry of datasets given by ACNL can be found in Appendix A.

This research will be carried out to discover the factors that might be related to the slot misuse of Schiphol airport to observe the slot regulation of the European Union. Even though the WASG states an airport coordination cannot be a solution for the fundamental problem of airport capacity, the research can make the interim policy recommendation as well as a suggestion for future research projects to keep monitoring the misuses.

1.1. Research Question

This chapter will introduce the research questions to achieve the objective of the study and their method to reach the conclusion. Following the main question, sub-questions to support the main question are formulated and will be introduced. To identify the slot misuses and potential causes of delays, the main research question is derived as follows:

> *Can behavioural patterns of airport slot users in the Netherlands regarding operating in a significantly different time from the allocated slot be exposed with the data-driven approach and support the dialogue points between coordinator and airlines in the enforcement phase?*

The main question will be addressed by using the mixed-method approach. First, to expose the misuse, the exploratory approach will be used with data analysis.

As Schiphol airport is a large hub airport in Europe with extensive connectivity that provides more than 300 destinations, often the cause of delay is not rooted on Schiphol airport. To track the itinerary of aircraft, obtaining external datasets will be essential to the research. In the following sections, details of the data collection methods will also be discussed by sub-questions.

First, to address what are the patterns of misuse, the general pattern should be found with exploratory data analysis. Behavioural patterns can be hypothesised from the literature study, then the research will be carried out to examine hypotheses and detect the patterns during the process.

> *Sub-Question 1: What kinds of behavioural patterns can be detected from exploratory data analysis?*

The exploratory approach is suitable when there is a lack of theory to explain phenomena. To fill this gap, data analysis of the exploratory approach is deemed suitable. To make hypotheses, a case study approach with literature review or interview will be used. The results of sub-question 1 will be the ground of sub-question 2 and 3. After exploring sub-question 2 and 3, the research will revisit sub-question 1 to expand the hypotheses based on the results.

In the next step, discovered patterns will be investigated to determine what would be considered as the misuse behaviour. The airport slot regulation term ‘misuse’ defined by dictionary, regulations or case studies will be reflected upon the practical cases from results of sub-question 1.

There will be numerous reasons for airlines not to abide by the allocated slot including unintentional consequences. Some of the reasons can be judged as incidental reasons from ACNL’s point of view, then the penalty for misuse will be merely required for this case. In other words, reactions from ACNL would vary according to the intention behind the non-conformity. Thus, the judgement of slot misuse should be discussed in the boundary of misuse.

Sub-Question 2: What kinds of discovered behavioural patterns can be deemed as the intentional misuse of slots?

As the result of a sub-question 2, an analytical framework can be built to clarify and operationalise the term of operating significantly different time slot. A case study approach with a literature review will be used to answer the question.

Although ACNL is already aware of misuse cases, there is a knowledge gap about what has caused that. Solely from data analysis, it is hard to define the causality, so instead, the possible correlation between discovered pattern and external factors will be analysed. It may be affected by origin or destination, or the time of the day or the date. These external factors could be determined by the hypothesis that led to detect the pattern or the exploratory data analysis. This leads to the next sub-question to sight correlation of slot misuse.

Sub-Question 3: What kinds of factors have a correlation to the discovered misuse case?

Sub-question 1, 2 and 3 are complementary to each other. In sub-question 3, possible factors would be identified and those could be the basis of another hypothesis to find a pattern. A sub-question 2 will be also revisited to expand the framework. The feedback loop of 1, 2 and 3 will be repeated until they are deemed to be satisfied. An exploratory approach will be used to answer this question using the results of sub-question 1 and 2.

To reach the objective of this research, the policy recommendation can be proposed to correct the pattern and prevent further occurrence. This will be done by providing the talking and negotiating points with airlines to ACNL. From sub-question 1, 2 and 3, several rules can be defined to improve the exposed patterns. The policy recommendation will be done to the new slot allocation as well as slot operations.

1.2. Research Approach

Sub-Question 1

What kinds of behavioural patterns can be detected from exploratory data analysis?

The desk study method is selected for a literature review and to conduct the case study. As the thesis is aimed to find a solution that is particularly suitable for the Netherlands airport, the interview can be arranged with workers of ACNL to have insight.

The data will be used by retrieving existing datasets from ACNL for the departing flights. The primary required dataset would be the scheduled/actual slot usages of Schiphol airport. To fill the gap of arriving flights to the Netherlands, data collection has to be done from origin airports and airlines. As of 2020 and 2021, the COVID-19 pandemic has affected most of the Netherlands including the aviation industry. This thesis will exclude the effect of COVID-19 and only analyse the non-COVID-19 era.

The desk study is selected to analyse data with Python programming tools to use various data analysis related libraries.

Sub-Question 2

What kinds of discovered behavioural patterns can be deemed as the intentional misuse of slots?

The desk study method will be done for making an analytical framework. A literature review will be done to organise the established definition, and a case study for the discovered patterns.

Sub-Question 3

What kinds of factors have the correlation to the discovered misuse case?

As mentioned earlier, sub-question 1, 2 and 3 are complementary. Consequently, the required dataset will vary by the results of sub-question 1. The data will be collected based on the formulated hypothesis or preliminary data analysis. The rest of the method will be the same as sub-question 1.

1.3. Thesis Outline

In chapter 2, an extensive literature review will be done to explore prior study related to airport slot coordination by each procedure.

In chapter 3, research methods will be discussed in detail. A model scheme of departure/arrival flights of airports to analyse delays is created in this chapter. The selected airports and data visuals for the case study are introduced with interesting points to look at. Furthermore, the external data source from open-source will be introduced.

In chapter 4, the case study with 5 airports is conducted to expose the correlation and pattern of misuses. The 5 airports are consist of three European airports - Josep Tarradellas Barcelona-El Prat Airport (BCN), London Heathrow Airport (LHR), Vaclav Havel Airport Prague (PRG), and two intercontinental airports - New York John F. Kennedy International Airport (JFK), Singapore Changi Airport (SIN). These airports were selected by the combination of exploratory data analysis and advice from ACNL.

In chapter 5, the discussion of results from chapter 4 will be done. Since the case study was executed with only five airports, a snowballing method would be applied to recommend the strategies for European airports and intercontinental airports. The exposed pattern will be fitted to the framework suggested by answering sub-question 2. In addition, the way of continuing research will be discussed. As the airport congestion caused by flight delays will not be solved in the near future, it is imperative to continue monitoring the misuse of slot allocation. The ways of continuing related research will be introduced.

In chapter 6, a conclusion of the research questions will be provided with the limitations of the research.

2

Literature Review

To identify the knowledge gap and have a grasp of the concept, a literature review was conducted. An exploratory literature search was done on Scopus with keywords such as ‘airport slot allocation’ or ‘airport congestion’. Only articles with the full text in the English language were selected. The slot coordination can be broke down into 5 procedure, slot allocation, slot monitoring, discussion, enforcement and sanction. The five procedures are aggregated into three-part, slot allocation process, monitoring and operations and the enforcement with the importance of slot coordination.

2.1. Importance of Slot Coordination

Cavusoglu and Macário (2021) stretched out the importance of slot allocation in order to achieve maximum efficiency. They reviewed the two types of slot allocation methods, market-based mechanisms that are used by American airports and administrative mechanisms that EU airports are currently following. From the review, they concluded slot auctions could be a strong instrument of current market demand. Although it can create a fair opportunity for buyers, it is not suitable for the Netherlands airports case.

The importance of efficient slot allocation can be emphasised with its impact on cost factors. Cook et al. (2004) specified delays into two categories, ‘short’ as 15 minutes delay and ‘long’ as 65 minutes delay. Another way to categorize the delay is strategic delay and tactical delay. Strategic delays cost during the planning stage such as cost of schedule buffers. On the other hand, tactical delays happen while operating flights, and these costs have been calculated as marginal costs. The primary tactical delay that happened to the first flight of the day had a knock-on effect on other aircraft, the reactionary delays. Because airlines anticipate delay costs while developing schedules, the strategic stage, they tried to absorb the uncertainty by adding buffers. The research showed that money spent on adding buffer minutes to the schedule is equal to the average tactical delay. Adding buffers only became cost-effective if 22% of flights were delayed more than 15 minutes.

As previous research was conducted based on the European airports, another research was done using the same model but to domestic US airline cost. The cost factors were between European airports and US carriers, the study suggested that it cost 176 million US dollars for delayed flights excluding cancelled flights (Ferguson et al., 2013).

The economic side of airport slot allocation was also discussed by Castelli et al. (2011) and suggested a mechanism that balances between high-valued flights and low-priority flights by financial payment or reimbursement. While they explored the penalty or financial factors of slot allocation, the paper mainly focused on the trade-off of allocation, not the consequences of misuse. Castelli et al. (2012) once again researched the mechanism to make a remark for a possibility to remove grandfather rights without greatly penalising airlines.

The cost of delay can be differed by the type of delays, the airborne delay and ground delay. The airborne delay occurs in the air, such as an aircraft changes its speed while operating. On the other hand, ground delay takes place during the preparation due to constrained resources. Balakrishnan (2016) compared the various algorithm to explore constraints and cost factor of the air transportation system. The research suggested that airborne delays are more expensive than at-gate delays. The ground and long delays are more expensive than short delays.

2.2. Slot Allocation

To manage the airport congestion, the slot coordinators thoroughly review the different ways to optimise the slot allocation. Brueckner (2009) divided the congestion-management methods is the twofold, price-based and quantity-based approach. To use the price based approach, each congested airport announces the price that airlines must pay to use the slots. The optimal tolls would be differentiated across carriers considering the scale of carriers, thus, uniformity charges are distorted choices for airlines. Quantity based approach first announces the total desired flight volume to allocate slots. Under the quantity-based approach, an airport distributes slots by an auction or free distribution. The analysis suggested that a slot-auction might achieve efficiency as long as the optimally chosen slots are distributed, but it will generate no revenue that will lead to other charges such as the weight-based landing fees.

The slot allocation has two infamous principles, which are a 'use-or-lose' requirement and the right of historic slots. The right of historic slots is well-known as the 'grandfather rights', an entitlement for the slot that has already been made use of by a certain airline. Starkie (1998) pointed out that most of the slots available are occupied by corresponding airlines because of the grandfather rights, and it gives a thin opportunity for the entrants.

One of the misuses type defined by IATA was to hold the slots without an intention of operating but to hinder other airlines to enter the market. Fukui (2012) conducted the empirical research from the US carriers to answer whether carriers hoard the slots in order to inhibit airport capacity usage. Hoarding slots not only abuses the slot allocation system, but also reduces the welfare of consumers by reducing the choices between competitors. The paper said it was almost impossible to obtain data of the evidence, thus, the research used the number of seats as a proxy of hoarding behaviour. The results showed that airlines with larger slot portfolios have been able to abuse the system, especially at the small-scale airport with less slot-constrained airports. In contrast, a big-scale airport such as John F. Kennedy airport was not affected by slot hoarding since there was still room for other entrants due to a rather large capacity. From the research, even though it is hard to obtain the data that represents the intention of airlines, one can choose another variable to refer to the intention.

To reduce the ground delay from the strategic level, Air Traffic Flow Management (ATFM) slot management system enters the process to limit the maximum rate of aircraft of the airport (Ivanov et al., 2017). ATFM detects the scarce capacity of the airport and resolves it by adjusting the traffic flow at a strategic process (Vossen et al., 2012). The objective of ATFM is to avoid congestion and delays, prevent imbalances from demand and capacity. An aircraft operator can embed a buffer time to compensate for the anticipated delays and improve the on-time performance, Ivanov et al. (2017) extensively studied how this buffer time can absorb the delay and reduce the delays from subsequent flights. The research suggested that it is possible to compensate for the delays from schedule buffers, but the current regulation does not necessarily meet the desires and goals of aircraft operators. While decreasing buffer can increase the risk of delay propagation, there are some benefits in the passenger welfare points of view. Support from the airports and capacity suppliers is necessary to decrease the schedule buffer and maintain the punctuality level.

In light of the importance of ATFM, Bolić et al. (2017) proposed the model that can contribute to AFTM in strategic flight planning. The proposed model will able to manage the dynamic evolution throughout the day and accurately represent the flight times of different route. However, the model did not take into account the uncertainties. Although, the research exposed that there is a significant gap between strategic and tactical in operations planning. One optimisation model had been made to point out the inefficiencies from failing to properly match the slots for what is requested (Zografos et al., 2012). The main solution was to reduce the gap between requested and allocated slots, but it hasn't identified the cause of misuse. There was an attempt to make a reallocation mechanism by the game-theoretic perspective that focuses on landing slot exchange (Baek & Balakrishnan, 2020). However, the mechanism assumed that the flights were landing at the right time.

Pellegrini et al. (2017) stochastic suggested the model named SOSTA, the model to allocate the airport slots at Level 2 and Level 3 - coordinated airports - in Europe. The SOSTA has big strength, it could allocate the slots based on user requests through optimisation. The other strength of the SOSTA is the flexibility, but because of this feature, it didn't take into account the right of historic slots.

Similar to but earlier than Pellegrini et al. (2017), Mukherjee and Hansen (2007) also suggested a stochastic model revise the ground delays especially based on weathers. While it had a good performance, it only focused on the delay at the ground. There was another optimisation approach suggested by Ribeiro et al. (2018), despite the performance of the model, it only applied to two Portuguese airports. Notably, the size of airports is small and medium, and the model optimised for those airports.

2.3. Slot Monitoring and Operations

During the operation of flights, relevant authorities such as ACNL monitors the operations whether the airlines comply with the allocation. Possible misuses of this phase are flight operated without slots, operated in a significantly different time slot or significantly different way than coordinated, operated in a curfew time and not operated at the allocated slots. Among these types of misuses, operating flights in significantly different ways and time slots can be detected with data and figure out how can be optimised with the right model.

EUROCONTROL (2021) publishes an Air Traffic Flow and Capacity Management (ATFCM) manual to serve Air Traffic Control (ATC) and Aircraft Operators (AOs). In this manual, phases of ATFCM that take place seven days or more prior to the day of operations until the post-operation are explained. Before the operation, strategic flow management and pre-tactical flow management are applied. They monitor the current situation and predict the available capacity on an operation day. If necessary, airlines have to make an adjustment for the operation.

To reinforce the prediction of operation day, several models were proposed from research. Weld et al. (2010) studied runway configuration management to maximise efficiency. Using the scheduled arrival and departure demand, forecasted weather conditions and unique runway characteristics, the model determines a schedule of runway configuration.

On the day of operations, tactical flow management steps in. If the airport is experiencing any disturbances such as staffing problem or meteorological phenomena, the scheduled operation might need to be adjusted. Khadilkar and Balakrishnan (2014) conducted simulations to maintain a steady traffic level at the airport. The proposed model took the airport surface as a network and the total taxi time to minimize the delay cost. When the model is calibrated accordingly, it can reduce the fuel burn of an aircraft at the surface. Menon et al. (2004) suggested a new approach towards air traffic flow with the Eulerian approach. The objective of the model is to synthesize arrival, departure and en route strategies to make a smooth flow of air traffic. The results show that the model used in the paper can be used in an automatic manner to aid the flow operations.

Tu et al. (2008) had performed the flight departure delay distributions of Denver International Airport in 2000 and 2001. The research divided the delays into three parts, seasonal trend, daily propagation pattern and random residuals. Results show that the delay mostly happened when the intervals of flight schedule are relatively short. On the other hand, Mayer and Sinai (2003) suggested that hub airports or hub airlines are the main reason for congestion.

AhmadBeygi et al. (2008) conducted research to find the cause of propagation of passenger flights, and to track down the cause, the article analysed from the root flight, the first flight of the day. AhmadBeygi emphasizes that there will be a limited slack between flights because of high resource utilization - aircraft and cockpit crew - and the limited slack will propagate the delay from the root delay.

Although not all slack time can recover the delay, strategies regarding the turnaround time between arrivals and departures can improve the schedule reliability. (Pyrgiotis et al., 2013)

Another important factor of aircraft delay is the weather condition. The study showed that 66% of the aircraft was delayed due to weather, while equipment and runway caused 20% of delay, 14% for the volume (Chatterji & Sridhar, 2005). The research used the data of Air Traffic Control of US airports.

Fleurquin et al. (2013a) Fleurpquin 2013 points the meteorological condition as the reason for the delay using the data of US air traffic, the congestion will be affected by the weather disturbances. However, Fleurquin et al. (2013b) suggested from another research that the seasonal factor did not change the delay model. Traffic was concentrated during the summer, but the winter had similar behaviour as well.

Post operational analysis is the last step of ATFCM, and similar to the discussion phase of slot coordination. With investigation and analysis, authorities carry out the discussion with stakeholders and go through the issues of actual outcomes. Pyrgiotis (2011) used the Approximate Network Delays model to examine the “ripple effect” of the delay to other airports. It observes the flights based on daily scheduled itineraries and captures if delays at one airport spread to other airports. The research was executed with data analysis to determine the minimum turnaround time of US airports, and it pointed out that the US and European air transportation system has a fundamental difference on the operation, the slot limitations. In virtue of the slot limitations to suppress excessive demand, European airports are less congested than US airports.

For a specific case of slot misuse, Katsaros and Psaraki (2012) carefully follow the case of Greek airport to detect the inveterate misuses by operating significantly outside of allocated time slots. The distinct characteristic of Greek airports are they are heavily influenced by the seasonal demand driven by tourism. During the peak months, there were systemic daily peaks, but in the remaining period, the airport infrastructure is underutilized. The research showed that airlines tend to operate closer to the originally requested slot, not the coordinated one. These slot misuses were the root of the delays and congestion, not the inability of the airport infrastructure.

2.4. Enforcement and Sanction

From the slot allocation and monitoring procedure, the slot enforcement to optimise the current results steps into the process. With the results of the operation, it can pose questions and suggestion to the next slot allocation process and models that will help the decision-making process.

Bertsimas et al. (2011) presented an integer programming model that can cover all phases of each flight such as takeoff, en route and landing to solve the flow management actions. A noticeable part of the model is the decision regarding rerouting for efficiency. The objective function is to minimise the cost of airborne delay and ground holding delay and considers a broad range of ATFM intervention options. The computational experiment showed that it is possible to reduce the airborne and ground delay by a small amount of rerouting action to justify the possible ATFM options of rerouting.

One might want to ask what if the capacity of the airport is changed to take congestion into account. The research of Dray (2020) answered a changed behaviour when the airport capacity was expanded in three different circumstances. First, the outcomes of changing capacity differ by individual circumstances. After the expansion, an unexpected decrease of demand can occur, for instance, recession, airline bankruptcies or more recent event of COVID-19. Expanded slots have remained unneeded or not usable. The results of expansion also behave differently depending on the existence of slot control. If an airport was slot-controlled, new carriers or new destinations were added rather than more frequent flights from the existing destination. Last, slot-controlled airports did not show the drastic decrease of peak schedule but an only limited amount of de-peaking happened. They rather maintained the schedule due to the difficulty of changing slots. Gathering the three types of results, only expanding slots might not be a solution for all.

Corolli et al. (2014) claimed that the increase of airport capacity is the prerequisite to cope with the traffic demand, but in the short to medium term, optimising the existing capacity is the way to alleviate congestion. The existing capacity is used by the lines through slot allocation. They suggested stochastic models for the solution, however, it didn't reflect the existing IATA (International Air Transport Association) rules.

Madas and Zografos (2006) explored five strategies that reflect the regulatory framework, fiscal instrument. Even though they are reflecting the current practice and regulation, they are aimed at an overall slot allocation strategy not correcting the specific causes and cases of slot misuses. Madas and Zografos (2008) had another research for the policy recommendations for a long debate about the scarcity of airport capacity for slot allocation. The research urged the current slot allocation regime to be drastically improved, as the existing system cannot cope with the current traffic volumes.

As an extension of the case of Greek airport as mentioned in the prior section, Katsaros and Psaraki (2012) emphasized the regulation should take into consideration the specific characteristic and economic activities of the region, for this case, the tourism. The research urged to intervene in the situation with sanctions to enforce conformity. As a tool of sanctions, appropriately defined penalty fees were proposed, especially for tour operators not to have more lucrative periods of operation. It also said that if the misuses behaviour was intentional and repeated, financial sanctions could be more effective.

In the end, slot coordination is a constant feedback loop. A model suggested during the monitoring and sanction would be useful to the slot allocation process, and might relevant to any phase of slot coordination.

The focus of the research should be the case of the Netherlands, recommendations targeted to Schiphol airports is required. The term 'misuse' could be operationalised using the case of Schiphol airports. The external factors that have a correlation to certain behaviour can be identified to recommend the policy.

Overall, there is a lack of knowledge of the causes of misuses and the patterns of misuse behaviour. Naturally, the existing solution would focus on improving overall slot allocation performance based on one factor rather than correcting specific existing patterns. Notably, a large number of solutions suggested the model in favour of airlines (buyers) than the decision support model to the slot coordinators.

3

Methods

This chapter explains the method and the model that will be used in the case study in chapter 4. At 3.1, the model scheme of departure and arrival flights of AMS is derived from prior studies but adopted to reflect the research question. 3.2 explains the data analysis using python to analyse and scrape the data. The visualisation technique that will appear chapter 4 is discussed in 3.3. For case studies, five airports were selected. The characteristic of each airport with reason of choice will be explained in 3.4 Finally, the external datasets were required after the initial exploratory data analysis, thus, the source and description will be explained at 3.5.

3.1. Model Scheme of Departure and Arrival

To create a model scheme of departures and arrivals of Schiphol airport, the paper refers to few prior studies. Frolow and Sinnott (1989) explained the potential delay from ATC for each perspective of a daily itinerary of an aircraft. Fundamentally, the delay occurs when the demand of the destination airport is exceeding its capacity, which this research will assume that this precondition was solved by the slot allocation. The aircraft might receive a delay if there is traffic on the runway. Once the aircraft leaves the ground, the flight follows the specific and predetermined route until it reaches its destination. Around the destination airport, the aircraft may face another delay due to traffic on runways or in the terminal area.

Simaiakis and Pyrgiotis (2010) proposed a schematic airport system including the taxiway and runway systems to analyse a queuing system. As depicted in Figure 3.1, a model starts with the arrival of flight through arrival paths, an aircraft would pass runways, taxiways, ramps and arrive at the gate. After the aircraft leaves the terminal (pushbacks) it starts to interact with other aircraft. If the taxiway is occupied by another aircraft taxiing, it would have to wait until entering or redirected to longer routes to minimise the congestion. Then the aircraft will line up to await takeoff in the departure queue. The model defines taxi time as the time between actual takeoff and pushback. The taxi time includes the time on the taxiway and runway queues. This model requires actual pushback time records, scheduled pushback time, actual takeoff time records, scheduled takeoff time.

Simaiakis and Balakrishnan (2016) broke down the departure process with more detail as two modules in Figure 3.2. Module 1 consists of ramp and taxiway delays and module 2 as departure queue and departure throughput, and named each module as travel time and queuing delay, respectively. In the end, these two modules are added as taxi-out time. In this research, phase ‘Taxi’ represents time spent on the taxiway and runway including queuing delay.

An airside module (Figure 3.3) of the decision support system was outlined in the study of Stamatopoulos et al. (2004). The runway capacity model determines the schedule of the slot, associated with departure and

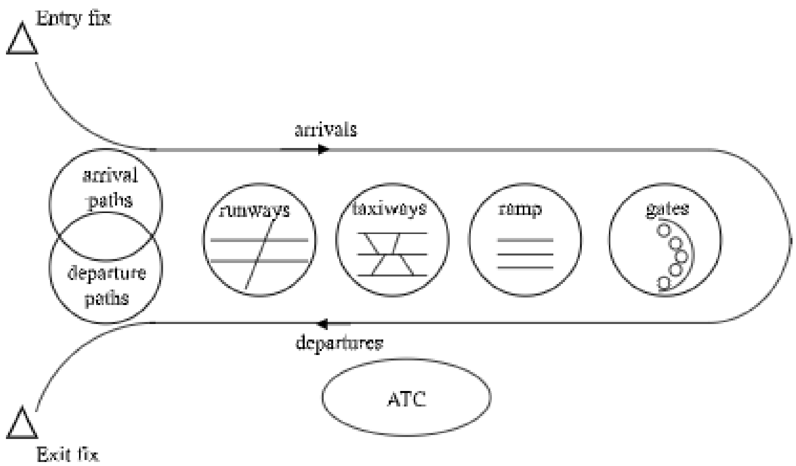

Figure 3.1: A Schematic Airport System of Simaiakis and Pyrgiotis (2010)

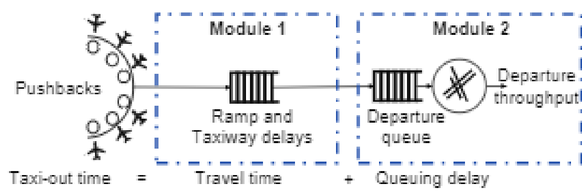

Figure 3.2: A Departure Process Model of Simaiakis and Balakrishnan (2016)

arrival capacity. It is notable that the capacity of arrival and departure runway systems are closely linked, it becomes more interdependent if a single runway is used for both arrivals and departures, there will be a direct trade-off between departure capacity and arrival capacity.

