Assessment of Inbound Air Traffic Flow Management Delay and Total Arrival Delay for Amsterdam Airport Schiphol

P.J.A. Post
4351037

Technische Universiteit Delft

Assessment of Inbound Air Traffic Flow Management Delay and Total Arrival Delay for Amsterdam Airport Schiphol

by

P.J.A. Post
4351037

to obtain the degree of Master of Science
at the Delft University of Technology,

Student number:	4351037	
Thesis committee:	Prof. dr. ir. J.M. Hoekstra,	TU Delft, supervisor
	Ir. P.C. Roling,	TU Delft
	Dr. A. Bombelli,	TU Delft
	F. Dijkstra,	KDC Mainport Schiphol

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Acknowledgements

I would like to thank my supervisors Jacco Hoekstra, Ferdinand Dijkstra and Maarten Zorgdrager. You have given me valuable feedback throughout the thesis and provided a critical view. Additionally, you enabled me to work on a subject I am genuinely passionate about, for which I am very grateful.

I would also like to thank my friends and roommates, with whom I grew very close over the years. Some of you provided feedback on this report and throughout the process, for which I am grateful. However, all of you made my years as a student in Delft the best it could possibly be.

Most importantly, I would like to thank Tessa and my family. Tessa, thank you for always being there for me, especially throughout the difficult times during my studies and my thesis. Also to my parents and my brother, thank you for always supporting me throughout my studies and in pursuing my dreams.

P.J.A. Post
4351037
Delft, May 2021

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Nomenclature

AAS	Amsterdam Airport Schiphol
ABM	Agent-Based Modeling
AIBT	Actual In Block Time
ANSP	Air Navigation Service Provider
AOBT	Actual Off-Block Time
ASMA	Arrival Sequencing and Metering Area
ATA	Actual Time of Arrival
ATC	Air Traffic Control
ATFM	Air Traffic Flow Management
ATM	Air Traffic Management
ATOT	Actual Take-Off Time
BN	Bayesian Network
CFMU	Central Flow Management Unit
CNT	Complex Network Theory
CTOT	Calculated Take-Off Time
DAG	Directed Acyclic Graph
ETA	Estimated Time of Arrival
FAA	Federal Aviation Administration
FIR	Flight Information Region
GDP	Ground Delay Program
ICAO	International Civil Aviation Organisation
IID	Independent and Identically Distributed
KNMI	Koninklijk Nederlands Meteorologisch Instituut
LVNL	Luchtverkeersleiding Nederland
MILP	Mixed Integer Linear Programming
MIP	Mixed Integer Programming
NMIR	Network Manager Interactive Reporting

NMOC	Network Manager Operations Centre
OTP	On Time Performance
RL	Reinforcement Learning
SIBT	Scheduled In Block Time
TBO	Trajectory Based Operations
TOBT	Target Off-Block Time
TTOT	Target Take-off Time

I

Scientific Paper

Assessment of Inbound Air Traffic Flow Management Delay and Total Arrival Delay for Amsterdam Airport Schiphol

P. J. A. Post*, J. M. Hoekstra†, F. Dijkstra‡, M. Zorgdrager§
Air Transport Operations, Faculty of Aerospace Engineering
Delft University of Technology, Delft, The Netherlands

***Abstract*—In recent years Amsterdam Airport Schiphol (AAS) has been the airport with the highest Airport Air Traffic Flow Management (ATFM) delay in Europe. EUROCONTROL delays inbound flights heading towards AAS on departure, due to reasons at or around AAS. There are two main reasons for Airport ATFM delay at AAS, Weather and Aerodrome Capacity. This study aims to find a better understanding of the operational conditions that cause ATFM Aerodrome Capacity delay, such that it can be addressed properly. This is done by applying a Bayesian Network (BN) to AAS data, that includes variables from the operational conditions at AAS. The BN shows the relationship between variables and is based on conditional probabilities, so it can show the stochastic behavior of the airport. A baseline model is created using expert knowledge and through Structure Learning (SL), additional relationships between variables are identified which result in a model that best represents the operational data. The results from the BN show that an increased chance of ATFM Aerodrome Capacity delay most often occurs in the first inbound peak of the day when the cumulative delay is still low. In these conditions, the percentage of capacity used according to the schedules is often between 75% and 100%. However, at the actual time of operation the percentage of capacity used is often above 100%, indicating that the available capacity is exceeded. Interestingly, the conditions that increase the chance of having ATFM Aerodrome Capacity delay do not increase the chance of arriving too late. Having an ATFM Aerodrome Capacity delay of 20 to 30 minutes, showed only a 35% chance of arriving with more than 15 minutes of delay. Moreover, there is a discrepancy in the strategic planning of the landing slots, and the actual arriving traffic. Additionally, airlines apply schedule buffers, that could nullify the ATFM Aerodrome Capacity delay, but are unknown to other operators in the air transportation system. More information should be