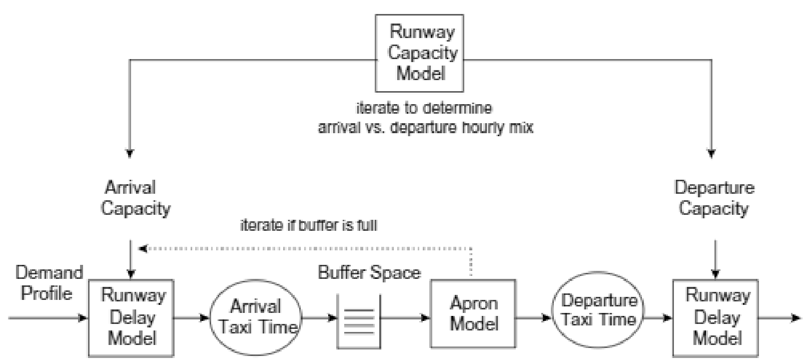

Figure 3.3: An airside module of decision support system (Stamatopoulos et al., 2004)

Another significant component of the airport model scheme of departure and arrival is the slack time. Departure delays can appear due to weather delays, the ground holds, mechanical problems, etc. Even if flights depart on time, they can arrive behind schedule by air traffic issues or weather conditions. To absorb those delays, slack time is used. The slack time should be used for the cockpit crew to shift between flights, prepare the aircraft to greet new passengers. An adequate amount of slack time can recover the time consumed by unexpected factors (AhmadBeygi et al., 2008), however, if the slack time is too narrow to absorb the delays, it will lead to delay propagation. In a real situation, airlines tend to schedule limited slack to utilise the resource as much as they can. If the aircraft is going off duty after the flight, the propagation delay would stop there, if not, it will be snowballed into the entire network and affect a large number of following flights.

In this research, the model scheme would adopt the severity of slack time. Since the paper concerns the delay of departing from / arriving at Schiphol airport, delays on the departing runway have less priority. In the bigger level of the network, as described earlier, delay on the taxi phase could act as the root delay and cause the propagated delay that eventually snowballed into arrival delays, nevertheless, the paper will focus less than the slack time at this point.

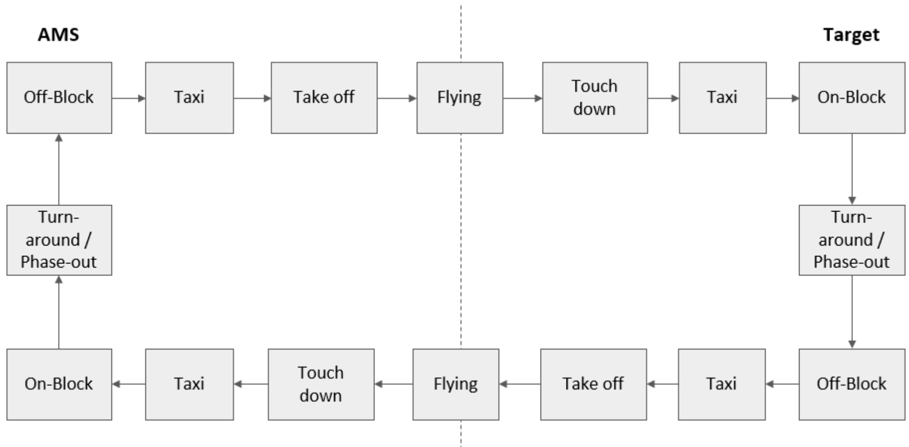

Figure 3.4: An overview of a model scheme of departure/arrival flights of AMS

Figure 3.4 depicts an overview of a model scheme that will be used in this research. The off-block time indicates the moment an aircraft leaves the terminal, and the 'Taxi' phase is adopted from Simaiakis and Balakrishnan (2016) research as it includes the time spent on taxiways, runaways, and queuing time to depart. The take-off time is the moment an aircraft leaves the ground to the air, once it reaches the target, it will touch down to the ground. The on-block time indicates the time when an aircraft reaches the gate.

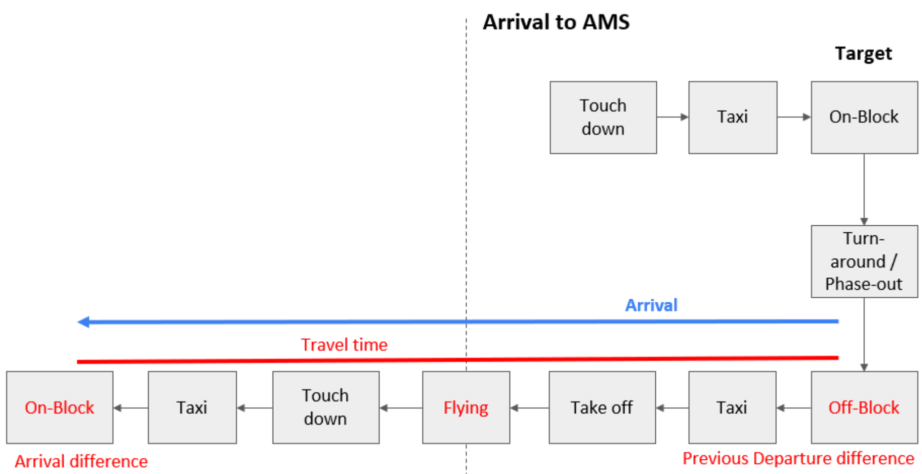

Figure 3.5: Arrival part of the model scheme

To have a close look at the arrival part of the model scheme, Figure 3.5 stresses a few points by colour. The arrival delay at AMS can be expected if an aircraft already departed later than scheduled at the origin airport. Whatever the reasons may be, the delay at the origin airport will directly affect the on-block time at AMS. Even though the flight follows its specific route to reach the destination, the flight time may be extended or shortened due to conditions. For instance, a jetstream would shorten the flight time by boosting an aircraft especially for intercontinental flights, or an aircraft might have to wait to confirm its landing for a long time because of the harsh weather at the surface.

All these factors should have been considered in the scheduled travel time. Travel time is determined by airlines when they apply for the slot allocation, and it includes the taxi in origin and destination airport, flight time. If an airline scheduled the travel time a bit longer than what is anticipated due to uncertainty, unexpected delay can be compensated by its long travel time. If the travel time is tightly scheduled around the expected flight time and taxi time, early or late departure at the origin airport will have a significant impact on the actual arrival time.

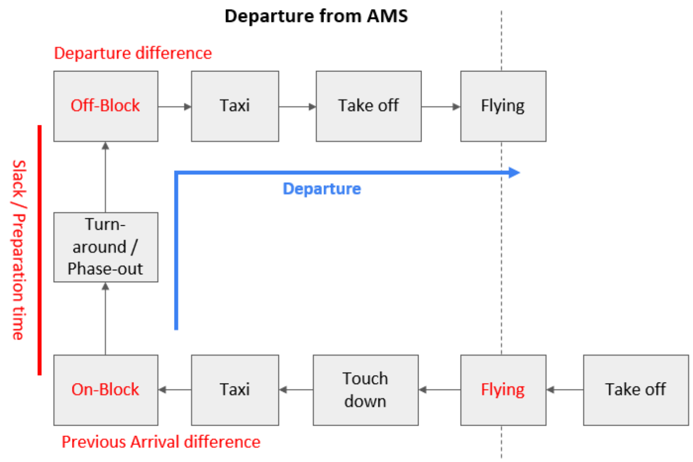

Figure 3.6: Departure part of the model scheme

On the other side, the departure part of the model scheme focuses on the on-block time and slack time. By tracking the tail number of aircraft, one can find the previously visited airport and its scheduled on-block time as well as actual on-block time. As it was seen in the arrival part, to know what caused the arrival difference between scheduled and actual time, flight time and the off-block time from the previous airport can be investigated.

The slack time is the difference between scheduled arrival time and scheduled off-block time of departure. The preparation time is calculated by the difference between actual arrival time, the time workers are able to prepare an aircraft, and scheduled off-block time of departure, the time workers should have finished preparing aircraft and greet the passengers. If the slack time is smaller than preparation time, it means the aircraft arrived earlier than expected and would give plenty of time to prepare as they planned in the strategic level of slot allocation. If the slack time is bigger than the preparation time, an airline would not have the time that they expected and might cause the off-block delay. It is possible that preparation time is calculated as smaller than zero, which shows that the flight was even behind the scheduled off-block time.

3.2. Data Analysis

For the exploratory analysis to find the case study and to answer the sub-question 1 and 3, extensive data analysis was executed with the programming language python. Data analysis using python can be described as four steps (Sahoo et al., 2019). First, exploratory analysis needs to be done. In this step, users can have a first look at the data set. The size and quality of data sets can be examined using visualisation or basic analysis techniques. If there are missing values in data or information that does not include in the data set, the researcher should make a plan for obtaining extra data sets. After having a short look at the data, data sets should be converted into the shape that can be used in the analysis. As the research concerns the flight schedule, one needs to check the type of data, for instance, whether it could be treated as the DateTime type. The data validation also has to be done in this stage, by removing irrelevant parts or correcting data.

Once the researcher obtains a handful of data in the correct shape, the statistical model or machine learning model can be made. To answer sub-question 3, a correlation between factors and discovered cases needs to be found, thus, the regression will be used. Regression can estimate the underlying linear relationship (Bewick et al., 2003), although it only can capture the linear relationship. To cover the weakness of linear regression polynomial regression can be done and visualised to see the relation. The last step is to present the result, the last amount of data will be concisely organised and presented as visuals.

The importance of EDA to this research can be summarised as threefold. First, raw data sets tend to have anomalies and mistakes. The research used the data scraping method to collect the additional data and most of them have an incorrect data type and miscellaneous, unnecessary data. These mistakes, anomalies and outliers can be detected using EDA. Second, hypotheses can be examined with EDA and as a result, relationships between data can be detected. Last, the new insight into data will be gain using visualisation of data.

As a step of exploratory research, a quick dashboard was created to have a faster look at the overall data. This dashboard does not include any external data set, therefore, any raw dataset of ACNL can be used to have a glance at data. It features two world maps, each for the departure and arrival delays. If the departure map has an orange-coloured circle around LHR, it indicates there were a certain amount of delays for the flight from AMS to LHR. The data is sorted by month and each size of the circle represents the severity of the delay. The bigger the size, the more delays occurred in a month. The colour of the circle represents the early or late arrival, each coloured as green and orange respectively. The user can move the slide bar to adjust the month and presume the trend of delay.

3.3. Data Visualisation

In this section, the data visualisation technique that used in the case study is explored with reasons for using them. Three types of visuals are used to find behavioural patterns. Each type will be introduced with reasoning and examples of visuals that were deemed to be not appropriate for the data analysis.

3.3.1. Histogram

As the period of the dataset is set to 3 years, it is hard to investigate individual entities to have a grasp of overall misuses. Instead, a trend of delay or early arrival for each airline and airport could be a good starting point. The data visualisation can work as 'sanity checks' for the large and complex datasets (Correll et al., 2019), hence, a histogram is selected to have a look at the distribution of data. The visualisation steps of EDA often start with univariate distribution Correll et al. (2019) with a parameter of interest. Moreover, histograms are useful for comparing the sub-groups in the data (Nuzzo, 2019), the different behaviour can be observed.

From the data of ACNL (section A.1), a few columns with numeric values can be explored with a histogram to examine the misuses of operating significantly outside of allocated slots. The first candidate is the taxi time. Taxi time is calculated from the dataset of ACNL by subtracting the off-block time from the take-off time for departure flights, and subtracting the touch-down time from the on-block time for arrival flights. The result of histogram with the taxi time was not sufficient for two reasons. For the case of JFK airport, 93% of flights have less than 20 minutes of taxi time regardless of airlines. In other words, there are no clear differences or trends between airlines. The relatively low significance of taxi time is another reason. The objective of data analysis is to find the intentional misuses caused by airlines, however, there is not much that airlines can do to exploit the taxi time for misuses. From the various steps of the 'Taxi' phase as explored in section 3.1, queuing delay would take most of the time during the taxi. The queuing delay is often determined by traffic on runways, not by the airlines. Therefore, taxi time is deemed to be not appropriate for a histogram.

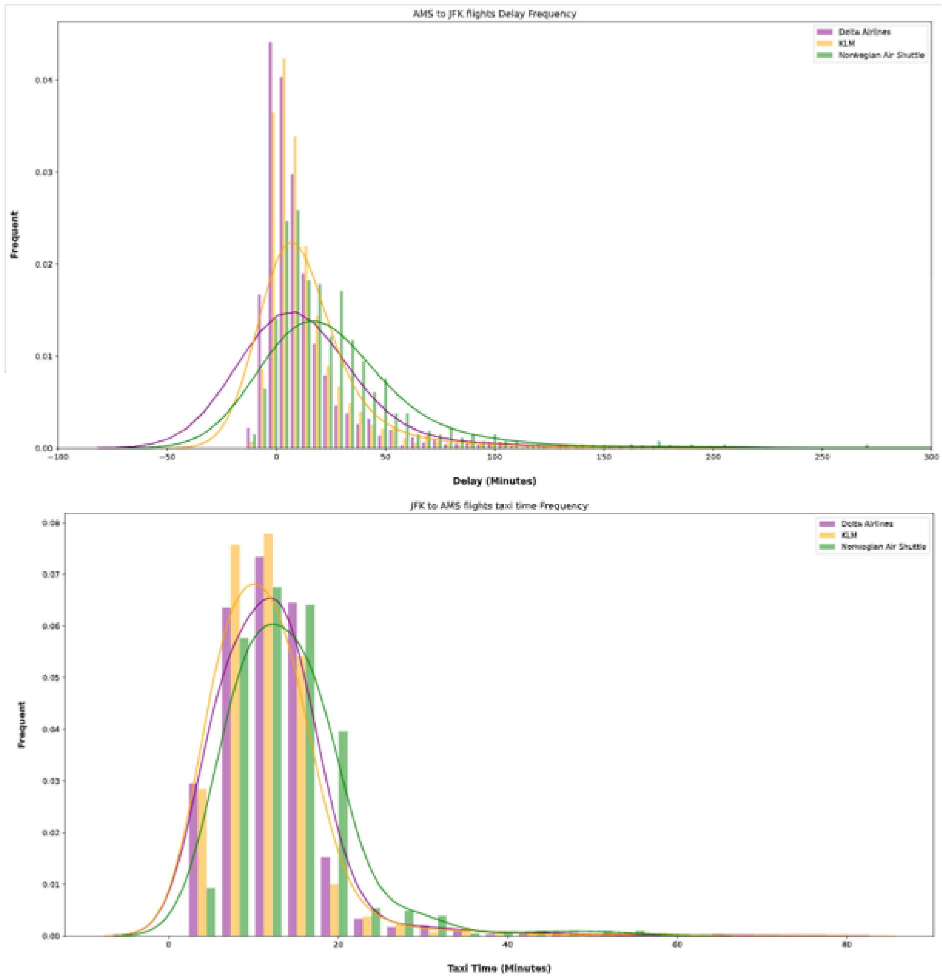

Figure 3.7: Histogram of delay time (above) and taxi time (below)

The next candidate is the delay time. The delay time is already registered as one of the columns of ACNL's dataset, it is the deviation in minutes between coordinated and on/off-block time. If the delay is a negative value, it means that a flight arrived or departed ahead of schedule, positive delay value represents that a flight arrived or departed behind the schedule. The delay time is good to represent the overall misuses of operating outside of allocated slots per airline. The Figure 3.7 shows the histogram of delay time and taxi time, as it is obvious from the visuals, a histogram of delay time has a more broad distribution opposite to taxi time. Thus, the delay time is selected to the parameter of histogram.

The frequency of operated flights between same airports may be different per airlines. Even though it might have operated one or two more flights a day, the total number of operated flights for three would be considerably different. The first histogram of Figure 3.8 is not normalised. At a glance, it may look like Norwegian Air Shuttle (green lines) have conformed the slot guidelines the most with short lines gathering around the delay=0. In fact, Norwegian Air Shuttle did not have a route between JFK to AMS until May 2018, the total number of flights were much lower than other two airlines. In the normalised histogram, it is evident that many of Norwegian Air Shuttle flights were arrived later than expected. Therefore, all histogram figures used in case studies are normalised to follow the overall trend of delays regardless of their total number of flights.

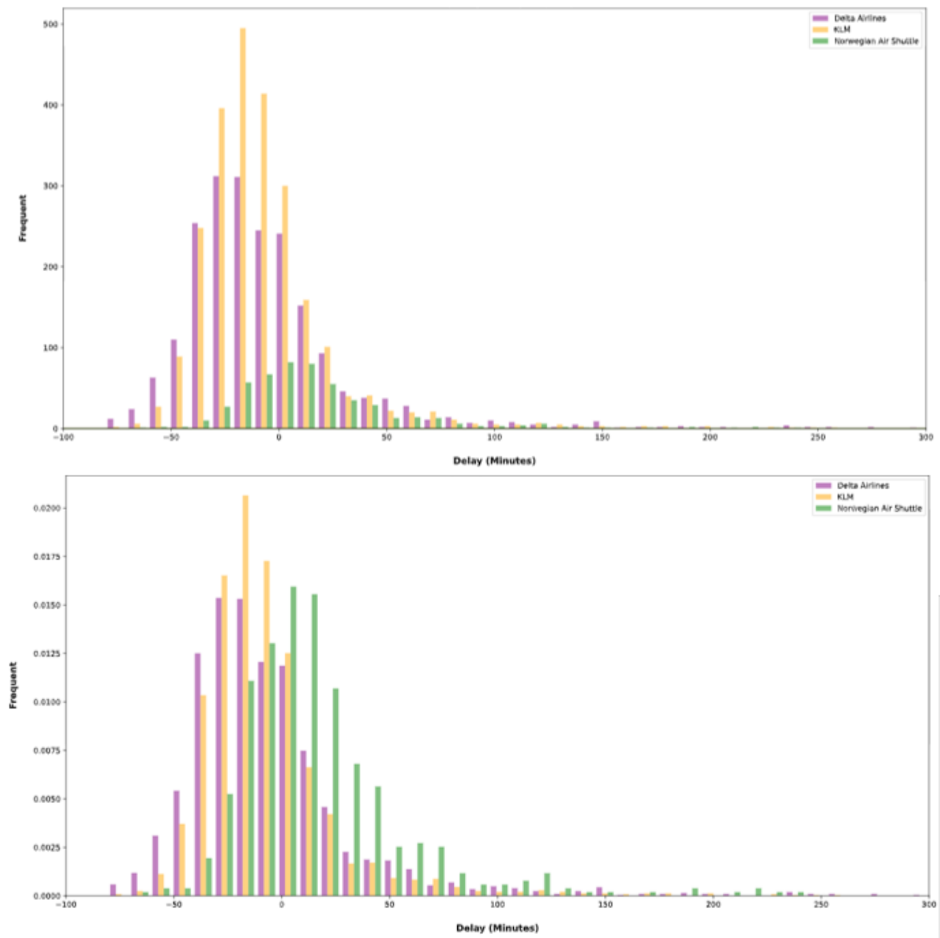

Figure 3.8: Not normalised histogram (above) and normalised histogram (below)

3.3.2. Regression Graph

Once the general trends of the delay are observed, the case study will look into the other components of model scheme to find which phase may have affected to the delay. The delay time is the time difference of the off-block time of a departure flight. The regression model is used to examine each component of the model scheme. The focal objective of using regression model is not to predict the exact delay time caused by various phases of model scheme, but to know which phase exhibits the correlation to the delay time. The candidate parameters are the time difference of the previous arrival on-block time, aircraft preparation time, taxi time and the flight time.

In order to find correlations, first, each phase and delay time per one aircraft will be illustrated in a scatter plot. The x-axis of plot would be the selected parameter, and the y-axis, dependent variable would be the delay time. From the scatter plot, one can observe whether two variables show the evident correlation by a first look. To confirm these relations, two types of regression methods are added to the scatter plot. The polynomial regression uses the powers of the independent variable on a dependent variable (Ostertagová, 2012). However, the case study does not try to find a precise prediction of the delay, accordingly, the analysis will not dig into the details to find the exact formula of polynomial graph.

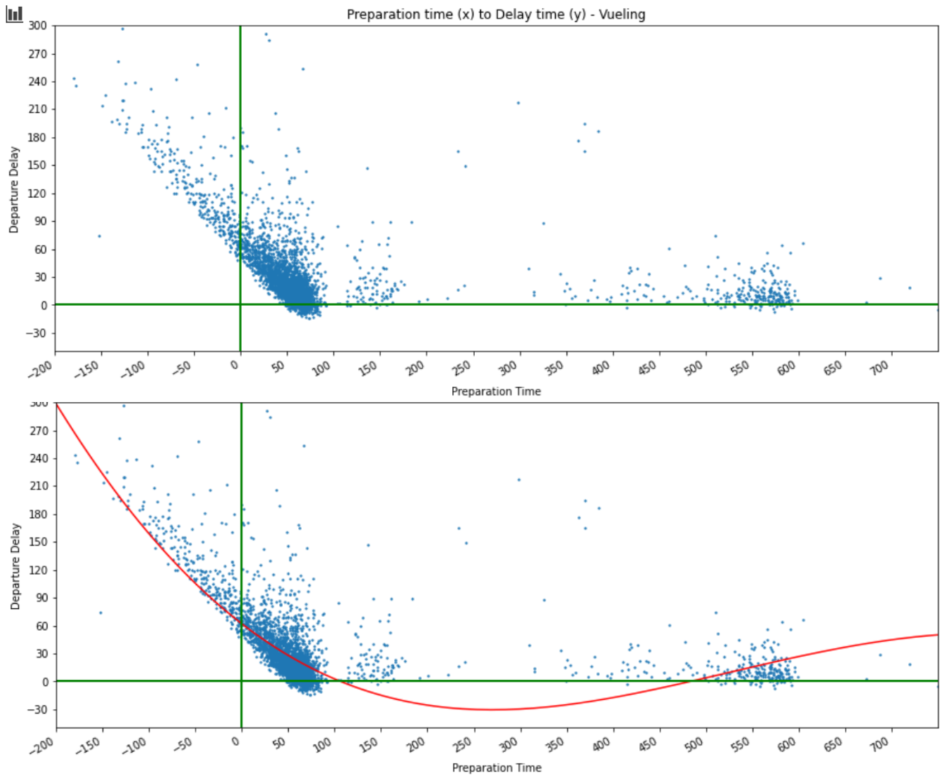

Figure 3.9: A scatter plot of the preparation time to delay time, without (above) and with (below) polynomial regression line

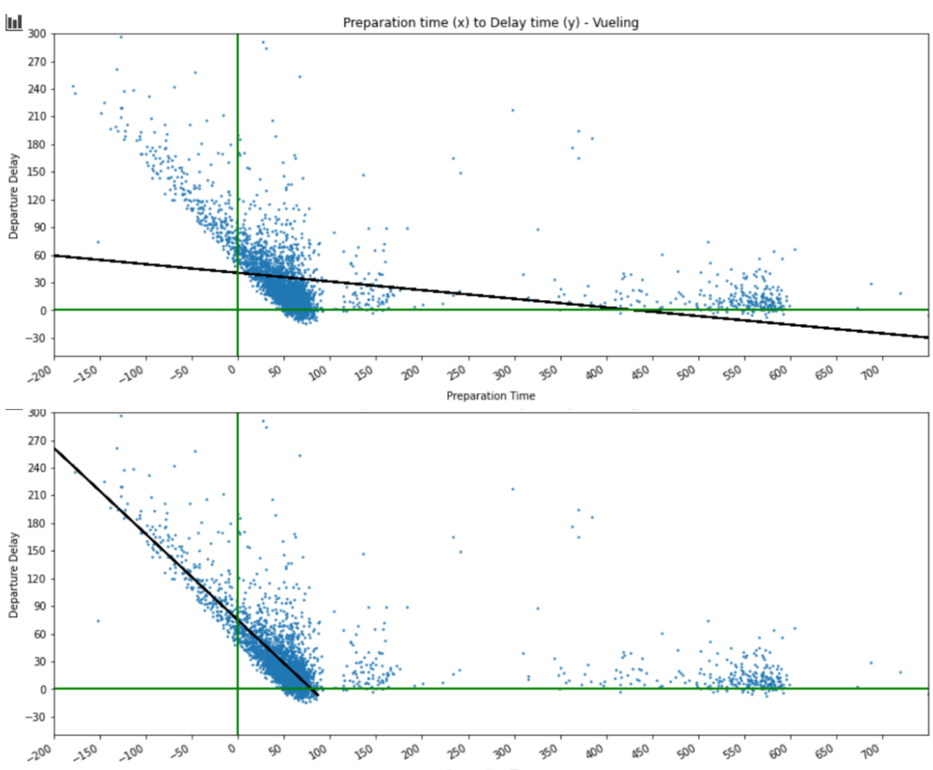

Figure 3.10: A scatter plot of the preparation time to delay time, (above) and with linear regression line

The first plot of Figure 3.9 shows the initial scatter plot. In this example, independent variable is set to the preparation time of Vueling Airline. The second plot with a polynomial regression line depicts that the relation between two variable has changed when the preparation time reached around 100 minutes. After the initial examination from the visual, the linear regression line can be drawn. The linear regression can find a linear relationship between data points while coefficients assess the association (Twomey & Kroll, 2008). However, as the behaviour of data points can be changed at some point, using a linear regression to whole data points and partial data points will show the different results. Figure 3.10 shows the two different linear regressions, first figure used the entire data points to calculate the linear regression whereas the second one used the partial points as suspected from polynomial graph. Unlike the first graph of Figure 3.10, the second figure shows the clear correlation between two variables.

Among the four candidate parameters, the time difference of the previous arrival on-block time and aircraft preparation time were selected at the end. The taxi time and the flight time did not have a wide range of data to find the linear correlation as it is shown in Figure 3.11. The range of x-axis is only 0 to 50 as opposed to y-axis has a range of -50 to 300.

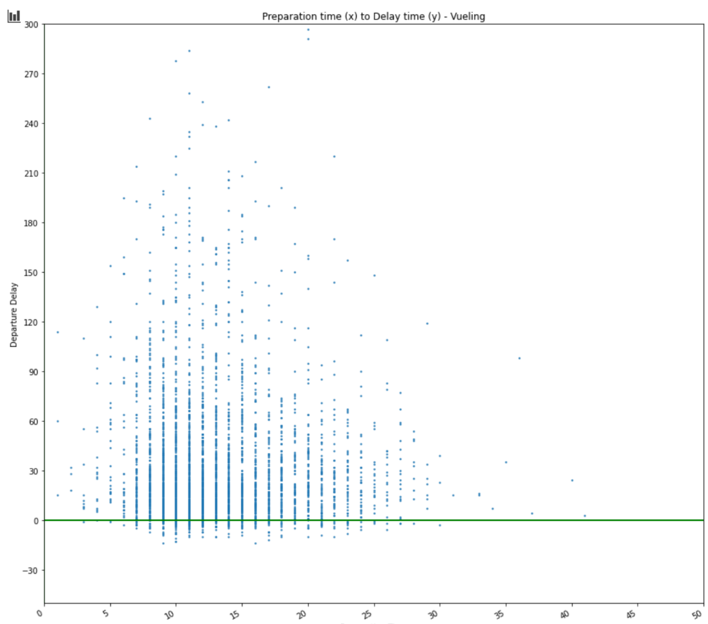

Figure 3.11: A scatter plot of the taxi time to delay time

3.3.3. Heat Map

The histogram can show the general trend of data and linear regression can detect the correlation between two variable by plotting individual data points. As a final step, trends of airports and airlines will be examined by clustering the data into monthly average. The datasets can be aggregated into the period of interest, however, considering amount of data and to detect the seasonal effect, monthly aggregation is selected. As a visualisation method, the heat map will be used. The clustered heat map compacts the large data to bring out coherent patterns with an assigned colour in the grid (Weinstein, 2008). It will use to find the seasonal affect on the airport and aircraft which might affect the delay time.

Initially, four candidates were considered to render into a heat map, departure and arrival delay, taxi time and flight time.

The first candidate is the flight time. Flight time is measured by the time between take-off and touchdown of an aircraft. The 'flying' phase is set to one of the important factors of both arrival (Figure 3.5) and departure (Figure 3.6) of the model scheme. The flight time have more effect to the delay time when it comes to the long-distance flight. In a short-distance flight, the total flight time is one to two hours. For the intercontinental flights, flight time goes over 6 hours and the jet stream can push or hinder an aircraft. The flight time is differed by jetstream more than half an hour, and colour scheme of heat map could give an intuitive visuals to find a pattern.

3.4. Five Airports for the case study

Josep Tarradellas Barcelona-El Prat Airport (Barcelona Airport, BCN) - Josep Tarradellas Barcelona-El Prat Airport, or simply Barcelona airport is the second busiest airport in Spain as it serves a gateway to Barcelona (BCN Airport, n.d.). The well-known low-cost carrier based on Spain Vueling has BCN as a hub airport. Among five selected airport, only BCN is not a hub airport for a flag carrier airline, but for the low-cost carrier. In light of that, the seasonal trend is expected during the summer for the tourists, as a low-cost airline are attractive to provide the affordable service to tourists.

Heathrow Airport (London, LHR) - 80.1 million passengers traveled through London Heathrow airport in 2018 LHR Airport (n.d.). As a hub airport of British Airways, the flag carrier of United Kingdom, British Airways exclusively uses the terminal 5 of LHR while KLM uses terminal 2. In the research of Efthymiou et al. (2019), a few reasons for delays at British Airways were revealed with interviews. They described ATC restrictions, strikes and crew limitations as the most common reasons. British Airways cancelled flights in a tactical reason to ensure that they have the right resources from disruption. The comparison between KLM and British related to the delays at LHR can be made.

Václav Havel Airport Prague (PRG) Prague airport is a base airport of Czech Airlines. The analysis of Zámková and Prokop (2015) revealed that 36% of carried out flights from PRG airport got delayed. The results also concluded that delays from aircraft technical issues are most frequent in Prague, alongside with operational control, limitation from the high concentration of air traffic. It would be interesting to see if the delays caused by technical issues are mostly coming the Czech Airlines based on PRG or also from KLM, another operator from PRG. In addition to that, from the results, one might be able to presume if the delay of Czech Airlines are crucial enough to assume that the delays of PRG are caused by Czech Airlines.

John F. Kennedy International Airport (JFK) John F. Kennedy International Airport is located in New York and is a hub airport for the Delta Airlines JFK Airport (n.d.). JFK airport had undergone challenges due to the growth in international traffic and the development of of a domestic hub for JetBlue Airways (Jacquillat & Odoni, 2014). Jacquillat and Odoni (2015) reported most delays in JFK airport created by imbalances between demand and capacity. It normally takes 7 hours flying from JFK to AMS, the different behaviour between long-distance and short-distance flight will be worth watching.

Singapore Changi Airport (SIN) Singapore Changi Airport has award the world's best airport by the Skytrax in seven years in row at 2019 (Independent, 2019). Changi Airport began the policy-making operations as an airport management firm (Bok, 2015) and branded themselves as a 'model' of airport management. With their renowned status of airport, the paper assumed that SIN airport would have the most conformity behaviour amongst five airports.

3.5. External Data Source

The initial data sets were limited to those provided by ACNL. The datasets include the date, flight number, registration number of flight, previous or next airport of flight, aircraft type, requested slot time, coordinated slot time, scheduled slot time, actual on/off block time, actual take-off/touch-down time. While it gives the information of departing and arriving flights from/to AMS, the data outside of AMS is not included. Once the case study airports were determined, external datasets were obtained to fill the gap. From exploratory analysis, it was hard to obtain the external datasets, with a concern of commercial usage. Most of the open-source website states that it is forbidden to use the dataset collected by them with a commercial purpose.

As the research focuses on the misuse of operating significantly different time from the allocated slot, the actual departure time data needs to be included in the data. In the dataset of ACNL, the requested time of airlines was included, however, open-source data only included the scheduled and actual departure time. The term 'departure time' was interpreted in two different ways depending on the source. It can be interpreted as the off-block time of aircraft or the take-off time of aircraft. To figure out the exact meaning behind the common term 'departure time' and verify the data, random rows were selected and cross-referenced to the ACNL dataset. If the entry matches or differs a maximum of one minute, it considered a suitable source and sorted between two definition. Table 3.1 shows the overview of the data source from the open-source. The details of data entry can be found at Appendix A. The data scraping is done by the python library 'BeautifulSoup'.

Table 3.1: List of External Data Source.

Data Source	**Description**
FlightAware	FlightAware provides the actual and scheduled times of on/off block, take off, touch down, taxi time at both airports, flight altitude, flight speed, flight route. However, each flight is separated by one page, and a free account can access the historical flight pages only if one knows the actual departure time. If an aircraft departs from outside of AMS, it is hard to track the actual take-off time and find a page.
Flightera	Flightera provides the scheduled on/off block time and actual take-off, touch-down time as well as tail number. The flights are searched by the flight number and month, hence, the flight number from ACNL's data can easily be linked to scrape the data. Despite the data being available in September 2017, quality data can be obtained with a free account.
PRG-aero	PRG-aero specifically provides data related to the arrivals and departures of Prague airport. While the available data begins from 2013, data sets between November 2018 to March 2021 are absent. In spite of data being limited to actual on/off-block time, data sets can be searched only with flight number.
Dutch Plane Spotters	Dutch Plane Spotters provide the scheduled and actual arrival time and scheduled, actual arrival time per aircraft. The search query solely requires the date, and all flights that departed or arrived at AMS will be provided.
California Regional Weather Server	California Regional Weather Server was used to examine the impact of jetstream on the flight time. It provides the picture of jetstream since 2017 with a 6 hours gap between pictures.
Time and Date	A website 'Time and Date' was used to confirm the daily airport weather condition that may have affected in flight schedule. It provides the daily and hourly analysis of weather all around the world. Conditions are including temperature, wind speed, wind direction, barometer and visibility.

4

Case Study

In this chapter, five airports around the world are selected to test the model scheme defined in section 3.1, and apply the data analysis explain in section 3.2, with the external datasets from section 3.5. Selected airports are Josep Tarradellas Barcelona-El Prat Airport (BCN), London Heathrow Airport (LHR), Vaclav Havel Airport Prague (PRG), New York John F. Kennedy International Airport (JFK), Singapore Changi Airport (SIN). These airports will be referred to as their IATA code. The short distance flights are characterized as flights operated within Europe. BCN, LHR and PRG are classed as short-distance flights. On the contrary, long-distance flights are characterized as departing/arriving outside of Europe from/to AMS. Intercontinental flights such as JFK and SIN are classed as long-distance flights.

4.1. Short Distance Flights

As mentioned earlier, short-distance flight airports are consist of BCN, LHR and PRG. The flight time of short-distance flights are around one or two hours, they are less affected by weather condition such as a jet stream. If the hub airport of the airline is not Schiphol airport, an aircraft is most likely would go back to its origin airport. In addition, as established earlier, airlines want to utilise the resource as much as they can. Thus, the slack time and preparation time at AMS, the difference between scheduled and actual travel time would be crucial to analyse the correlation of slot misuse.

4.1.1. Josep Tarradellas Barcelona-El Prat Airport (Barcelona Airport, BCN)

Table 4.1 summarises the passenger flights operated between AMS and BCN. From 1-Jan-2017 to 31-Dec-2019, 25111 passenger flights were operated between Schiphol airport and Barcelona airport.

Table 4.1: Total number of flights from 1-Jan-2017 to 31-Dec-2019 between AMS and BCN

Airline	Airline code	# of registration code	# of flights (D + A)
Vueling Airlines	VK, VY	152	9512 (4747 + 4765)
KLM	KL	58	10830 (5417 + 5413)
Transavia Holland	HV	56	4748 (2372 + 2376)

From Figure 4.1, the overall trend of early or late departure can be detected. Figure 4 is normalised by 1 regardless of the total number of flights. Vueling Airlines had a total of 4747 flights that departed from AMS to BCN, and KLM had 5417 flights. However, considering the shape of the graph, the purple line – Vueling

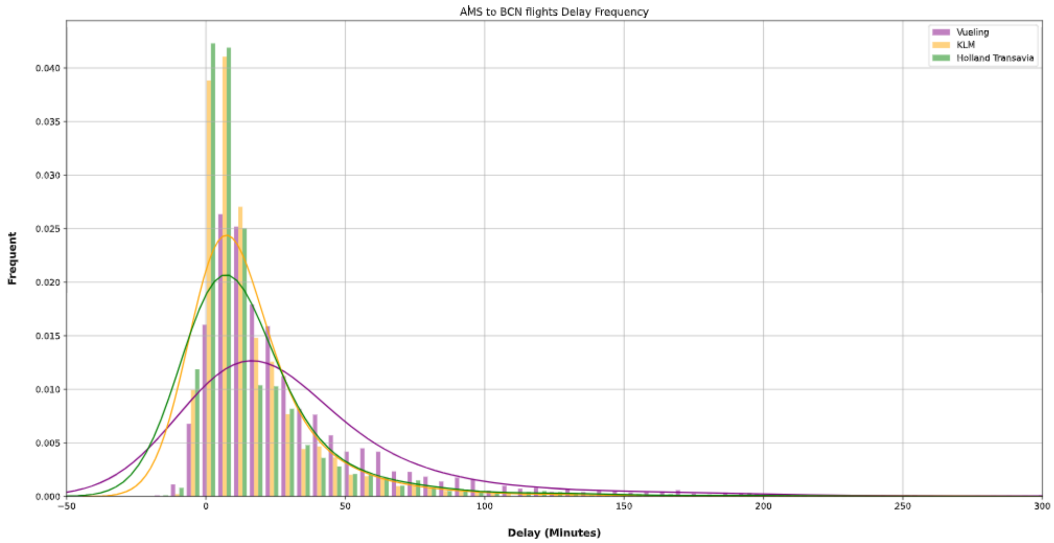

Figure 4.1: Normalised histogram of flights delay frequency from AMS to BCN

Airlines – has an overall high rate of departure delay. The model scheme of departure defined that the previous arrival time of aircraft and slack/preparation time act as a crucial part of departure delays.

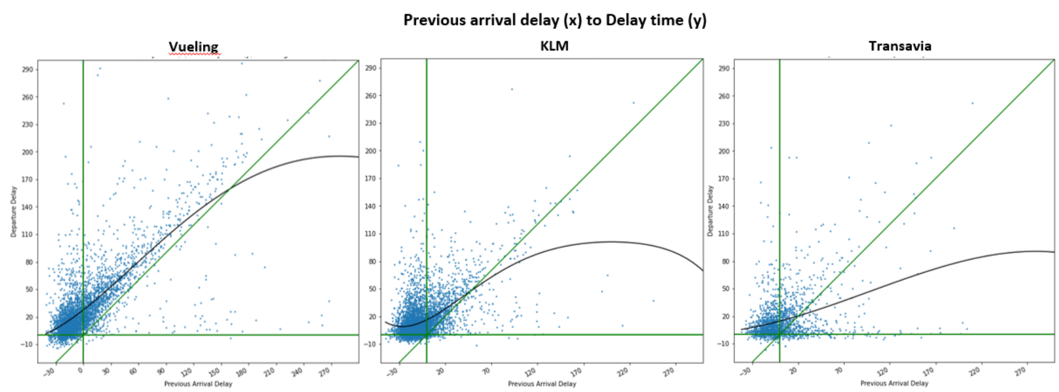

Figure 4.2: Previous arrival delay to delay time of three airlines that operated from AMS to BCN

Each figure of Figure 4.2 represents the relation between one aircraft's early or late arrival and its early/late departure after preparation. If arrival time was later than what was scheduled, naturally, the time for preparing aircraft for the next passenger would be shorter than expected and would lead to delay. If the dot locates in the second quadrant, it means despite the aircraft arriving at the AMS earlier than was expected, the departure after the preparation was delayed than scheduled. If the dot locates at the first quadrant, it means the aircraft not only arrived late at AMS but also departed later than scheduled. Moreover, if the dot in the first quadrant is located higher than the y=x green line, it represents the departure delay in minutes was later than its arrival delay in minutes. The black graph indicates the polynomial regression of x and y.

KLM and Transavia do not have a strong correlation between previous arrival delay to delay time, but Vueling has a weak correlation. The R-square value of linear regression for Vueling is 0.46. The previous arrival time is directly linked to the preparation time. Arriving behind the schedule would make the preparation time shorter than the slack time.

The preparation time is calculated by the difference between the actual on-block time of previous arrival flights and the scheduled off-block time. Thus, the preparation time refers to the given time to airlines to alight the passengers, clean and prepare the aircraft, and board the passenger to depart on the scheduled

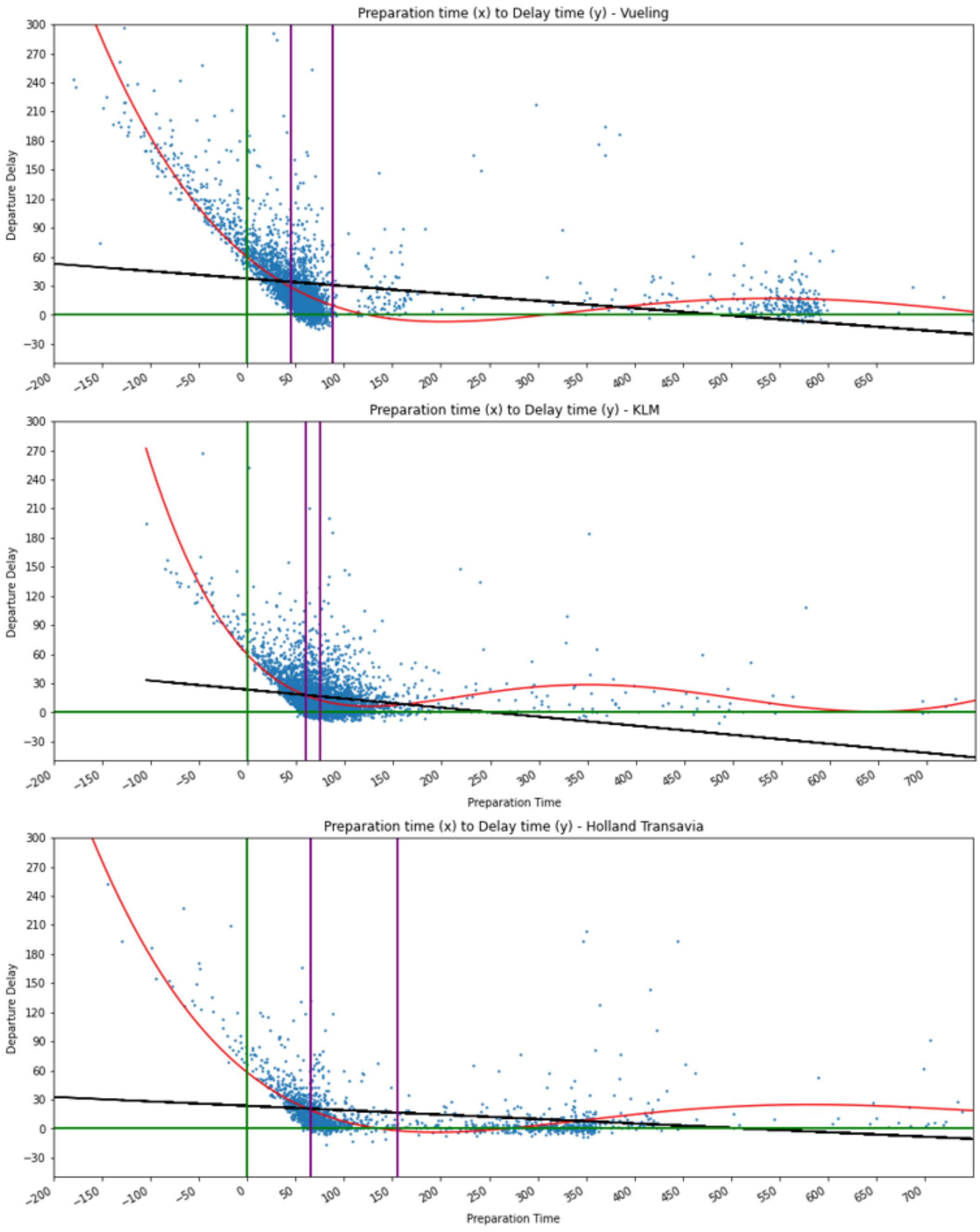

Figure 4.3: Preparation time to delay time of three airlines that operated from AMS to BCN

time.

Table 4.2: Mean/median value (minutes) of slack time for three airlines operated from AMS to BCN

	Mean Value	**Median Value**
Vueling Airlines	88.3	45
KLM	74.1	60
Holland Transavia	154.8	65

Purple lines of figure 6 indicate the mean or median values of slack time. Slack time is the difference between scheduled arrival time and scheduled departure time, which airlines would have believed to be enough time to prepare the aircraft. If the dot is located to the left-hand side of lines, the aircraft would have arrived behind schedule, consequently, the airline would have less time to prepare than what was expected. The red line is the polynomial regression of x and y, and the black line is the linear regression of x and y. If the preparation time is smaller than zero, the flight would have arrived later than the slack time, in the case of Vueling, most likely more than 45 minutes.

Compared to the other two airlines, most Vueling Airlines' points are scattered to the left of both purple lines, and the possibility of getting behind schedule of departure flights significantly increased with it. From the visual, one can assume that Vueling would have a linear correlation if the flights are limited to those that have a preparation time of fewer than 88 minutes, the mean value of the slack time for Vueling. The R-square value of linear regression for the limited Vueling flights is 0.7, stronger than before. One notable point of figure 6 is that KLM and Vueling have similar mean and median values of slack time. However, unlike Vueling Airlines, KLM has relatively well-distributed preparation time around slack times. From figure 5 and 6, one can suspect that KLM might have compensated their time from late arrival by preparation time, on the other hand, Vueling's tight preparation time only accelerated the delay of departure.

The departure part of the model scheme and the arrival part are closely linked. Especially for turnaround flight, as it was shown in earlier figures, arrival delay shortens the preparation time and affects the departure delay. The arrival scheme needs to be applied with external datasets to analyse the departure delay.

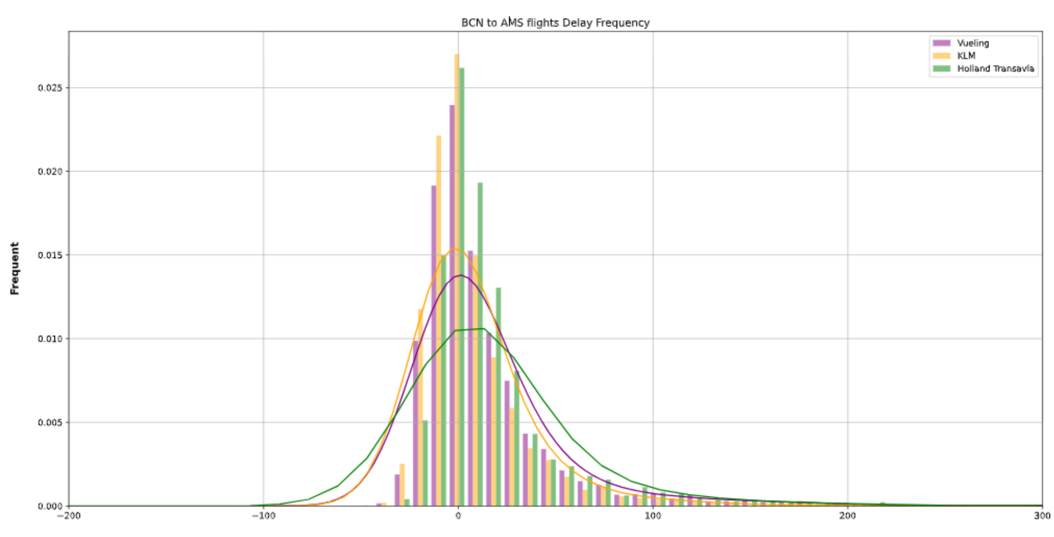

Figure 4.4: Normalised flight delay frequency from BCN to AMS

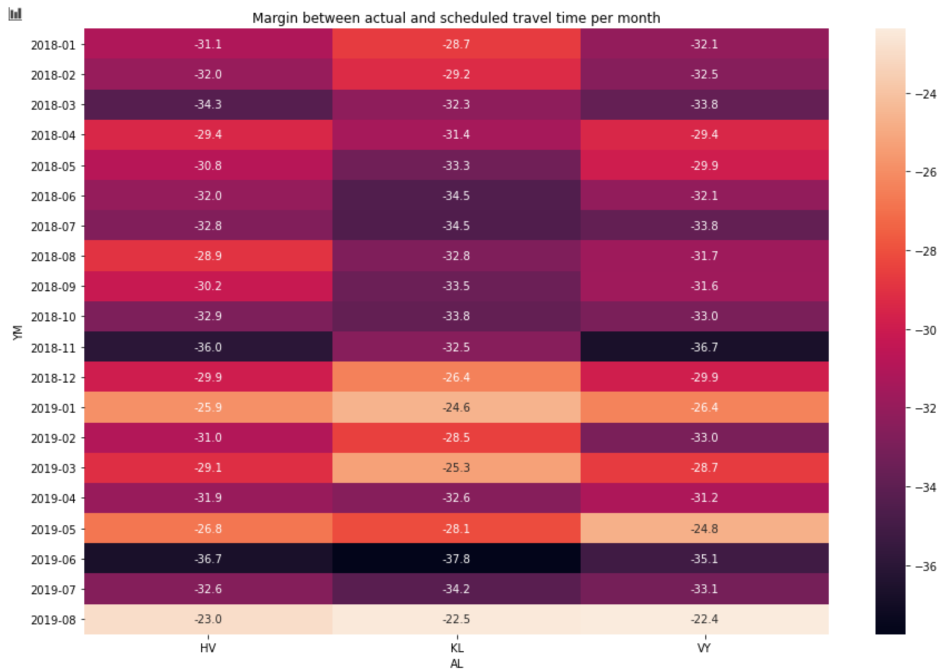

Figure 4.5: Margin between actual flight time and scheduled travel time from BCN to AMS per month

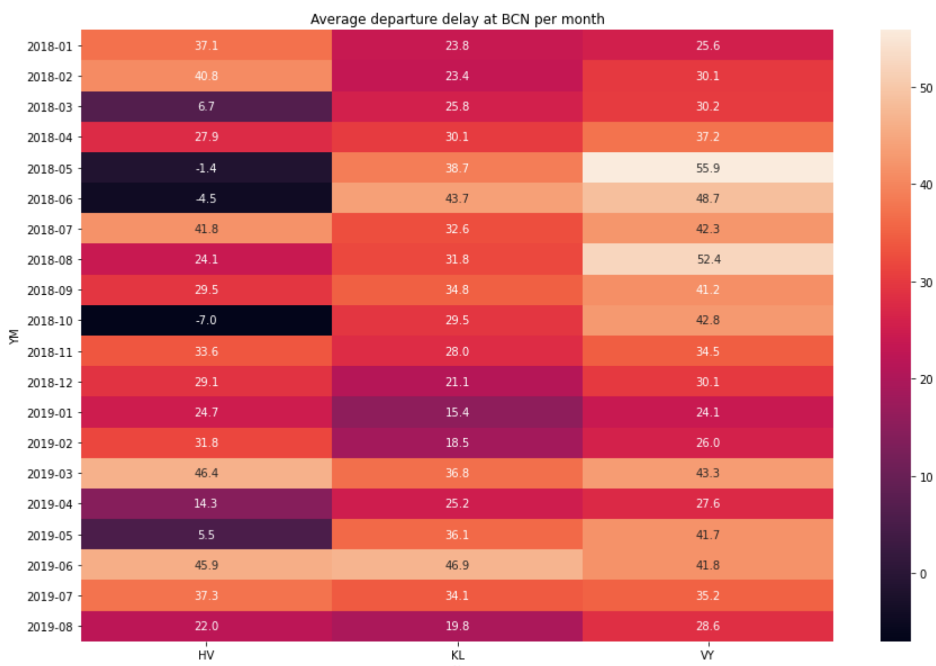

Figure 4.6: Average departure delay at BCN heading to AMS per month

Figure 4.4 depicts the histogram of arrival delay from BCN to AMS. Vueling and KLM have a similar shape and well-distributed around zero.

For the arrival flights, once the external datasets were obtained, it was possible to calculate the travel time. The travel time includes the taxi time at the previous airport, flight time and taxi time at AMS. If the scheduled travel time has a large margin, an airline can manage a sudden change that affects the longer travel time. On the other hand, if scheduled travel time does not have any margin, longer taxi time or unexpected delay in the air would directly affect the delay.

Figure 4.5 depicts the margin between actual flight time and scheduled travel time from BCN to AMS. All three airport have a marginal time of around 30 minutes, since the flight time does not include the taxi time at both airports, airlines would have approximately 30 minutes to taxi. From the EDA process, the paper assumes that combined taxi time at both airports is 15 minutes. It leads to another figure, Figure 4.6, average departure delay time at BCN.

Airlines would have 15 minutes of buffer time that can absorb unexpected delay. Nevertheless, if the delay was longer than the buffer time the impact will appear at the arrival delay, consequently, at preparation time. Vueling had bigger than 30 minutes of delay, which the buffer time cannot redeem. As a result, the consequence of the off-block time at BCN is implied in Figure 4.7.

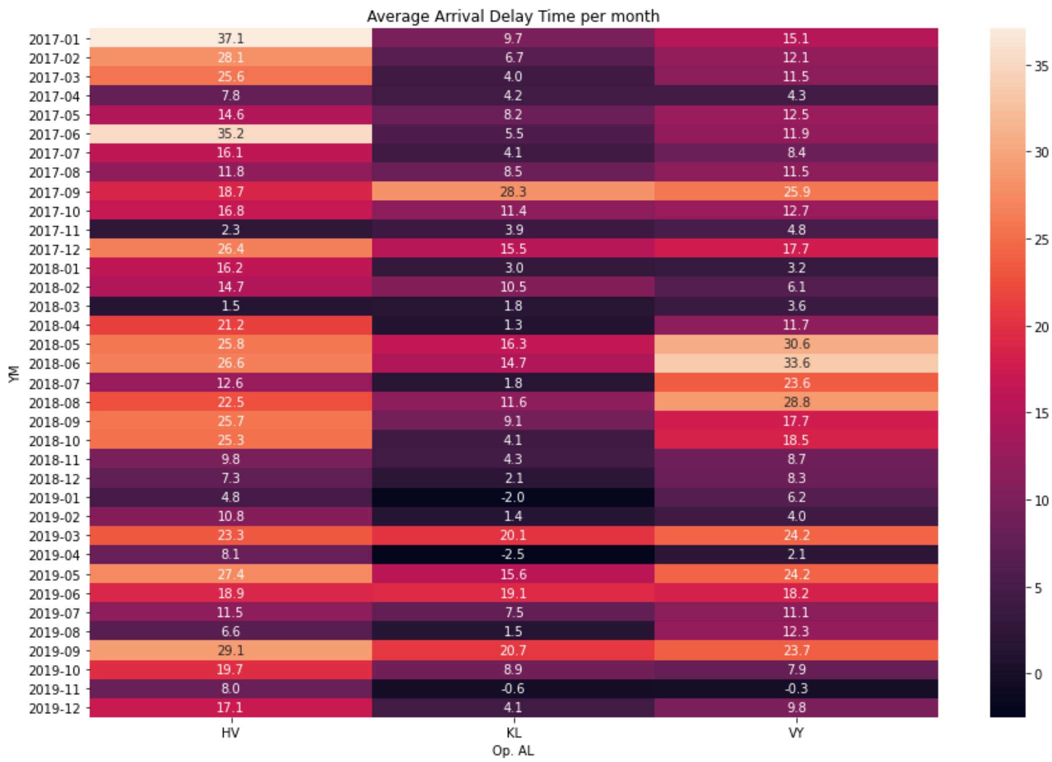

Figure 4.7: Average arrival delay time at AMS per month

4.1.2. Heathrow Airport (London, LHR)

From 1-Jan-2017 to 31-Dec-2019, 38776 flight were operated between LHR and AMS, detail breakdowns are explained in Table 4.3.

Table 4.3: Total number of flights from 1-Jan-2017 to 31-Dec-2019 between AMS and LHR

Airline	Airline code	# of registration code	# of flights (D + A)
British Airways	BA	144	17288 (8652 + 8636)
KLM	KL	119	21488 (10730 + 10718)

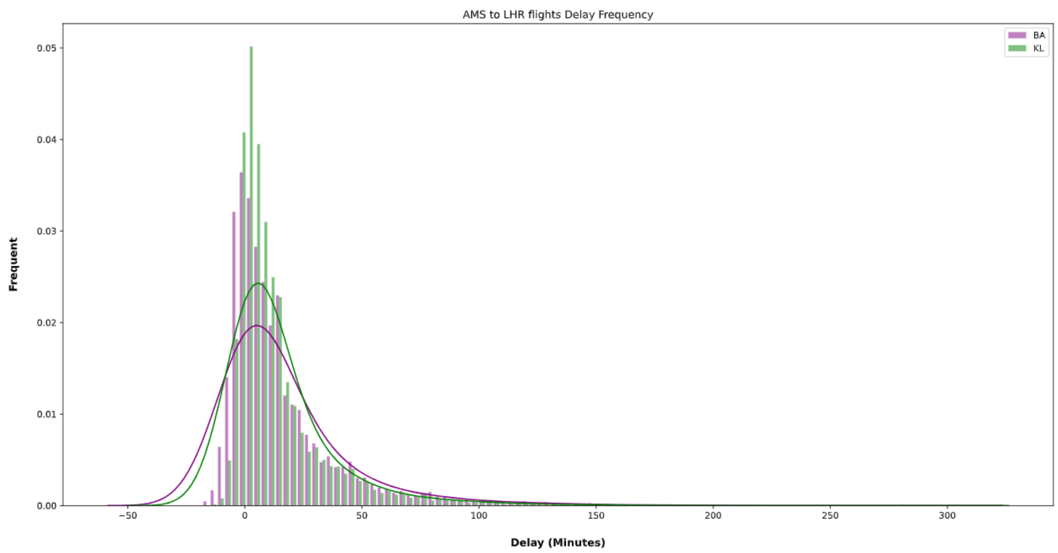

Figure 4.8: Normalised delay frequency from AMS to LHR

Similar to the BCN case, KLM showed better conformity behaviour to allocated slots. British Airways appeared to have slightly more delay or early departure than KLM. In Figure 4.9, the potential cause for the departure delay can be found.

British Airways and KLM have different behaviour on the relation between previous arrival delay and departure delay. From the visual, the strong correlation between two parameters can be sensed, the linear regression (black line) has 0.8 degrees of slope, intercept of 18, and 0.63 R-square value. If the British Airways aircraft arrived behind the schedule, the delay time of departure from AMS to LHR will be expected to be 18 minutes plus 0.8 times of the previous arrival delay time. If British Airways scheduled plenty of slack time, some amount of delay time can be recovered during the preparation time.

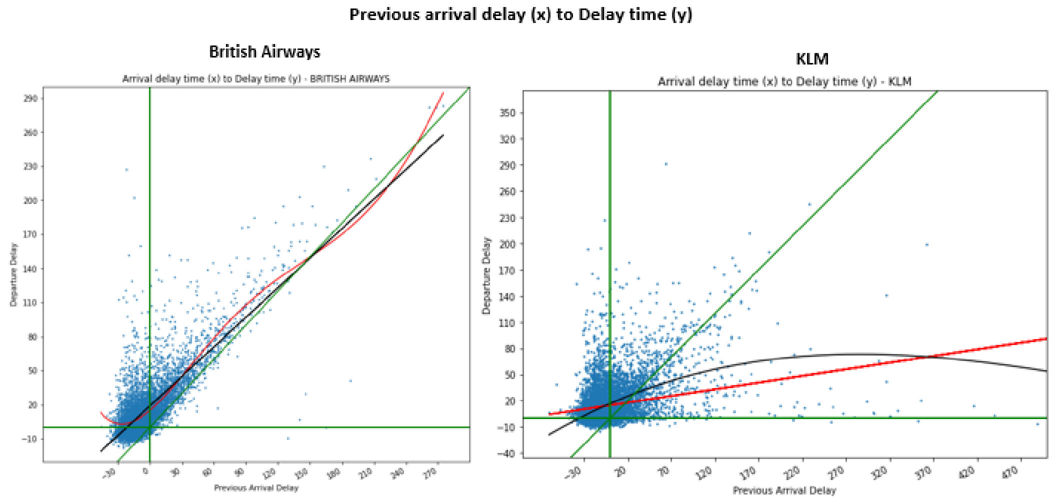

Figure 4.9: Previous arrival delay to departure delay time of flights operated from AMS to LHR

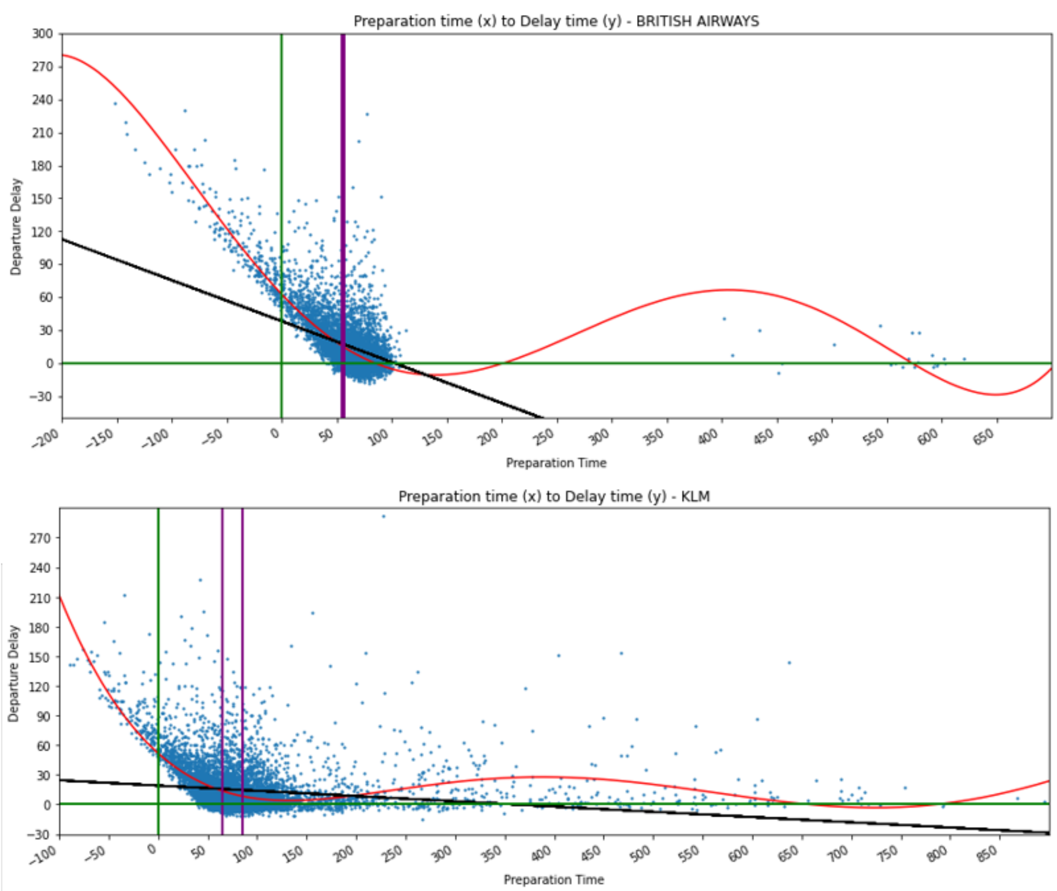

Figure 4.10: Preparation time to departure delay time of flights operated from AMS to LHR

Table 4.4: Mean/median value (minutes) of slack time for three airlines operated from AMS to LHR

	Mean Value	**Median Value**
British Airways	56.8	55
KLM	84.6	65

However, this is unlikely based on Figure 4.10 and Table 4.4, median and mean value of the slack time are 55 minutes and 57 minutes, respectively. While 20 percent of flights departed earlier than scheduled, 35% of flights were departed behind the schedule despite they had preparation time larger than 55 minutes. It can be interpreted as even though an aircraft had more preparation time than what was expected, there is 60 percent of chance of getting delayed on departure. On the other hand, KLM has more dynamic and ample slack time and preparation time than British Airways, therefore, they could prevent the previous delay to snowball into departure delay.

To track the potential cause of the previous arrival delay, the arrival flights from LHR to AMS were investigated. The relation and values between (actual flight time - scheduled travel time) and the average departure delay at LHR had very similar results as BCN case. Marginal time for taxiing at airports are around 30 minutes, but departure delays at LHR was not small enough to cover by marginal time. The detail values are depicted in Figure 4.11.

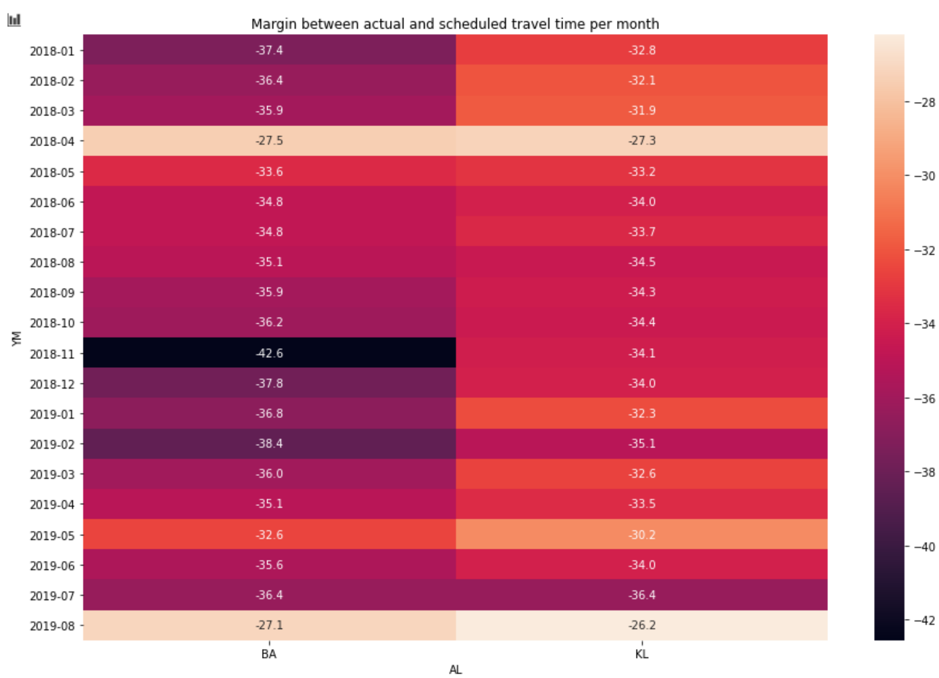

Figure 4.11: Average margin between actual flight time and scheduled travel time per month

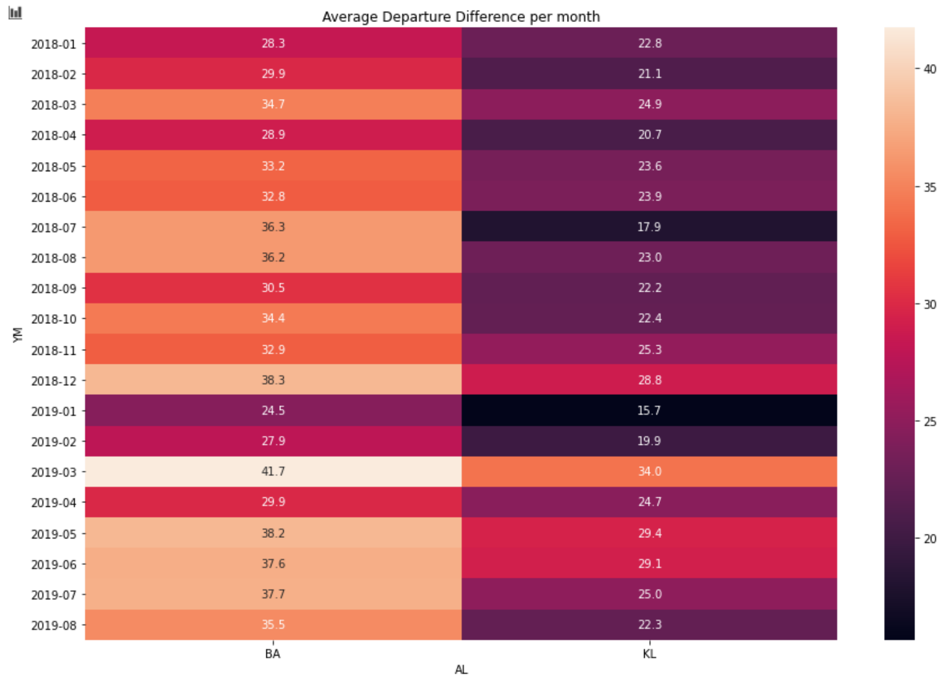

Figure 4.12: Average departure delay at LHR heading to AMS per month

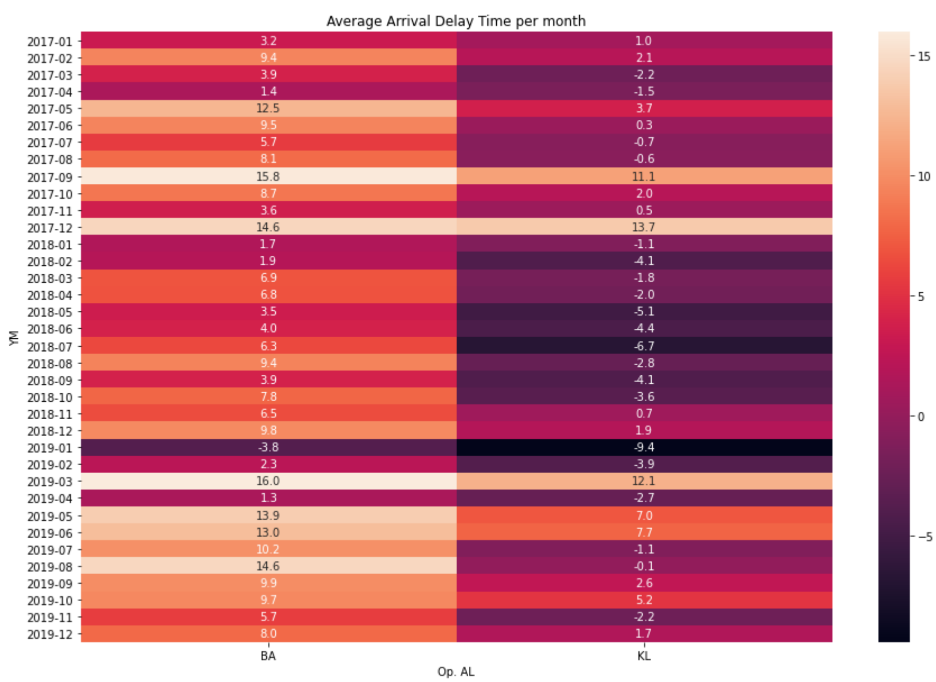

Figure 4.13: Average arrival delay time in AMS per month

4.1.3. Václav Havel Airport Prague (PRG)

Three passenger airlines with a total number of 16422 flights were operated from 1-Jan-2017 to 31-Dec-2019. Among three airlines, easyJET changed their IATA code from EZY to EJU on 30 March 2019.

Table 4.5: Total number of flights from 1-Jan-2017 to 31-Dec-2019 between AMS and PRG

Airline	Airline code	# of registration code	# of flights (D + A)
EasyJET	EJU, EZY	220	3520 (1761 + 1759)
KLM	KL	121	8915 (4462 + 4453)
Czech Airlines	OK	57	3987 (1992 + 1995)

Figure 4.14 shows that KLM had higher conformity behaviour, easyJET and Czech Airlines had more delays than KLM. Notably, a line of Czech Airlines (green line) leans toward the right-hand side. Czech Airlines is the flag carrier of the Czech Republic, and has a PRG airport as a hub. Since an extra external dataset was available for PRG and most Czech Airlines flights departed from PRG to AMS and went back to PRG, the extra analysis would be possible.

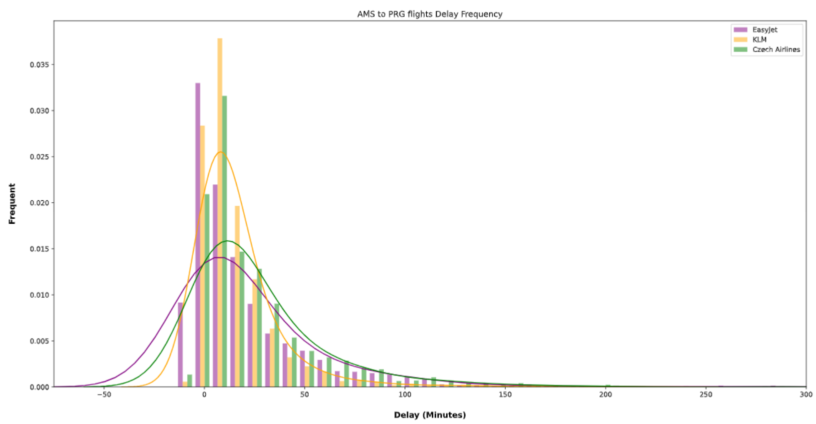

Figure 4.14: Normalised histogram of flights delay frequency from AMS to PRG

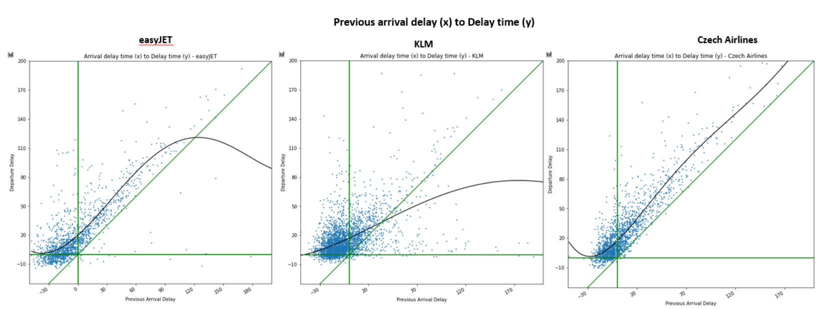

Figure 4.15: Previous arrival delay to departure delay time of flights operated from AMS to PRG

In Figure 4.15, 70% of KLM flights had a minus previous arrival delay time. The negative value of the previous arrival delay time indicates that an aircraft arrived earlier than scheduled. As shown in Figure 4.16, despite having sufficient preparation time as an airline expected, the departure delay still occurred. Considering that the KLM flights are not necessarily travelled from the airport of destination, departure delay could have created from another reason, such as delays at the gate or mechanical problem, etc.

Table 4.6: Mean/median value (minutes) of slack time for three airlines operated from AMS to PRG

	Mean Value	Median Value
easyJET	48	30
KLM	89.2	55
Czech Airlines	47.2	45

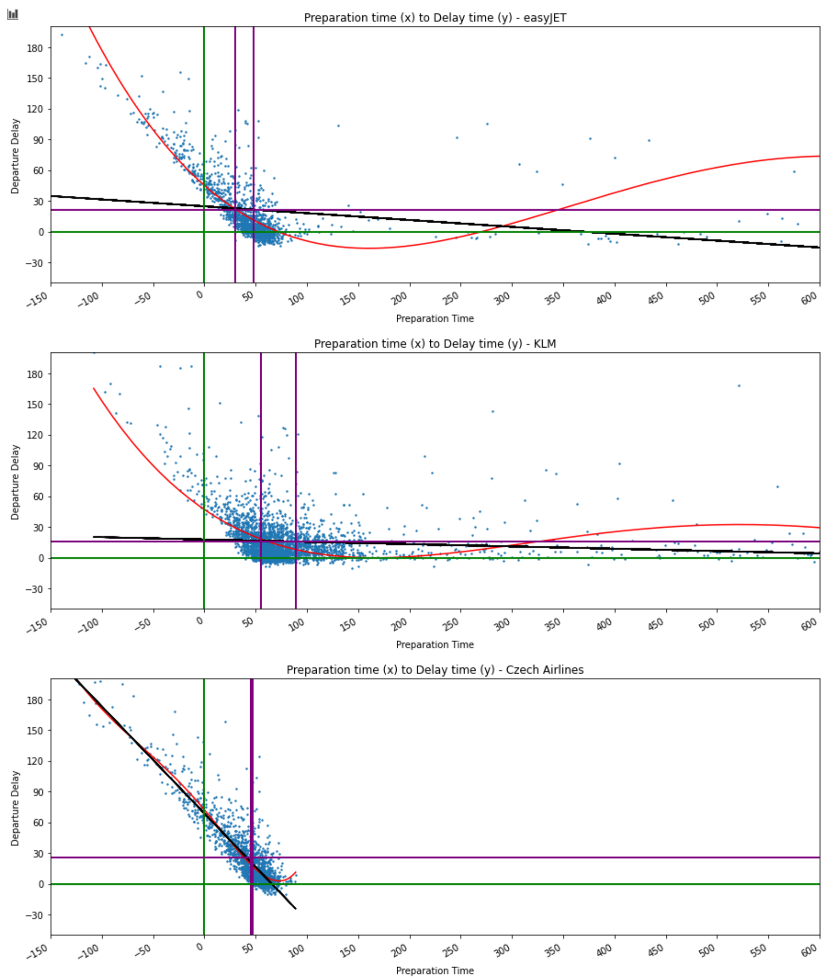

Figure 4.16: Preparation time to delay time of flights operated from AMS to PRG

On the other hands, Figure 4.15 and Figure 4.16 show a correlation between each parameter and departure delays. The linear regression of the previous arrival delay time to departure delay has a 0.76 R-square value. The slope and intercept of linear regression are 1.1 and 19, respectively. As all flights of Czech Airlines were a turnaround flight, 66% of flights had 45 minutes of slack time and 28% of flights had 50 minutes of slack time. The linear regression of Czech Airlines in Figure 4.16 showed 0.76 R-square value, -1 of coefficient and 68 of intercept. It implies that even though an aircraft arrived on time, the prediction of departure delay would be 23 minutes. Moreover, unlike the aforementioned KLM, most Czech Airlines flight travelled from PRG and departed to PRG, thus, previous flights of Czech Airlines would have a direct impact on its delay on departure.

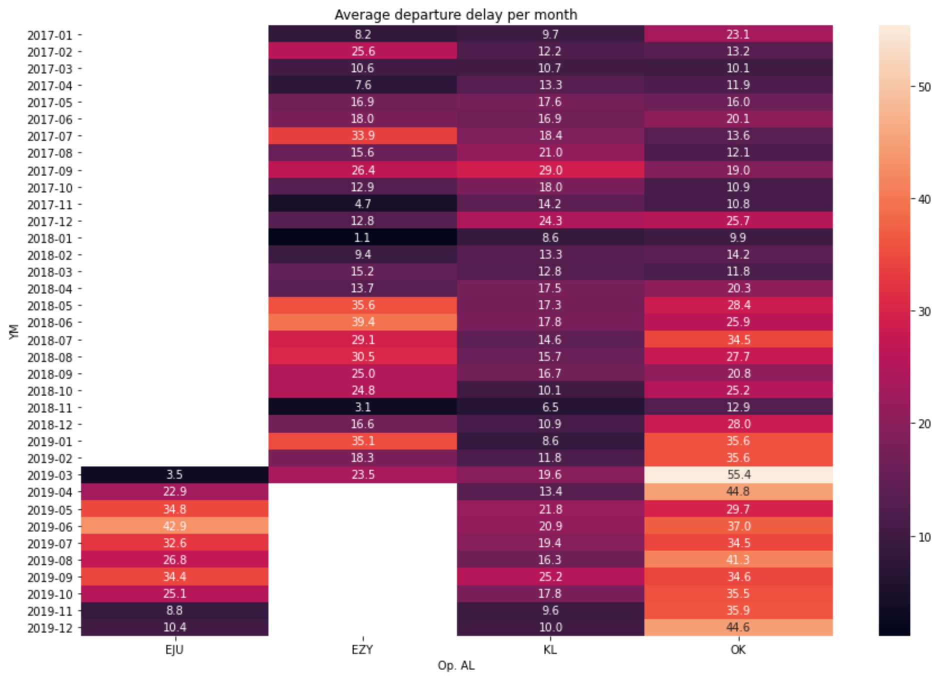

Figure 4.17: Average departure delays at AMS per month

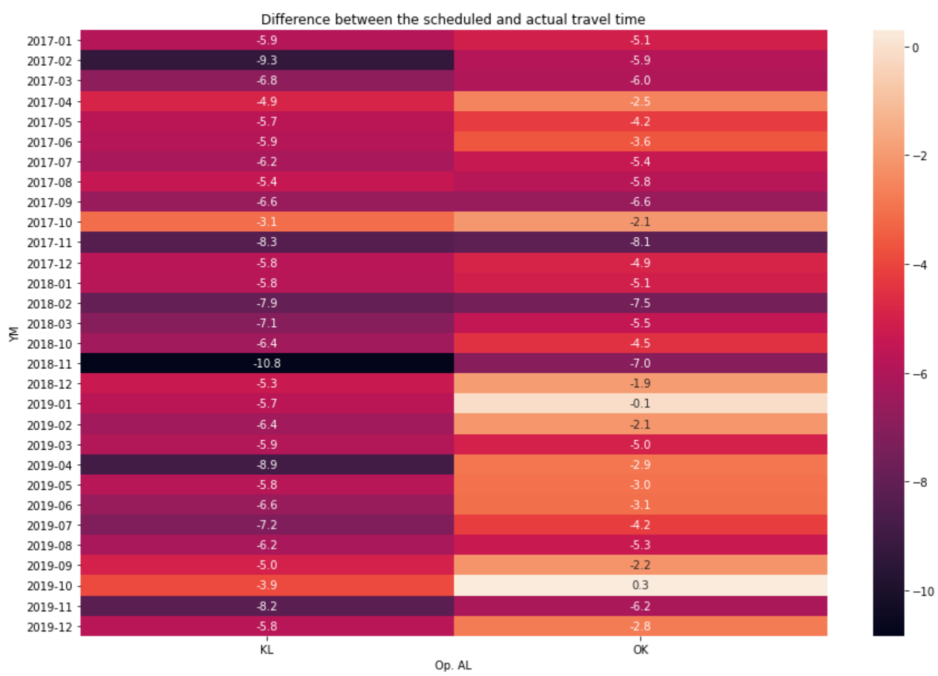

Figure 4.18: Difference between the scheduled and actual travel time per month

As it observed at Figure 4.15 and Figure 4.16, flights of the Czech republic had a correlation between departure delay and previous flights. To follow the previous flights, flight time from the previous airport, in this case PRG, to AMS is worth looking at. Figure 4.18 illustrates the difference between scheduled travel time and the actual travel time. It was defined at section 3.1 that travel time includes the flight time and taxi time at both airports. The difference remained under 10 minutes, and the gap was more narrow for Czech Airlines. With a combination of Figure 4.17, chronic delay can be observed March 2019 and onward for Czech Airlines.

The small difference between scheduled and actual travel time implies that the off-block delay in PRG would immediately affect the arrival delay, and will be snowballed to the departure delay at AMS. To confirm this hypothesis, data of scheduled and actual off-block time at the PRG was used.

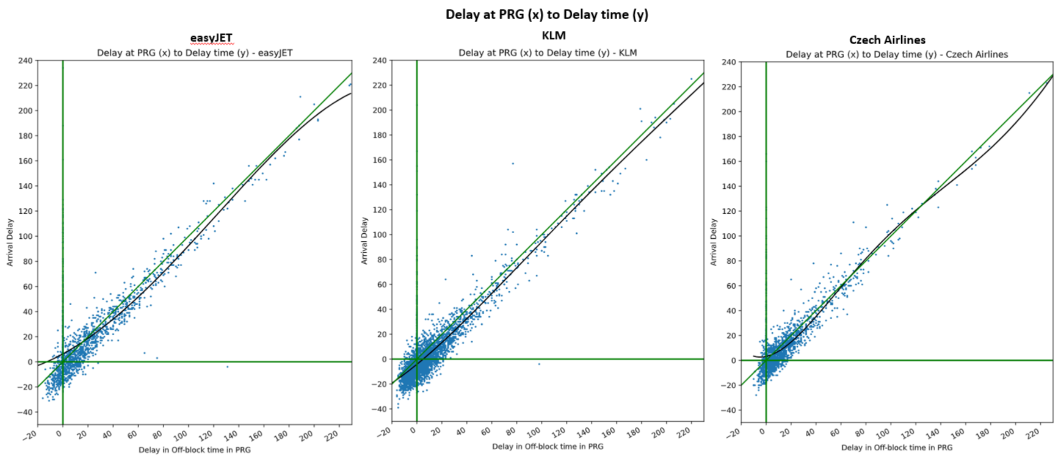

Figure 4.19: Departure delays at PRG to Departure delays at

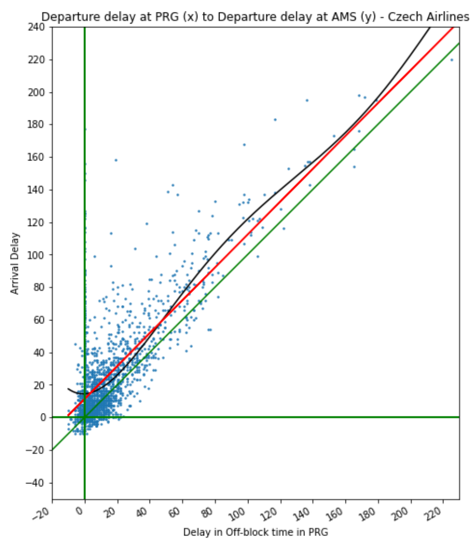

Figure 4.20: Departure delays at PRG to Departure delays at AMS

It was proven in Figure 4.18 that a correlation between the off-block time at PRG and the arrival delay has strongly appeared in all three airlines. Since all flights of Czech Airlines travelled from PRG, all recorded flights of Czech Airlines have the data of off-block time at the previous airport. Figure 4.20 presents the correlation between departure delays at PRG and departure delays at AMS. The linear regression of it can be summarised as $y = 11.4 + x$ with R-square value of 0.53. As a result, the departure delays at PRG would snowball into the congestion in AMS. In section 3.4, the assumption was made that delay of Czech Airlines are crucial that would affect overall delays of PRG. It is unclear the exact cause of delays from Czech Airlines. Nevertheless, with a combination of Zámková and Prokop (2015), PRG airport and Czech Airlines should not rule of the possibility of technical issue to delays.

Czech Airlines are crucial enough to assume that the delays of PRG are caused by Czech Airlines.

4.2. Long Distance Flights (Intercontinental Flights)

Long distance flights travel across the continent. Naturally, the flight time is long enough to affect by the jetstream. The long-distance flight can face more unexpected delay with their longer flight time. To prevent it from having a snowballing effect on the subsequent flights, airlines schedule a longer travel time and longer slack time. As a result, passenger for intercontinental flights may experience an aircraft arriving earlier than expected. Airport congestion can be created not only with delay but also for early arrivals. In this section, the research will look into what kinds of factor would make the nonconformity behaviours.

4.2.1. John F. Kennedy International Airport (JFK)

From 1-Jan-2017 to 31-Dec-2019, 10092 passenger flights were operated between Schiphol airport and JFK airport.

Table 4.7: Total number of flights from 1-Jan-2017 to 31-Dec-2019 between AMS and JFK

Airline	Airline code	# of registration code	# of flights (D + A)
Delta Air Lines	DL	109	4143 (2070 + 2073)
KLM	KL	73	4896 (2451 + 2445)
Norwegian Air Shuttle	EY	38	1053 (528 + 525)

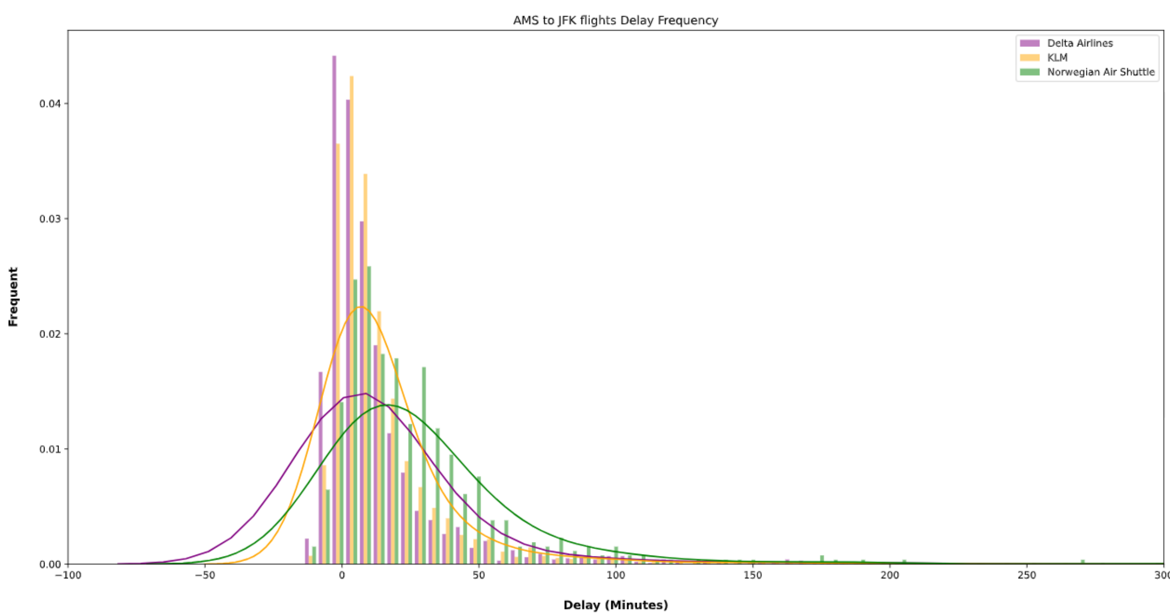

Figure 4.21: Normalised histogram of flights delay frequency from AMS to JFK

Looking at the shapes of Figure 4.21 KLM departure delay is concentrated near zero, indicating most of the flights departed within the 30 minutes range. Delta Air Lines, purple line is flatter than KLM but leans towards 0, indicating there had been some early departure as well. The green line, the Norwegian Air Shuttle, has relatively frequent delays.

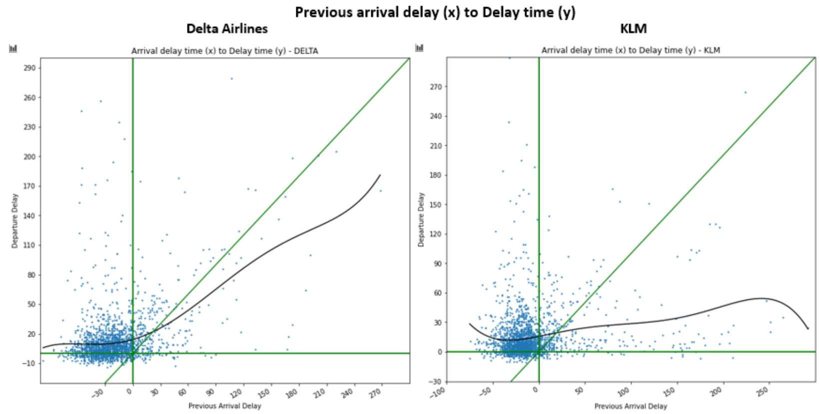

Figure 4.22: Previous arrival delay to delay time of three airlines that operated from AMS to JFK

Figure 4.22 depicts the relation between the delay time of departing flights from AMS to JFK, and the delay time of the previous airport that arrived at AMS.

The right-hand side figure of Figure 4.22 - a figure of KLM - has a noticeable point, that points are cornered to (y=0) line, and the polynomial regression graph. The slope of the graph is flatter than Delta. It represents that even though the previous arrival time (x-axis) was delayed by far, the most departure flight was not delayed more than 30 minutes, thus, the preparation time does not affect the delay time as much as Delta's preparation time. This can be explained by Table 4.8, KLM has more than 90 minutes longer average preparation time than other airlines. Therefore, even though the flights were delayed at the previous airport for any reason, it can recover time in the Schiphol airport with longer preparation time. This can be also proven in figure 10.

Table 4.8: Mean/median value (minutes) of slack time for three airlines operated from AMS to PRG

	Mean Value	**Median Value**
Delta Air Lines	164.2	145
KLM	272.2	195
Norwegian Air Shuttle	172	135

The first graph of Figure 4.23, the preparation time to delay time of Delta Air Lines, shows that if the preparation time is shorter than around 2 hours, the possibility of departing late is getting significantly higher. Purple lines of figure 10 indicate the mean or median values of slack time. As already stated in Table 4.8, KLM has the longest slack time among the three airlines. The second graph of Figure 4.23 proves the effect of longer slack time, which is that even though the flights had shorter preparation time than what was expected, it did not significantly affect departure delay as they had marginal time to recover.

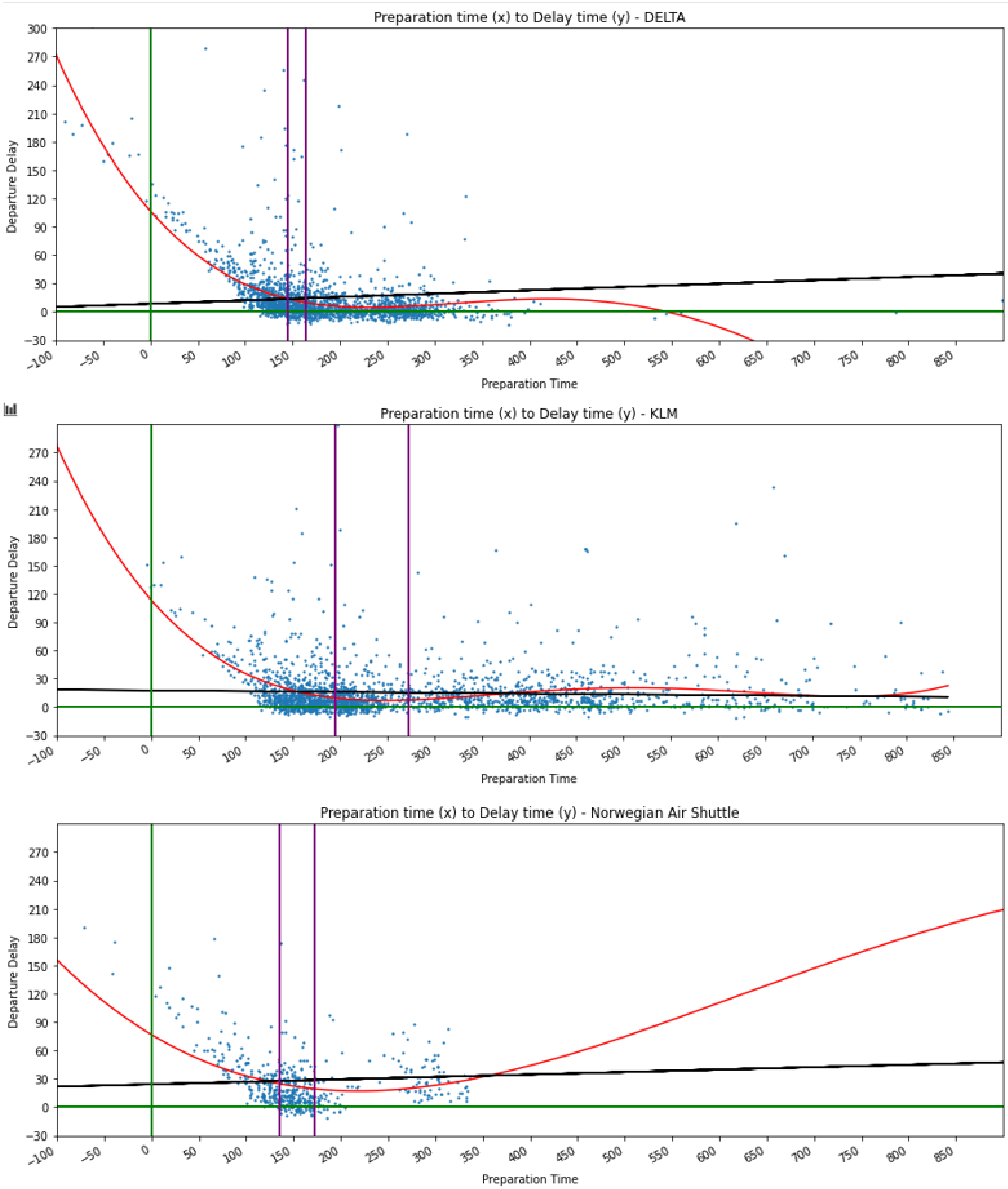

Figure 4.23: Preparation time to delay time of three airlines that operated from AMS to JFK

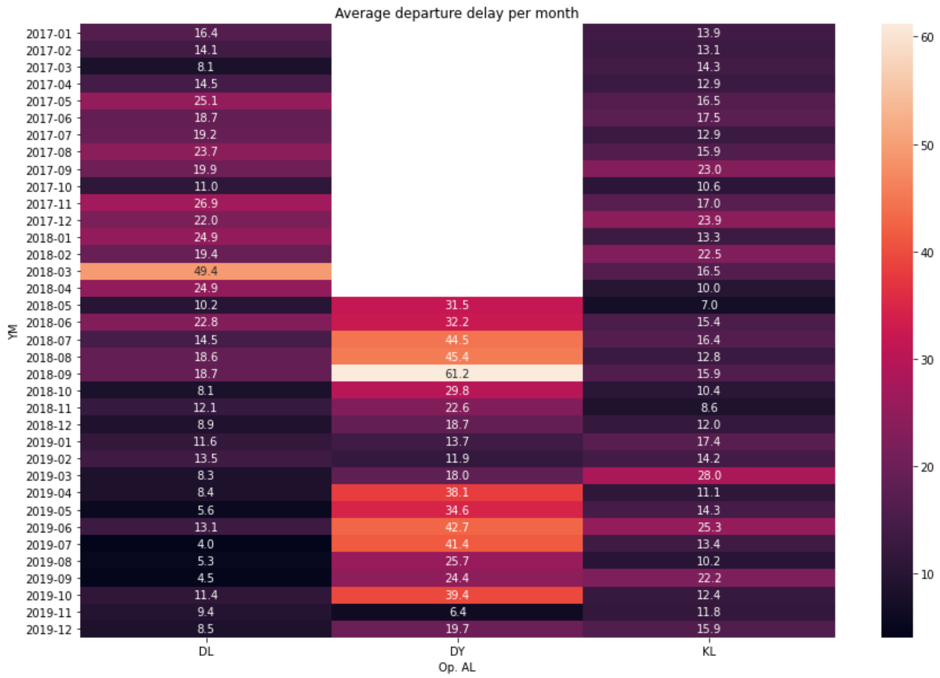

Figure 4.24: Average departure delay per month and airlines

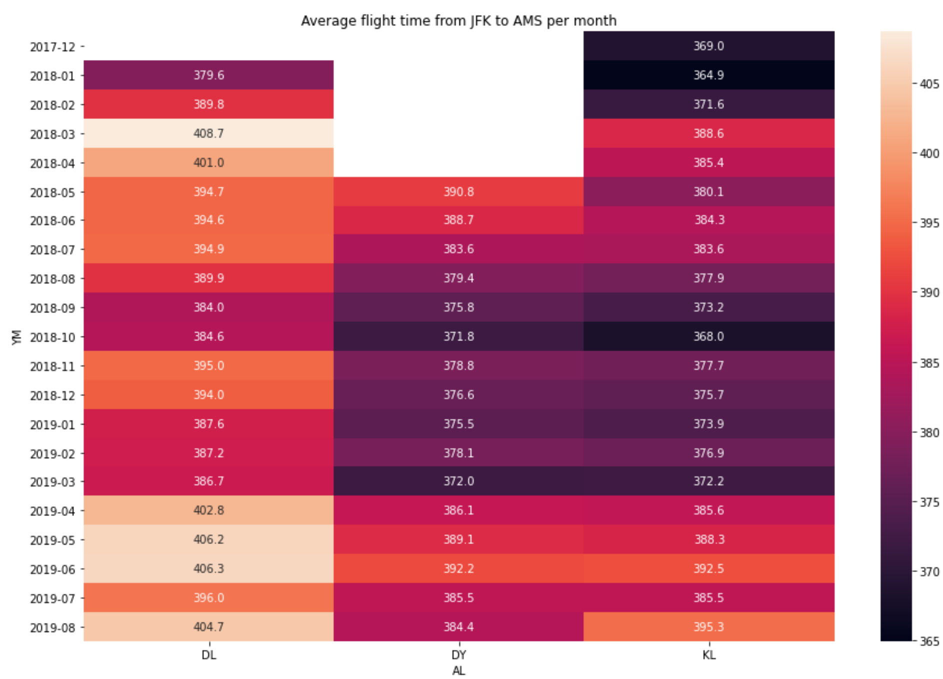

Figure 4.25: Average actual flight time from JFK to AMS per month

Figure 4.24 shows the average delay time of departure flights from AMS to JFK per month and airline. Compared to the previous airport - short distance flights - flights to JFK have longer preparation time, mostly longer than 2 hours. Thus, seasonal factors did not affect the departure delay time as much as they did to the flights heading to BCN. Nevertheless, the Norwegian Air Shuttle, which has the shortest slack time, had more delays during the summer season.

As the flight from JFK is an intercontinental flight, it has a longer flight time than the flight within Europe. Normally, from Delta or KLM website, they specify that the travel time which includes taxi time and flight time is around 8 hours. The flight-tracking website 'FlightAware' states the average taxi time of the JFK to AMS flight in the JFK airport is 20 to 40 minutes. If one assumes that on average, the flight will take 30 minutes to taxi in JFK and 15 minutes in AMS, the flight time would be around 435 minutes. Figure 4.25 depicts the average flight time from JFK to AMS per month and airline. The flight time is calculated as the time between take-off and touchdown when the aircraft flies through the air.

To see the impact of jetstream on flight time, two random days that have relatively high and low flight time were selected. Selected days are 31-May-2018 and 12-Nov-2018, and two airlines' flights on selected days were analysed with flight speed, flight altitude and the jetstream images of the day.

Table 4.9: Flight time of two randomly selected days (minutes)

	KL642	**DL46**
31-May-2018	413	432
12-Nov-2018	358	368

Generally, Delta had a slightly longer flight time than Norwegian Air Shuttle and KLM as seen in Figure 4.25, the simple reason for this is the type of aircraft. For two selected flights, Delta operated the Boeing 767-300 aircraft with twin-jet, on the contrary, KLM operated the Boeing 747-400 with quad-jet. As a side note, KLM currently operates an aircraft that has a twin jet, the result related to aircraft type may not reflect the current situation.

Figure 4.26 presents the jet stream map of North America. On 31 May, both flights had relatively longer flight time. Due to the difference in aircraft type, KL642 arrived 19 minutes earlier than DL46. Figure 4.26 shows that there was no strong jet stream on the route of flights, in fact, the direction wind is not matched to the direction of flight. The flight time is solely determined by the ability of the aircraft. On 12 November, there was a strong jet stream in North America with the same direction of the flight route. The jetstream can power the speed of an aircraft and reduce the flight time by 55 minutes for KLM, 64 minutes for Delta.

This is not a unique event of the month, according to the colour scheme of Figure 4.25, an average flight time is longer from May to July and shorter during wintertime. The evidence of jetstream powers the aircraft can be found in Figure 4.27, the flight speed (yellow line) was faster on 12 November, when there was jetstream.

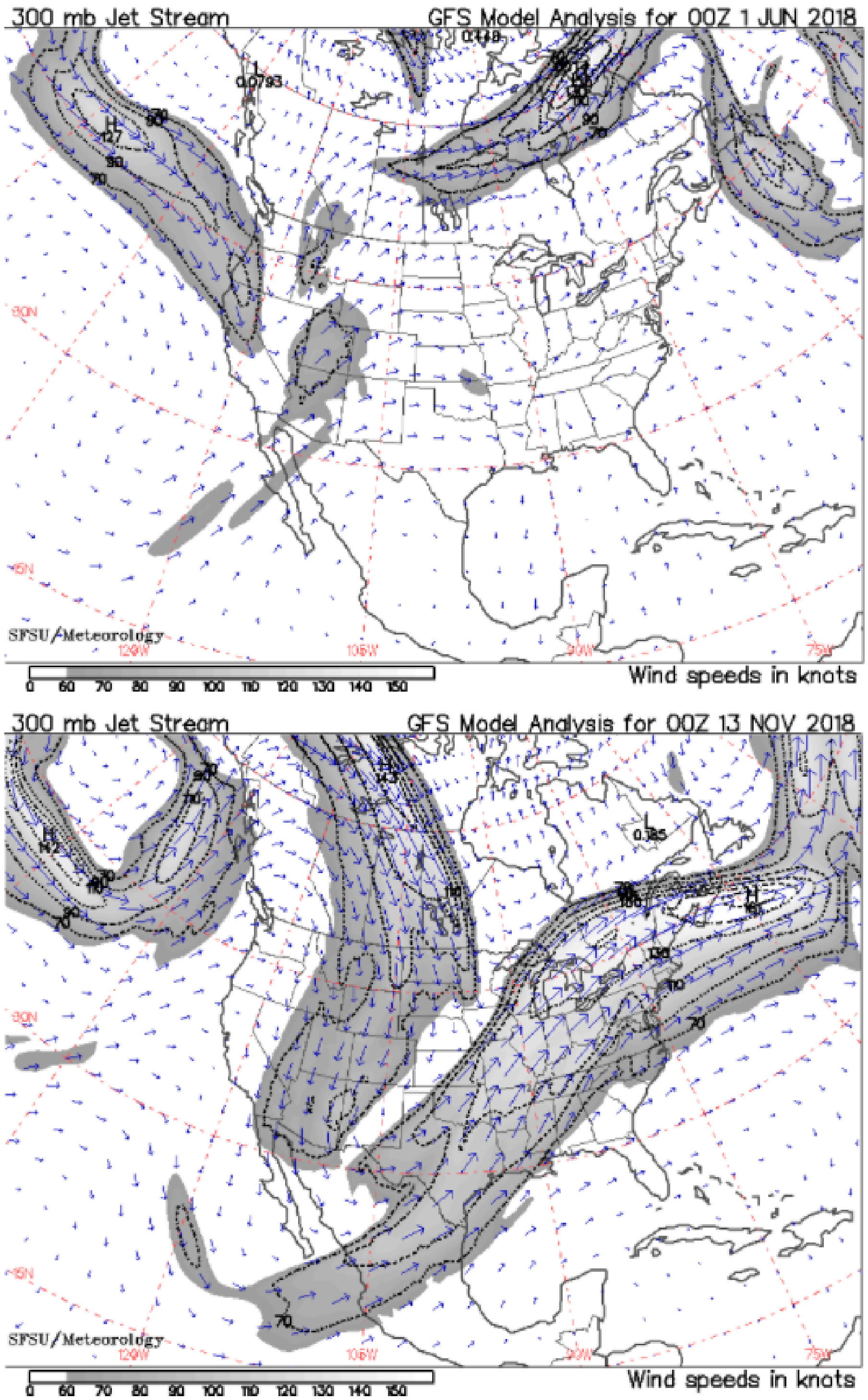

Figure 4.26: Jetstream satellite image of 20180601 (above) 20181113 (below)

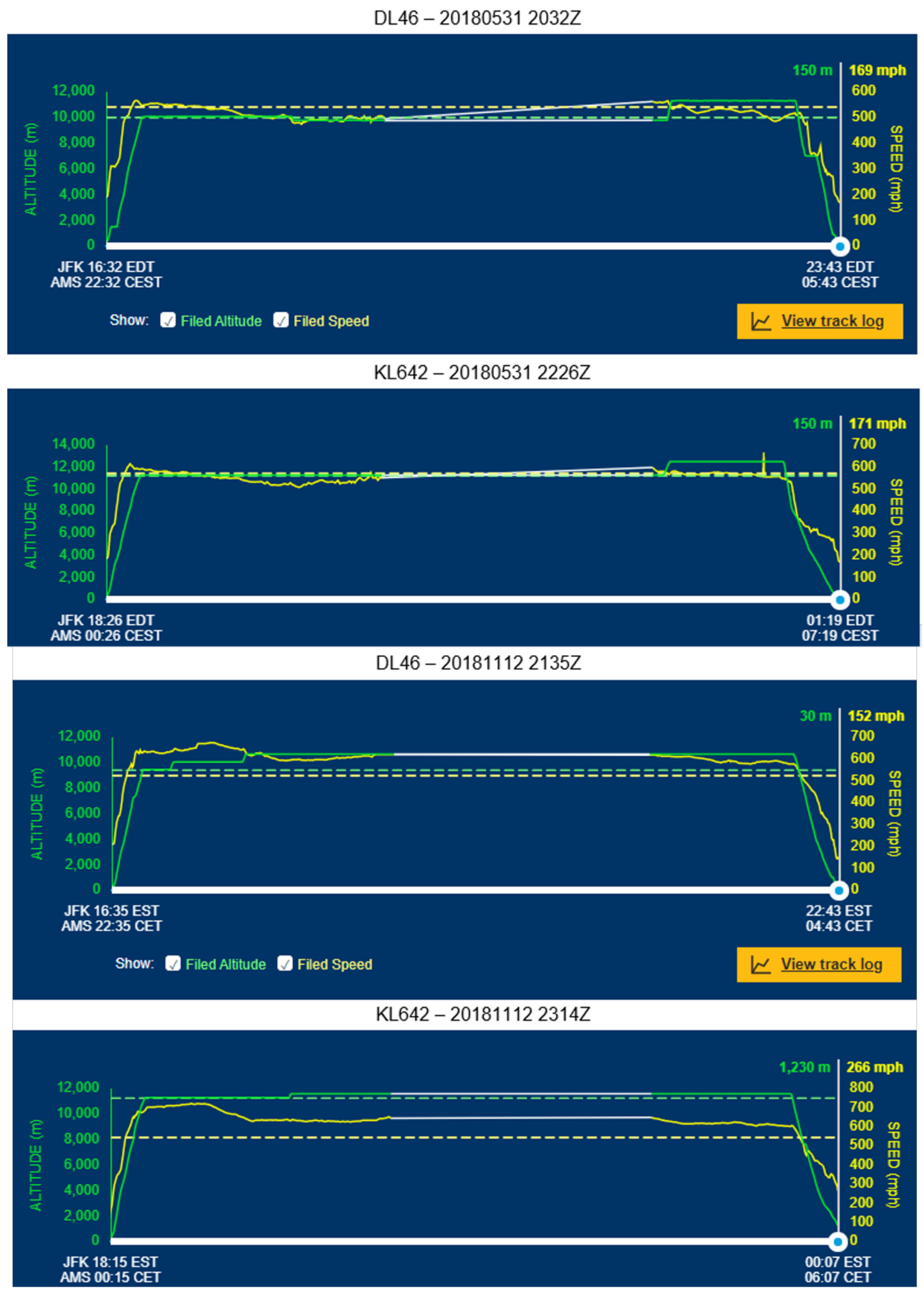

Figure 4.27: Altitude and speed of operated flight in described days and flights

4.2.2. Singapore Changi Airport (SIN)

From 1-Jan-2017 to 31-Dec-2019, 3948 passenger flights were operated between Schiphol airport and SIN airport. There is an absence of data from April 2018 to September 2018 for KLM.

Table 4.10: Total number of flights from 1-Jan-2017 to 31-Dec-2019 between AMS and SIN

Airline	Airline code	# of registration code	# of flights (D + A)
Singapore Airlines	SQ	32	2195 (1097 + 1098)
KLM	KL	27	1753 (877 + 876)

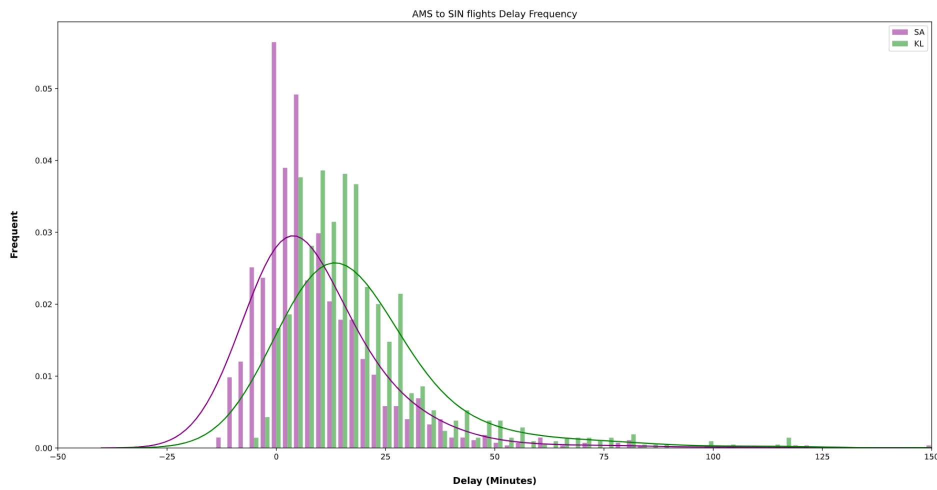

Figure 4.28: Normalised histogram of flights delay frequency from AMS to SIN

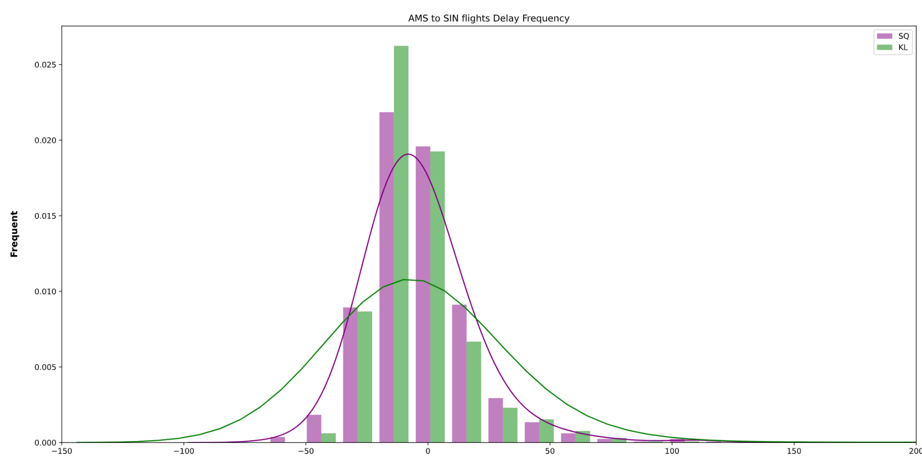

Figure 4.29: Normalised histogram of flights delay frequency from SIN to AMS

Singapore Airlines had good conformity to the schedule. Similar to the JFK case, SIN has a large travel time, and slack time and a steady record of on-time arrival. Notably, arrival flights from SIN ten to arrive ahead of schedule than getting behind.

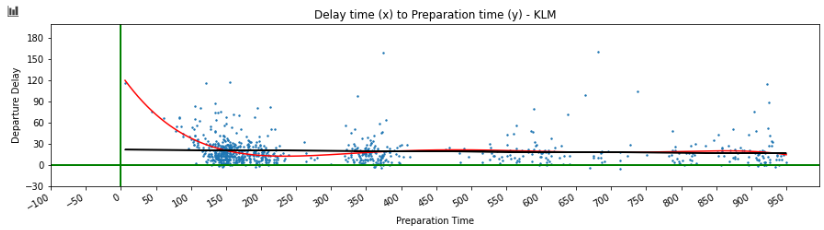

Figure 4.30: Preparation time to delay time of KLM that operated from AMS to SIN

The reason for a good conformity behaviour can be found in Figure 4.30. Slack time is large enough to absorb the impact, and considering Figure 4.29, both airlines tend to arrive ahead of schedule. Needless to say, the slope of linear regression from both airlines is close to zero, indicating that the previous arrival time and the preparation time have an extremely small impact on the case of SIN.

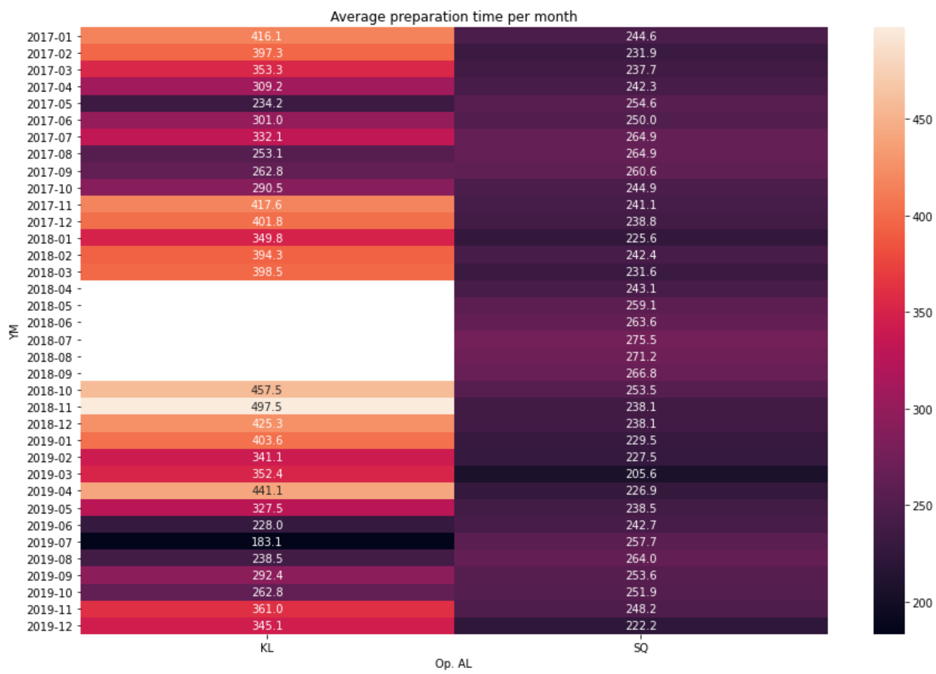

Figure 4.31: Average preparation time of flights from AMS to SIN per month

The average preparation time of flights from AMS to SIN (Figure 4.31) has a steady behaviour, especially the behaviour of Singapore Airlines. During the summer season, the preparation time of Singapore Airlines got slightly longer than the others. This behaviour is caused by the flight time, both KLM and Singapore Airlines had shorter flight time during the summer. Airlines already considered the changes in the flight time and reflected in the scheduled travel time in Figure 4.33, the scheduled travel time between April to October is 30 minutes shorter than winter. Eventually, the changes in scheduled travel time made a balance in the preparation time to maximise the resources.

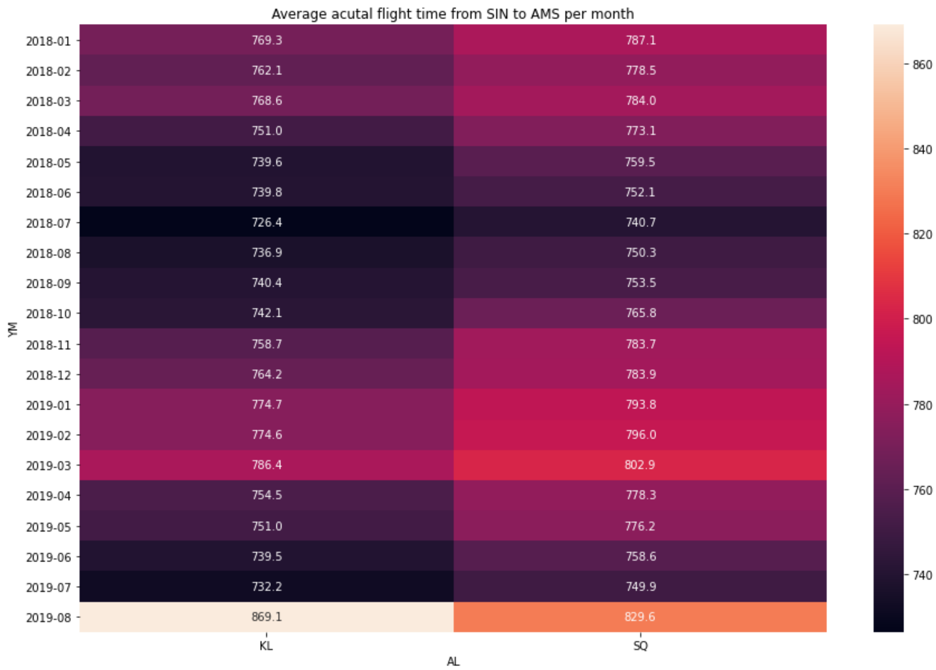

Figure 4.32: Average flight time of flights from SIN to AMS per month

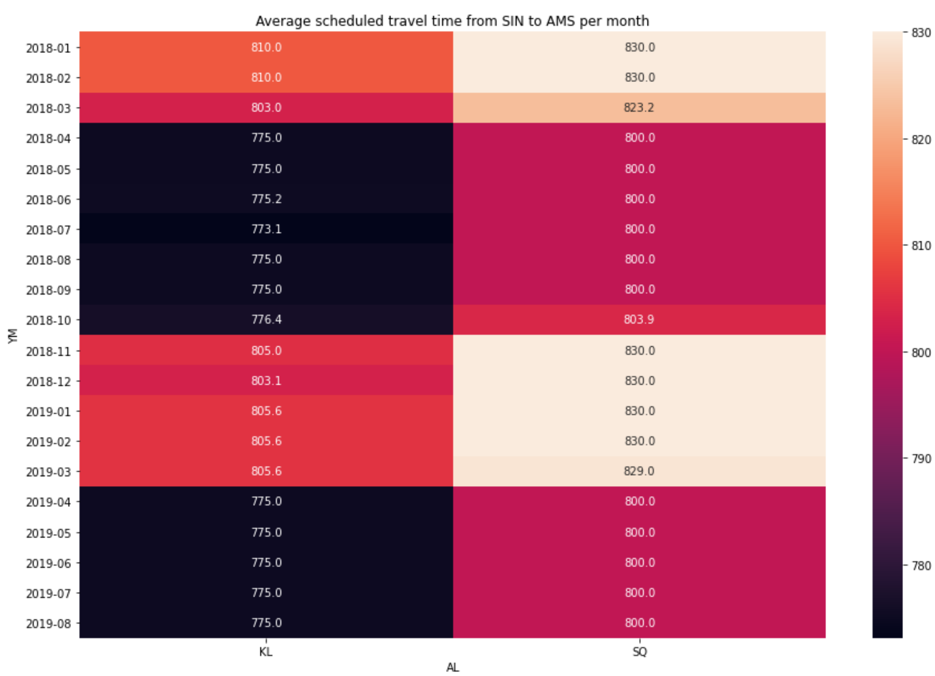

Figure 4.33: Average travel time of flights from SIN to AMS per month

From the above, it is clear that the misuses of SIN cases are not coming from any component of the model scheme of Figure 3.4. From Figure 4.34 and Figure 4.35, the departure delays at SIN does not significantly affect the arrival delay. The delay would have caused by external factors of the model scheme such as mechanical problem, the problems at the gate or airport.

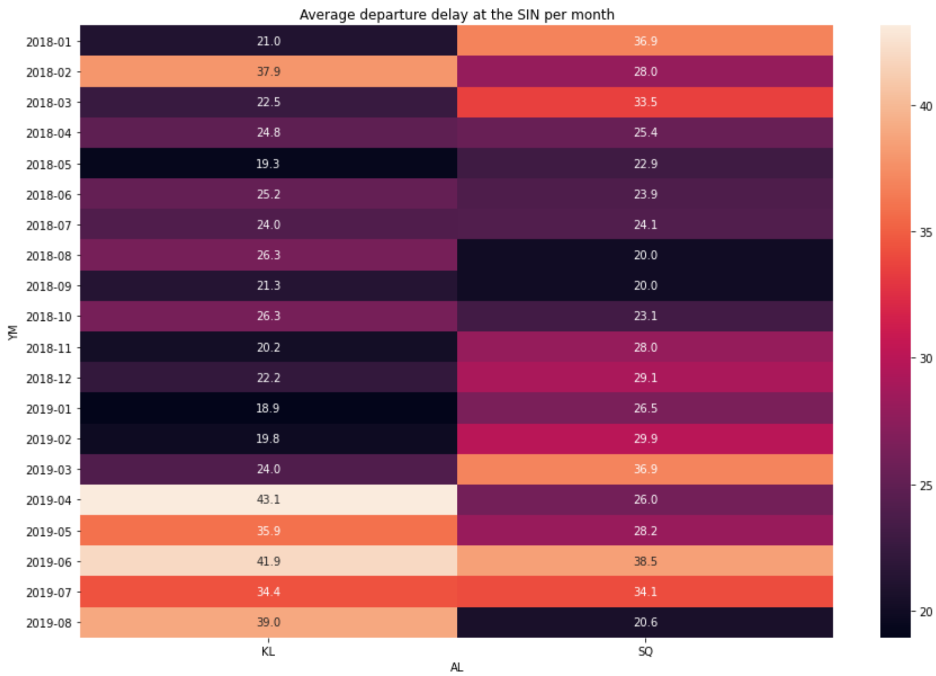

Figure 4.34: Average departure delay time at SIN

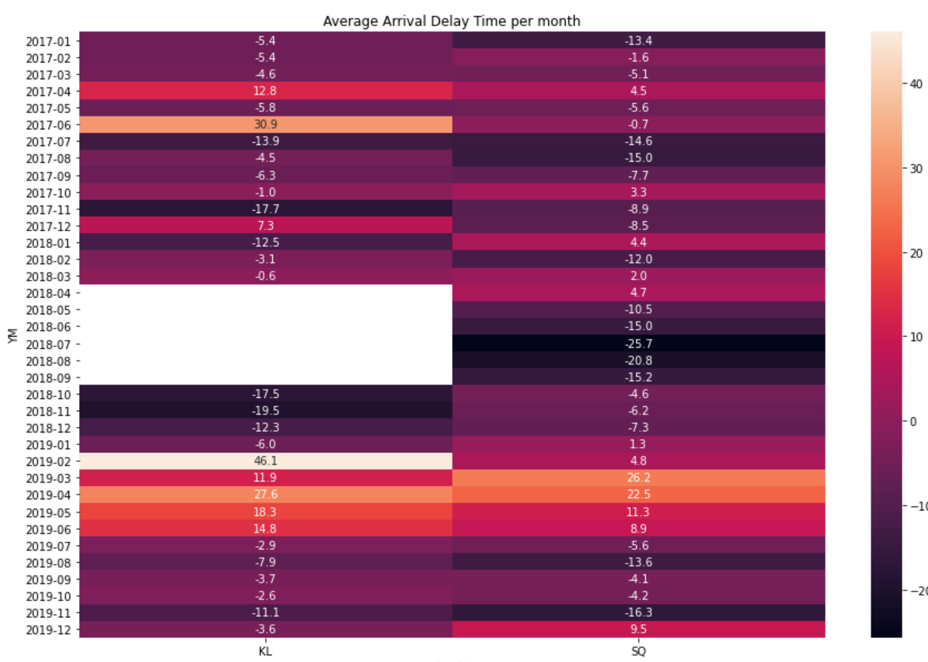

Figure 4.35: Average arrival delay time of flights from SIN to AMS per month

5

Discussion

In this chapter, the results of chapter 4 will be discussed. The exposed correlations and behaviours need to be defined with the term ’misuse’. To do this, the term ’misuse’ is categorised into parts as illustrated in Figure 5.1. To formulate the classification of the term, exploratory data analysis has been used and each case was standardised into the category.

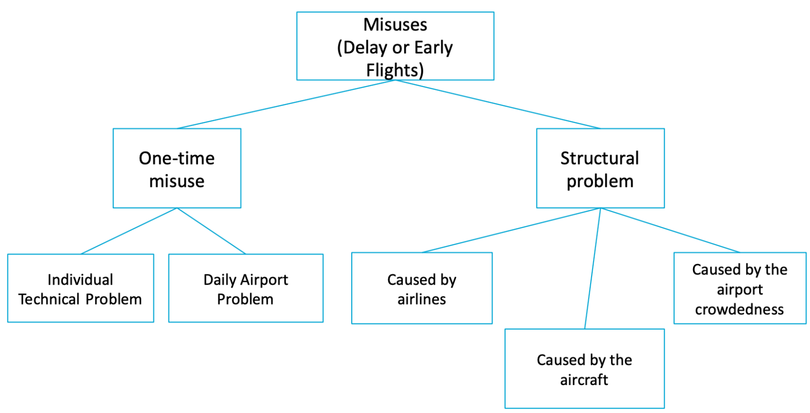

Figure 5.1: Categorised the term ’misuse’

First, overall misuses can be split into the one-time occasion and structural problem. The one-time misuse has abnormally high or low values than the other record and shows up as a spike or delay in the visual. This can be divided into two other categories, an individual technical problem and a daily airport problem. An individual technical problem is caused from the side of the airline, while preparing the aircraft for a turnaround, an aircraft may have technical issues. As the severe technical issues are not likely to happen often, or should not have happened often, an airline would have to cope around it with alternatives.

In doing so, a problem would be recorded as one abnormal entry in the airport database. The one-time technical problem would be easier to detect if the database is coming from an airline. The aircraft has an itinerary to follow and a major delay at one airport would definitely affect the subsequent flights. In this case, the individual technical problem becomes the root cause. The impact of the technical problem will be severe if an aircraft is a short-distance flight with a tightly scheduled travel time and slack time, and expected to be a turnaround flight. Although the misuse by an individual technical problem has a substantial impact on the airline and airport, this is not expected to happen daily or weekly basis. Moreover, it is hard to anticipate when and where it will happen, accordingly, it is hard to correct it by a policy.

The next category of one-time misuse is a daily airport problem. A daily airport problem can be caused by various reason, most commonly, weather issues. If the weather condition that hinders departure and arrival of flights such as wind, rain, snow is too strong to operate the flights, the entire flights with a certain time block would be grounded. Through the weather forecast, phenomenally bad weather can be expected by experts, but there is very little things can do about it. Even if an airline tried to cope with the bad weather, they have limited options such as cancelling the flight or postponing it. Of course, the latter option will be harder than the first one as once the weather got better, the usually scheduled flights need to be operated.

Another possible cause of daily airport problem is by failing to manage the resource of an airport. Normally around the summer season or holidays, more passengers would visit an airport to enjoy their vacation but since the resources of an airport are limited, it would take more time to process a large number of passengers. The slow speed to prepare in the process of on-boarding would lead to delay. The failure to manage the resource can be caused by a technical issue, such as power or fuel resources.

This type of misuse would be registered in the database as abnormal values in all flights during a certain time block. From the side of the airport, it is easy to detect than an individual technical problem. The one-time misuses will be discussed in section 5.1.

On the other hand, there is a structural problem. The structural problem may be solved by enforcing the policy. The first category of structural problem is the issues caused by airlines. As mentioned in the section 4.1, the short-distance flights have the narrow travel time without marginal time, and short slack time to maximise the utility of resources. The delay caused due to the airline's scheduling is defined as 'caused by airlines'. This will be extensively discussed in section 5.2.

In a structural problem, there is a misuse caused by the type of aircraft. The aircraft type can affect the flight time which would lead to late or early arrival at the airport. The paper devoted a large portion to delayed flights among the misuse type, early arrival also contributes the airport congestion. The problem of aircraft will be discussed more in section 5.2.

Last, there is a structural problem caused by the airport crowdedness. It differs from the daily airport problem from the one-time misuse as one-time misuse's daily airport problem would have a seasonal factor. Some of the airports had steady departure delays at the origin airport which lead to the arrival delay. This cannot be solved from the side of ACNL nor from Schiphol airport, but would be assigned as a structural problem of misuses.

5.1. One-Time Misuse

In this section, 10 days with the high number of delays from 2017 to 2019 will be discussed with a reason for the delay and their behaviour in data. The European Union established an EU air passenger right (Union, n.d.) that if a passenger experience a delay of more than 2 hours at departure, the airline must give a written notice to set out the rules for compensation and assistance. In this analysis, 120 minutes as a parameter of delay and 60 minutes as a reference to the trend of the delay.

First, flights can experience a delay due to adverse weather conditions. 13-September-2017 and 10-December-2019 recorded the highest number that exceeds 120 minutes of departure delays.

On 13 September 2017, Schiphol airport experienced a high speed of wind (Independent, 2017), especially around 6 am 3 pm. As a result, 65 flights were departed later than 120 minutes and unlike more than 1000 aircraft were operated every day in the same week, only about 800 aircraft were operated. From 10 December 2017 to 11 December 2017, Schiphol airport was suffered from heavy snow (NL Times, 2017a). As a result, 65 and 35 flights were departed later than 120 minutes on 10th, 11st, respectively. Only 577 aircraft on 10th and 491 aircraft on 11st were operated whereas around 800 aircraft were operated every day on the same week.

The impact of a high-speed wind can be detected at Figure 5.2, after 6 am, scheduled flights were started to ground. After 6:30 am, the figure shows a pattern in which the green line of the actual departure time is slightly later than the blue line of the scheduled departure time. The aftereffect of early grounded flights is started to show around 9:30 am, the red line of flights that departed 120 minutes later than scheduled draws a smaller pattern to the actual departure time. The effect did not finish at AMS, Independent (2017) reported that British Airways had to cancel at least a dozen flights that scheduled to fly from/to LHR due to winds in AMS. As a paper mentioned at section 4.1, British Airways has an average of 56 minutes of slack time, thus, the delay time than short slack time would have affected the returns of flight to LHR, and subsequent flights as a collateral effect.

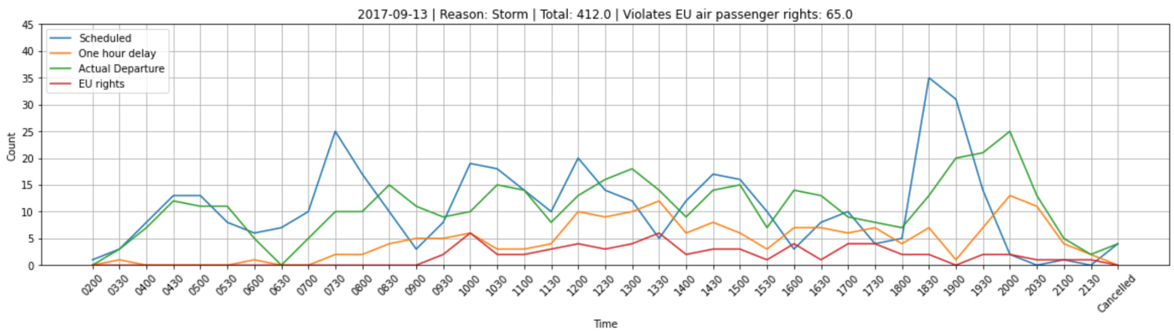

Figure 5.2: Scheduled and operated flights on 2017-09-13

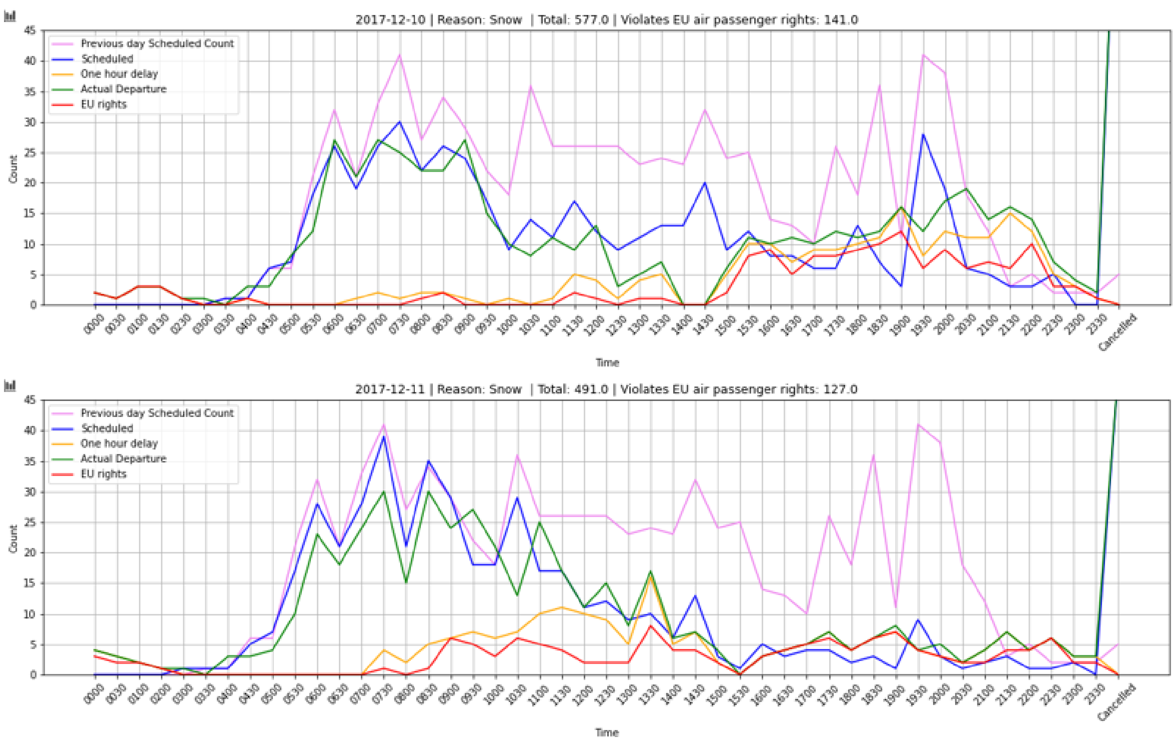

Figure 5.3: Scheduled and operated flights on 2017-12-10 2017-12-11

The effect of weather condition is more severe in case of snow. The total number of operated flights were significantly lower than other days, meaning that the most of flights were cancelled due to snow. According to TimeandDate (n.d.), it started snowing around 12 pm on 10 December, the number of actual departures decreased after 12:30 pm in Figure 5.3. From 2 pm to 3 pm, none of the flights was departed from AMS. Once the flights resumed departing again after 3 pm, the orange line of one hour delay and green line of actual departure often overlapped, and a red line of 2 hours delay is right beneath to two lines. The situation got worsened on 11 December, NL Times (2017a) reported that KLM cancelled nearly 300 flights on a corresponding day. It can be confirmed with the second figure of Figure 5.3, after 11 am, almost every flight were grounded or departed considerably late. The cancellation of flights becomes more apparent comparing a pink line of the previous day - the day flights operated normally - and a green and blue line.

The misuses problem can be originated from air traffic control. On 18 February 2018, the ATC in Amsterdam had technical problems that caused a substantial delay at AMS in a certain time block. The flights showed a good conformity behaviour until around 12 pm, when the technical problem occurred. The actual departure line drastically dropped until the matter was resolved around 4 pm (Reuters, 2017). Meanwhile, ATC did not function, as usual, departure flights were held in AMS and arrival flights were diverted to nearby airports such as Brussels, Frankfurt, and London (NL Times, 2017b). After the situation got normalised, departure/arrival flights were resumed sequentially, this is well depicted in Figure 5.4. Unlike morning hours, the green line of actual departure exceeds the scheduled departure as well as scheduled departures of the previous day, and most of them are delayed flights. It took a while to return to normalcy around 7 pm.

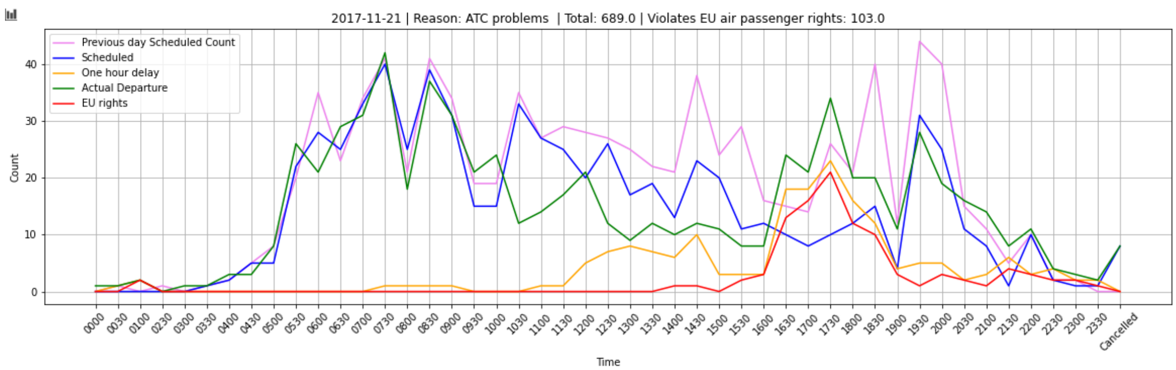

Figure 5.4: Scheduled and operated flights on 2017-11-21

In a close look at non-conformity behaviour, it did not only initiate from an airport level but from an airline level. On 19 February 2018, pilots of Transavia Holland went on strike, resulting in 18 flights from Schiphol airport were delayed or cancelled (NL Times, 2018). A left-hand side figure of Figure 5.5 exemplifies a typical day of Transavia Holland without any major delay. On a day of stroke (a right-hand side figure), only one flight was operated until 11 am, whereas many of Transavia Holland should have been operated in morning hours as seen in the left figure. Around 1 pm, a spike with over 120 minutes of delays can be found, and compared to the previous day, almost half of flights were cancelled.

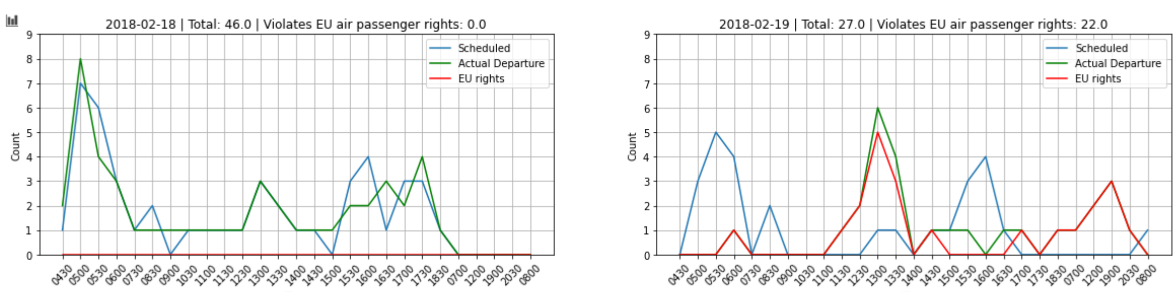

Figure 5.5: Scheduled and operated flights on 2018-02-19

From the figures above, several ways to check for misuses caused by deteriorating weather condition, technical problems. First, compared to close days, the total number of operated flights could be considerably low. This is often the case when an aircraft is unable to take off or touch down at all from the airport such as a snowy day of 2017-12-11. As opposed to this, the number of operated flights can be abnormally lower and higher than normal circumstance. This behaviour can be observed when a matter can be settled in some time, so airlines can gradually perform according to the schedule as planned. The same behaviour can be noticeable at an airline level, too.

5.2. Structural Problem

The first part of the structural problem is identified as misuses caused by airlines.

In the section 4.1, three airports were selected to perform the analysis. In Barcelona Airport, BCN, Vueling Airlines had most often delays. The delay of departing and arriving flights had the highest correlation with the preparation time. If the preparation time is shorter than the slack time, an airline would not have enough time to transfer an arrival flight into a departure flight as they expected. The same correlation was found in British Airways of LHR and Czech Airlines of PRG, too. For the flights from/to LHR, British Airways had the median slack time of 55 minutes with frequent delays. 35% of early arrival British Airways flights departed behind the schedule. In the case of PRG, it was possible to analyse a correlation between Czech Airlines departure delays at PRG and their departure delays at AMS thanks to an external dataset, and because all flights of Czech Airlines had flown in and gone back to PRG. The relation between departing time at two airports contains the results of actual off-block time, travel time, preparation time, and their wide effect on the departure delays in AMS. The correlation between departure delays at PRG and AMS had an R-squre value of 0.53 (Figure 4.20), the preparation time and departure delay of Czech Airlines had an R-square value of 0.76 (Figure 4.16).

The margin between actual flight time and scheduled arrival time was around 30 minutes for the flights from/to BCN and LHR, indicating that an aircraft should taxi, queue and take off/touch down at the origin and destination airport in this marginal time. The actual travel time was shorter than the scheduled travel time but not enough to offset the delays.

If an aircraft departed later than scheduled in an origin airport, an arrival delay or a departure delay can be offset by two factors. The first one is the travel time. By preventing any unexpected delays on the runway or in the air, an airline can set the larger travel time. However, the current travel time gives a small amount of buffer to compensate for a delay as it is slightly larger than the actual travel time. Accordingly, setting a larger travel time is not recommended.

Another strategy is to set the larger size of slack time. section 4.1 mentioned that KLM often recovered their delay time from a large slack time whereas Vueling Airlines, British Airways and Czech Airlines had a tight slack time. The expanding slack time is not only important to AMS but also to other airports as well. From the Figure 4.20 and section 5.1 which a British Airways had to cancel the flights in LHR as a result of high-speed winds in AMS, it is proven that the delay at one airport affects directly the other airports. Since the short-distance flights are mostly turnaround flights. An arrival delay is likely to cause the departure delay, and it affects not only the itinerary of an individual aircraft that will travel to other airports.

It is not only the case for short-distance flights. The Norwegian Air Shuttle provided the flight between JFK and AMS, although it only lasted from July 2018 to March 2020. Unlike the other two airlines operated between JFK and AMS, Norwegian Air Shuttle had a relatively short preparation time with a high frequent delay. On contrary to short-distance flights, long-distance flight only departed/arrived once a day per airlines due to their distance and travel time. Naturally, an intercontinental aircraft is bigger than short-distance flights to carry more passengers and has a larger slack time. Calculating an adequate slack time considering the characteristic of flights would be imperative to this strategy.

In addition, Schiphol airport is a hub airport and the research of Guimerà et al. (2005) ranked Schiphol airport as the 17th most central cities in the worldwide air transportation network. The delay may affect the AMS at a network level and cause another root delay as a collateral effect. Therefore, to airlines, expanding slack time contributes to conform the slot allocation at a network level.

Another structural problem is the misuses caused by the aircraft.

In this paper, the misuses caused by the aircraft were only found in long-distance flight. In the section 4.2, two airports that are outside of Europe were analysed. Two airports, JFK and SIN had one behaviour in a common, which is an early arrival of flights. For Singapore Airlines that flies between SIN and AMS, most flights were arrived within plus/minus 50 minutes of range, and more than half of the flights have arrived ahead of schedule. Singapore Airlines showed a good behaviour of conformity to the allocated slots, the Figure 4.31 showed the steady behaviour of keeping a certain preparation time. Judging by inference of Figure 4.31 and Figure 4.33, the steady increase and decrease of preparation time is caused by the average scheduled travel time that varies by the season.

Similar behaviour can be observed from JFK, especially from Figure 4.25. Figure 4.25 also showed a steady change of actual flight time affected by the season. The reason for this behaviour can be explained with Figure 4.26. that the existence of strong jetstream powered an aircraft. The altitude and speed are influenced by the jetstream. Moreover, the not only jet stream has a season effect on boosting the actual flight time, it also varies on the amount of boosting an aircraft depending on its type. Delta operated Boeing twin jet aircraft while KLM operated Boeing quad jet for AMS-JFK route. On the other hand, Singapore airlines used Airbus company and KLM used Boeing for the AMS-SIN route.

For a scatter plot with a regression graph, the individual points refers to one entry of flight and three years of data were plotted into a figure. If the scatter plot exhibits a linear relation between two variables, flights for three years were operated under the correlation, therefore, considered as a pattern. The behavioural pattern became more obvious when it comes to the heat map. The colour of heat map varies slightly in the nearest grid and pattern of colour repeats over a year, it can be deemed as the airline or airport showed a pattern.

Overall, due to large slack time, flights operated between JFK and AMS did not have a correlation between departure delays and arrival delays. Instead, the flight time can be used to have as a factor. To prevent the early arrivals at AMS, airlines could shorten the travel considering the type of aircraft and season, however, there would be a high chance of turning into delays.

Finally, it is mentioned briefly earlier that good conformity behaviour is important to all airports since it connected with the air transportation network. For the case of LHR, PRG, it was evident that the departure delays at an origin airport caused departure delays at AMS as a knock-on effect. The airport congestion is not solely Schiphol airport or ACNL's problem, it is most airports problem since it influences the airports in the network. A hub airport like AMS would have a bigger impact to have the airport crowdedness as the structural problem, and it has to be covered at a network level in future research.

5.3. Continue the Monitoring Behaviour

It is crucial to continue the monitoring to expand the framework and collect the case. The paper only covered one type of misuse regarding the time difference of scheduled and actual operation time. However, throughout the analysis, the potential to expand the research to cover more misuses was found. The research carried out to support the slot monitoring and discussion phase, the five types of misuses can be studied with additional data collection. The five types are; a flight operated without an allocated slot, a flight operated in a significantly different way to the allocated slot, a flight operated in curfew or another restricted operations period without an allocated slot in the corresponding period and no operation in allocated slots.

The misuses of operating in significantly different ways to the allocated slot such as aircraft subtype or capacity can be investigated with additional data collection. For instance, short-distance flights have a relatively short slack time. Naturally, if the number of passengers was high, the airline crews would face more workload to clean the aircraft and prepare to take passengers on board. For instance, Vueling from Barcelona airport experienced delays during the summer as it can be seen at Figure 5.6. The analysis excluded it as a 'pattern' as the seasonal effect was not evident for the other two operators, KLM and Transavia even though the assumption of seasonal impact of tourist was made in section 3.4. With a lack of passenger information, the research can only assume that the number of passengers of Vueling Airlines was larger than others. If the passenger data can be obtained, it will be possible to examine the impact of the volume of passengers on delays. This leads to the point of misuses, if the airline reported a capacity of aircraft smaller than operated aircraft in order to allocate the short slack time, it can be exposed with an additional dataset.

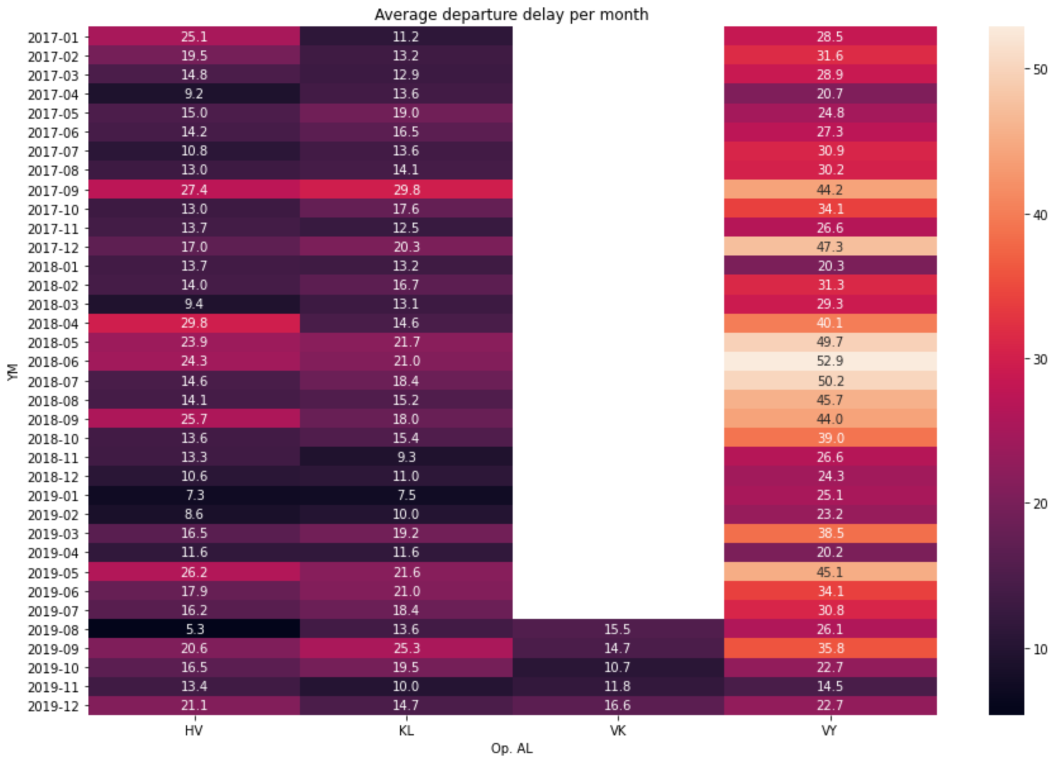

Figure 5.6: Average departure delay time at AMS per month

The ACNL dataset includes the aircraft type (section A.1). The flight time of long-distance flights was affected by the type of aircraft. The question arises that in order to avoid the delay and possible passenger compensation caused by delay, can an airline operate the different type of aircraft favoured by an airline. With an insight into the technical part of aircraft, this question can be answered, too.

Moreover, no operation in allocated slots and operating without allocated slots can be analysed with a current dataset by comparing the coordinated and operated flights. However, it might be hard to find a pattern or intention behind the misuses, but it can be a good starting point to initiate the conversation with operators.

Finally, operating in curfew or restricted operations can be an extension of the current research. In this research, the analysis only focused on the deviation between the actual and scheduled arrival/departure time to find a pattern. This can be expanded with a question if the flight arrived or departed outside of the allocated slot, which period of time in a day the misuse happened. The research wants to propose the method to conduct this analysis. Using the current analysis, each flight can be labelled as a 'conform' or 'misuse'. One day would be divided into 96 time slots, the division of 24 hours a day by 15 minutes of time slot. Each flight that is labelled as misuse will be assigned into the time slot of operation, and create a new dataset consisting of date, time slot, number of misuses and flight information for each misused flight. As the definition of misuse type specifies it as a flight operated during the curfew or restricted operation, the corresponding time slots can be selected. By analysing the frequency and trends for each airline, the misuses may be exposed.

On a strategic level, misuses of holding slots and requesting new slots with the purpose of undermining slot coordination can occur. This analysis can help to identify the misuse cases. Among four types of strategic level misuse type, holding slots without the intention of operation and requesting new slots without the intention of operation can be supported with the previous behaviour of airlines. Assuming that the analysis for the no operation in allocated slots is conducted prior, slot coordinators can pinpoint the airlines of interest for the extensive investigation of the intention behind the newly requested slots or holding slots.

There is a difference between finding misuse cases and finding a pattern of misuses. Finding a pattern requires the constant nonconformity behaviour from airlines. The process and analysis of slot monitoring should not prematurely judge the airlines that have misuse cases as a chronic problematic airline.

The analysis can be used the airport outside of five cases as well by dividing into two categories. Depending on the type, the key components to look at would be different. The exploratory analysis suggested that most long-distance flights are not low-cost carriers but flag carrier with larger capacity. Moreover, it is more likely to have a big aircraft alongside plenty of slack time. Therefore, the seasonal impact on the aircraft and a type of aircraft would have a bigger impact on the delay time. If it is a short-distance flight, the biggest factor to focus on is the slack time. IF it is the flag carrier, an aircraft is most likely to go back to the hub or previous airport whereas a low-cost carrier such as EasyJet might visit another airport, For the flights that travelled back to the previous airport, it would be easier to conduct the research on the slack time.

6 Conclusion

For a conclusion, this chapter addresses the overall results of the analysis by answering each question posed in chapter 1. Then, the contribution of this paper will be address as well as the limitation, thereby, recommendations for future research.

6.1. Research Questions

1. What kinds of behavioural patterns can be detected from exploratory data analysis? / What kinds of factors have the correlation to the discovered misuse case?

   From the case studies of five airports explained in chapter 4, a few patterns were found. In a combination of sub-question 1 and 3, discovered patterns and correlated factors will be discussed.

   - **Slack Time** The short-distance flights tend to depart later than what are expected due to the narrow slack time.

     The airport slot coordination is a means of managing scarce airport capacity (Airport Council International, 2020), and to maximise their profit and utility, airlines would schedule the slack accordingly. On account of the relatively small scale of passengers and aircraft, airlines for three investigated airports scheduled less than an hour of slack time to cope with the scarcity of airport. Despite the effort of adding buffer time to absorb the uncertainty (Cook et al., 2004), it did not have a substantial impact on departure flights from Schiphol Airport. Consequently, the overall departure delays for short-distance flights were found. This pattern was particularly conspicuous for airlines that do not have Schiphol airport as a hub. As Tu et al. (2008) already suggested in prior research, delays mostly occur if the intervals of flight schedules are short, in other words, the short slack time.

   - **Preparation Time** Most airlines had less preparation time than the slack time.

     The slack time is what an airline would have anticipated during the strategic phase that might be enough time to turn around the aircraft and greet new passengers. As the airport network is heavily connected to each other, a hub airport such as Schiphol airport suffers more delays than others (Mayer & Sinai, 2003). Mayer and Sinai (2003) suggested that departure flights from a hub airport would require 4 to 7 minutes of excess travel time, and this would not be an exception for the flight that departed from a hub airport to AMS. The paper cannot affirm that it would be the cause of delay, nevertheless, numbers of short-distance flights had less preparation time. Assuming from the case of PRG, the departure delays at the previous airport would have contributed to the shorter preparation time. This pattern is more applicable to short-distance flights which had a shorter slack time as stated above, if the flight had a long slack time such as long-distance flights, the impact was absorbed by the slack time. Together with the narrow slack time and shorter preparation time, the delay frequency was accumulated.

- **Flight Time** The flight time for long-distance flights is affected by the seasonal factor.

  In both cases of long-distance flights, the monthly flight time got differed by the seasonal impact or by the aircraft. On the contrary to short-distance flights, flights time changed almost an hour depending on the jet stream. In spite of the effort of adapting the different flight time by adjusting the travel time per month, the scheduled travel time was bigger than the actual flight time and led to the early arrivals.

2. What kinds of discovered behavioural patterns can be deemed as the intentional misuse of slots?

   The misuse type of operating significantly different time slot from the allocated slot was divided into two categories, the one-time misuse and structural problem. The one-time misuse can take place because of airport or airline crew strike, adverse weather, or a technical problem of an airport or air traffic control. These cannot be predicted or prepared ahead except postponing the flights or cancelling them. Therefore, it concludes as one-time misuse is unintentional.

   On the other hand, the structural problems caused by airlines, aircraft or airport crowdedness are different. The aforementioned patterns of slack time and preparation time can be defined as the airlines' side of the problem whereas flight time categorised as an aircraft side of the problem. Above all, the airlines could have coordinated such matters at a strategic level, as the slot coordination happened twice a year.

   The airport crowdedness could not be addressed with this research but is a part of the airport capacity problem. With the current traffic volumes that cannot be coped with the existing system (Madas & Zografos, 2008), the number of passengers is assumed to be higher than what can be handled with the current capacity of the airport. The close connection of airport capacity and at-gate delays (Wang et al., 2002) would be another structural problem.

Gathering the answers for the sub-questions, the main question is addressed.

- Can behavioural patterns of airport slot users in the Netherlands regarding operating in a significantly different time from the allocated slot be exposed with the data-driven approach and support the dialogue points between coordinator and airlines in the enforcement phase?

The behavioural patterns of airport slot users in the Netherlands are stated above. To conduct the case study with the data-driven approach, additional datasets from open-source were collected to fill the gap of absence of departure data information from five selected airports. Then, the exploratory data analysis using python had done.

During the discussion or slot allocation phase of the slot coordination procedure, the ACNL and airlines can have a discussion of the current conformity of airlines to the slot allocation to improve the performance. In this dialogue, the decision-making process behind the current slack time would be the main point. The analysis has pointed out existing problems of allocated slack time, meanwhile, airlines would have reasons for the requested slack time was reasonable from airlines' point of view. Cooperation between ACNL and operators should be made. Furthermore, for the long-distance carriers, a means of reducing the frequency of early arrival should be discussed with the results of deviation between the travel time and flight time.

The research can be expanded with other airports as well as other airlines, using the framework and similar process of data collection.

6.2. Limitation and Future Research Recommendation

The study had limitations from several challenges, these limitations are listed with recommendations for further research.

- **Dialogue in the strategic level**

  The research focused on the performance of current slot allocation. Despite the non-conformity behaviours and problems, airlines would have given an effort to optimise their resources while conform the slot regulations at the strategic level. The research ruled out the airlines' logic behind the decision. With the current performance, the research of investigating the airlines during the slot allocation process can be done. The results of new research can be a starting point of other types of slot misuses such as holding shots without the intention of operation, holding slots to deny capacity to other airlines, requesting new slots without the intention of operation, requesting slots with intention of gaining improved priority.

- **Collecting, verifying and using the external data**

  As the data analysis is performed with external datasets, a data scraping from the open-source needed to be done. However, the verification of the data set and the usage outside of research are very limited. This limitation got bigger considering one of the structural problems of misuses, airport crowdedness. Airport and flight networks are heavily linked around the world and the Schiphol airport is one of the most connected airports in the world. In order to find the correlations and the causes of misuses that may lead to airport congestion, all flights record that flew into AMS would be required to obtain. The size of the dataset will be rapidly increased with a global connection of AMS, and a researcher would face a limitation to collect the data by web scraping. In future research, collaboration with airports is urged to reduce the burden of data collection.

- **Airport crowdedness**

  To track the root cause and fundamentally solve the problem, the issues from airport crowdedness should be identified. However, as much as the misuses caused by an airport network is an important topic, it is a hard topic since the purpose of slot allocation is to prevent airport congestion and the delay is caused by crowdedness, in other words, airport congestion. Whatever the exact cause of airport crowdedness and constant delays, relevant research is urged to address it. As a start, it can be started with exploratory research to find the airports that heavily connected to AMS in terms of flight network. The range of data should be expanded to the passenger information, such as the capacity of aircraft and the number of passengers on board. With the new information, seasonal influence on airport congestion can have a deeper focus. As it was performed in this paper, a couple of case studies and expanding to the global level could be done.

- **Guideline for the slot enforcement code**

  The slot enforcement code is draft and enforced by ACNL and ILT. Even though the paper explored one type of slot misuse, the different time operations, but the results do not suggest the precise time limitation for the term 'a significantly different time'. It could be a relatively vague term whereas the other types of misuses such as no operations or operation without allocated slots have specific criteria. Since the structural problem of slot misuses from airlines needs to be corrected, a reference point for time deviation and misuse frequency needs to be established. Continuous research to establish a reference point considering the frequency and time of misuses should be added to help the slot enforcement code.

- **Research focuses on the airline level**

  The term 'root cause' was discussed in this paper, the root cause of flight affected the subsequent flights. The study only focused on the one airport level and investigated the difference of scheduled and operated time slots. It would be interesting to follow one specific airline to identify the root cause. In that case, the data should not be limited to the airport, but need to be expanded to all information including daily airport congestion or itinerary of an aircraft, the number of passengers. The daily airport congestion data can assume the time spent on preparing aircraft as the crew of the airport would have more workload than usual, and the uncertainty of passengers onboarding on time will be differed by the congestion level. The itinerary of an aircraft can examine the workload of airline crews which can have an impact on the preparation time. To do this, a collaboration with an airline will be essential. This research will help to address the intention behind the no operations or operating at the curfew as it follows closely to airlines' daily behaviour.

- **Involvement of air traffic control**

  This research mainly focused on the Schiphol airport, and the data and information are limited to the time information, not what happened during the operating the flights or in an origin airport. Interviews in (Efthymiou et al., 2019) identified the ATC restriction as one of the main cause of delays. In this regard, the research could be expanded to the side of air traffic control to have a bigger picture. The role of ATC and the intervention of aircraft operating from ATC can be studies.

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A

Data Entry

A.1. Dataset given by ACNL

Table A.1: Data entry of datasets given by ACNL

Data Column	Data Type	Description
Date	String	Date of operation. Two number of date and three alphabet of month (01MAR)
D	Integer	Opsday. (1-Monday, 7-Sunday)
Airport	String	Airport in IATA code
Coord. Flight#	String	Flight number of coordinated movement.
Registration	String	Registration of coordinated movement (not used for commercial flights)
Coord. AL	String	Coordinated Airline
Coord. Trip#	Integer	Coordinated tripnumber
Coord. Suffix		Coordinated suffix
STC Service	String	Type code of coordinated movement. Detail can be found at A.2
A/D	String	Arrival (A) / departure (D) flag of coordinated movement.
Prv/Nxt	String	Previous or next airport of coordinated movement, IATA airport code
A/C	String	Aircraft type of coordinated movement.
Req	Integer	Requested time of coordinated movement. 24 hours time converted into four numbers (16:30 - 1630)
Coord	Integer	Coordinated time of coordinated movement. 24 hours time converted into four numbers (16:30 - 1630)
Load Value STT		The load value based on the coordinated time *(not used)*
#Min.		The additional minutes of the coordinated movement *(not used)*
Reason	String	Critical flag if available. Detail can be found at A.3
Operated Flight#	String	Flight number of operated movement.
Op. AL	String	Operated airline
Op. Trip#	Integer	Operated tripnumber
Op. Suffix		Operated suffix
Registration	String	Registration code of operated movement.
Operated STC	String	Service type code of operated movement.
Operated AD	String	Arrival (A) /departure (D) flag of operated movement.

Table A.1: Data entry of datasets given by ACNL

Data Column	Data Type	Description
Prv/Nxt	String	Previous or next airport of operated movement, IATA airport code
A/C	String	Aircraft type of operated movement.
Seats		Seats *(not used)*
STA/D	Integer	Scheduled time of operated movement. 24 hours time converted into four numbers (16:30 - 1630)
Diff.	Integer	Deviation in minutes between coordinated and scheduled time
ON/FB	Integer	Onblock or offblock time of operated movement. 24 hours time converted into four numbers (16:30 - 1630)
IOBT		Initial on/off block time *(not used)*
Delay	Integer	Deviation in minutes between coordinated and on-block/offblock time
ATA/D	Integer	Actual time of operated movement. 24 hours time converted into four numbers (16:30 - 1630)
Callsign		*(not used)*
Load Value STT		The load value based on the scheduled time *(not used)*
Load Value ON/FB		The load value based on the onblock/offblock time *(not used)*
Load Value ATT		The load value based on the actual time *(not used)*
#Min.		The additional minutes of the operated movement *(not used)*
Org/Fin	String	Originator of operated data (airport or DFS), IATA airport code
Airport	String	Origin or final airport of operated movement, IATA airport code
Handling		*(Not used)*
FPL Status		Flight plan status *(not used)*

A.2. Details of ACNL Dataset

Table A.2: Data entry of STC from ACNL datasets

Value	Description
J	Scheduled Passenger
S	Scheduled Passsenger
G	Non-scheduled Passenger (Normal Service)
B	Non-scheduled Passenger (Shuttle Service)
C	Charter (Passenger Only)
O	Charter (Special handling - Migrants/Immigrants)
L	Charter (Passenger and Cargo and/or Mail)
R	Additional Flights - Passenger/Cargo
Q	Scheduled Passenger/Cargo in Cabin
F	Scheduled Cargo/Mail (Loose loaded cargo and/or preloaded devices)
M	Scheduled Cargo/Mail (Mail only)
A	Non-scheduled Cargo/Mail
H	Charter (Cargo and/or Mail)
V	Scheduled Cargo/Mail (Surface Vehicle)
U	Scheduled Passenger (Service Vehicle)

Table A.3: Data entry of Reason from ACNL datasets

Value	Description
AT	Aircraft category mismatch
CO	Mismatch of coordinated and scheduled time supplied by the airport
CS	Code sharing
DV	Diversion
ID	Matched GA flight without airportslot-ID at a fully coordinated airport
MF	Multiple flights
MG	Multiple GA flights
NP	No Ops
NR	No Rec
PN	Deviation of Previous/Next
SD	Swapped digits
SO	Another registration of the same owner
ST	Service type category mismatch
TP	Increase/decrease trip number
XX	Manual assignment

A.3. Dataset scraped from Flightera

Table A.4: Data entry of datasets of Flightera

Column	Type	Description
From	String	Departure airport in an IATA code
TO	String	Arrival airport in an IATA code
FLIGHT	String	Operated flight number
DATE	String	Operated date
STATUS	String	Landed/Cancelled
STD	String	Scheduled departure time with the corresponding time zone (17:50 EST)
STA	String	Scheduled arrival time with the corresponding time zone (06:55 CET)
ATD	String	Actual departure takeoff time (18:06)
Departure Diff	String	Deviation in hours and minutes between scheduled and actual departure time (27min early)
ATA	String	Actual arrival touch-down time (06:27)
Arrival Diff	String	Deviation in hours and minutes between scheduled and actual arrival time (16min late)

A.4. Dataset scraped from PRG-aero

Table A.5: Data entry of datasets of PRG-aero

Column	Type	Description
Scheduled	String	Scheduled date and time of departure
City	String	Arrival city
T.	String	Terminal number that a flight used at PRG
Gate	String	Gate number that a flight used PRG
Plane		*Not used*
Status	String	Departure time and actual departure time (Departed 08:52)
FLIGHT	String	Flight number
DATE	String	Operated date (DD/MM/YYYY)
SD	String	Scheduled departure time (08:50)
AD	String	Actual departure (off-block time) (08:52)
Year	Integer	Operated year
Departure Diff.	Integer	Deviation in minutes between scheduled and actual arrival time

A.5. Dataset scraped from Dutch Plane Spotters

Table A.6: Data entry of datasets of Dutch Plane Spotters

Column	Type	Description
DATE	String	Date of operation
CARGO	String	Indication of cargo plane
AIRCRAFT	String	Aircraft type of operated flight
REG	String	Registration number of operated flight
GATE	String	Gate that a flight used at AMS
ARR FLIGHTNR	String	Flight number of operated flight that arrived at AMS
PLACE FROM	String	Previous airport of operated flight
STA	String	Scheduled arrival time (00:00)
ETA	String	Actual arrival on-block time (00:00)
Status	String	Status of operated flight that arrived at AMS
DEP FLIGHTNR	String	Flight number of operated flight that departed from AMS
PLACE TO	String	Next airport of operated flight
STD	String	Scheduled departure time (00:00)
ETD	String	Actual departure off-block time (00:00)
Status	String	Status of operated flight that departed from AMS

B
Python Code

Only main pieces of python for visualisation and cleaning will be explained in the appendix.

B.1. Data Cleaning of ACNL

Time All columns that expressed the time were set to integer with a 'hhmm' format. The data type was converted to the DateTime type of Python.

```
def actualtime(df):
    if df['ATA/D'] == 0.0:
        t = str(df['ATA/D'])
        time = pd.to_datetime('0000', format='%H%M')
    elif df['ATA/D'] < 10.0:
        t = str(df['ATA/D'])
        time = pd.to_datetime('000' + t[:1], format='%H%M')
    elif df['ATA/D'] < 100.0:
        t = str(df['ATA/D'])
        time = pd.to_datetime('00' + t[:2], format='%H%M')
    elif df['ATA/D'] < 1000.0:
        t = str(df['ATA/D'])
        time = pd.to_datetime('0' + t[:3], format='%H%M')
    elif df['ATA/D'] >= 1000.0:
        t = str(df['ATA/D'])
        time = pd.to_datetime(t[:4], format='%H%M')
    else:
        time = None
    return time
```

Figure B.1: Python code for converting integer type to DateTime type

B.2. Data Cleaning of External Dataset

Data scraping required library Figure B.2 listed the required python libraries for data scraping from the open-source.

```
from selenium import webdriver
from selenium.webdriver.support.ui import WebDriverWait
from selenium.webdriver.support import expected_conditions
from bs4 import BeautifulSoup
import re
import pandas as pd
import numpy as np
from datetime import date, timedelta, datetime
import time
```

Figure B.2: Required python libraries for scraping data

Data scraping The data collection can be done with any site by changing the address and collecting data type in Figure B.3.

```
def scrape(flight, month, year):

    global results


    url = "https://www.flightera.net/en/flight/Delta+Air+Lines-New+York-Amsterdam/" + flight +
"/" + month + "-" + year + "#flight_list"
    print("\n" + url)

    chrome_options = webdriver.ChromeOptions()
    agents = ["Chrome/90.0.4430.212"]
    print("User agent: " + agents[(requests%len(agents))])
    chrome_options.add_argument('--user-agent=' + agents[(requests%len(agents))] + '"')
    chrome_options.add_experimental_option('useAutomationExtension', False)
    chrome_options.add_argument('--no-sandbox')

    driver = webdriver.Chrome("chromedriver.exe", options=chrome_options,
desired_capabilities=chrome_options.to_capabilities())
    driver.implicitly_wait(5)
    driver.get(url)
    time.sleep(10)

    soup=BeautifulSoup(driver.page_source, 'html.parser')
    table = soup.find('table', {"class": "min-w-full divide-y divide-gray-200"})
    rows = table.find_all('tr')
    data = []

    for row in rows[1:]:
        cols = row.find_all('td')
        cols.append(flight)

        data.append(cols)

    df = pd.DataFrame(data, columns=['DATE/STATUS', 'FROM', 'TO', 'DEPARTED', 'ARRIVED',
'extra', 'FLIGHT'])
   # Total = soup.find_all('span', attrs={'class': 'flightPageProgressTotal'})

    results = pd.concat([results, df], sort=False)
    print(date)

    driver.close() #close the browser

    time.sleep(5)

    return "success"

#Create an empty dataframe
results = pd.DataFrame(columns=['DATE/STATUS', 'FROM', 'TO', 'DEPARTED', 'ARRIVED', 'extra',
'FLIGHT'])

requests = 0

year = ['2018' , '2019']
month = ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec']
flightlist = ['KL642']

for f in flightlist:
    for y in year:
        for m in month:
            requests = requests + 1
            while scrape(f, m, y) != "success":
                requests = requests + 1

results.to_csv("JFK_KL642.csv", index=False)
```

Figure B.3: Python code for data scraping

B.3. Data Cleaning of External Dataset

Once the required data is obtained, data needs to be cleansed as a required format. The collected data contained some HTML format with <>, only necessary information was remained by Figure B.4.

```
for i in range(len(results)):
    for j in range(5):
        results.iloc[i,j] = re.sub("\<.*?\>","",str(results.iloc[i,j]))

results = results[results["FROM"].str.contains("JFK")]
results = results[results["TO"].str.contains("AMS")]
```

Figure B.4: Data cleaning of external dataset

Time Zone The operated time from open-source data was displayed in different time zone, the operated time maintained consistency by Figure B.5.

```
def timediff1(df, col, colref, colref2):
    global date
    if df["STATUS"] == "Landed":
        if "CEST" in df[colref]:
            date = str(df["DATE"]) + " " + str(df[col])[0:5]
            date = pd.to_datetime(date, format= '%d. %b %Y %H:%M')
            date = date - pd.DateOffset(hours=2)
            if int(df[colref2][0:2]) > 10:
                date = date + pd.DateOffset(days=1)
        elif "CET" in df[colref]:
            #else:
            date = str(df["DATE"]) + " " + str(df[col])[1:6]
            date = pd.to_datetime(date, format= '%d. %b %Y %H:%M')
            date = date - pd.DateOffset(hours=1)

            if int(df[colref2][0:2]) > 10:
                date = date + pd.DateOffset(days=1)
            else:
                date = ''
        else:
            date = ''

    else:
        if "CEST" in df[colref]:
            date = str(df["DATE"]) + " " + str(df[col])[0:5]
            date = pd.to_datetime(date, format= '%d. %b %Y %H:%M')
            date = date - pd.DateOffset(hours=2)
            if int(df[colref2][0:2]) > 10:
                date = date + pd.DateOffset(days=1)
        elif "CET" in df[colref]:
            #else:
            date = str(df["DATE"]) + " " + str(df[col])[0:5]
            date = pd.to_datetime(date, format= '%d. %b %Y %H:%M')
            date = date - pd.DateOffset(hours=1)

            if int(df[colref2][0:2]) > 10:
                date = date + pd.DateOffset(days=1)
            else:
                date = ''
        else:
                date = ''

    else:
        date = ''

    return date
```

Figure B.5: Python code for converting different time zone for consistency

B.4. Data Visualisation

Histogram Histograms of exploratory analysis are made with slight adjustment per airport in Figure B.6

```
plt.hist([jfk_dl['Delay'], jfk_kl['Delay'], jfk_dy['Delay']], bins=300, alpha=0.5, color=
['purple', 'orange', 'green'], label=['Delta Airlines', 'KLM', 'Norwegian Air Shuttle'],
density=True)
plt.legend(loc='upper right')
plt.rcParams["figure.figsize"] = (20,10)

sns.kdeplot(jfk_dl['Delay'], bw=0.5, color='purple')
sns.kdeplot(jfk_kl['Delay'], bw=0.5, color='orange')
sns.kdeplot(jfk_dy['Delay'], bw=0.5, color='green')
plt.xlim([-100,300])
plt.title("AMS to JFK flights Delay Frequency")

    # Set x-axis label
plt.xlabel("Delay (Minutes)", labelpad=20, weight='bold', size=12)

    # Set y-axis label
plt.ylabel("Frequent", labelpad=20, weight='bold', size=12)


plt.show()
```

Figure B.6: Python code for histogram figures

Regression Graph on a Scatter Plot First 10 lines of code are making linear and polynomial regression graph, rest of the lines are creating a scatter plot corresponding to the regression graphs.

```
X = jfk_dl[['Prepare']]
y = jfk_dl["Delay"]
X_seq = np.linspace(X.min(),X.max(),300).reshape(-1,1)
degree=4
polyreg=make_pipeline(PolynomialFeatures(degree),LinearRegression())
polyreg.fit(X,y)

regr = linear_model.LinearRegression()
regr.fit(X, y)
prediction=regr.predict(jfk_dl[['Prepare']])

fig, ax = plt.subplots(1,1, figsize=(15,15))
fig.suptitle('', fontsize=16)
ax.scatter(jfk_dl["Prepare"], jfk_dl["Delay"], s=2)
ax.plot(X_seq,polyreg.predict(X_seq),color="red")
ax.plot(jfk_dl["Prepare"],prediction,color="black")
ax.set_yticks(np.arange(-30, 500, 30))
ax.set_xticks(np.arange(-100, 900, 50))
ax.set_ylim([-30,300])
ax.set_xlim([-100,900])
ax.set_title('Preparation time (x) to Delay time (y) - DELTA')
ax.set_xlabel('Preparation Time')
ax.set_ylabel('Departure Delay')
ax.axvline(0, color="green", linestyle="-", lw=2)
ax.axhline(0, color="green", linestyle="-", lw=2)
ax.axvline(jfk_dl['Slack'].mean(), color="purple", linestyle="-", lw=2)
ax.axvline(jfk_dl['Slack'].median(), color="purple", linestyle="-", lw=2)
ax.set_aspect('equal')
#plt.setp(ax.get_xticklabels(), rotation=30, horizontalalignment='right')
fig.autofmt_xdate()
```

Figure B.7: Python code for regression graphs with a scatter plot

Heat Map The columns with interest are aggregated with Figure B.8. The aggregated data was created into heat map by Figure B.9.

```
jfk_a_mean = jfk_a_1.groupby(['AL', 'YM'])["FLIGHT TIME"].mean().to_frame()
```

Figure B.8: Python code for aggregating data for the heat map

```
hmap = pd.pivot_table(jfk_a_mean,values='FLIGHT TIME', aggfunc='mean', index='YM',columns='AL')
hmap.head()

plt.figure(figsize=(15,10))
plt.title("Average flight time from JFK to AMS per month")
sns.heatmap(hmap,annot=True, fmt=".1f")
plt.show()
```

Figure B.9: Python code for the heat map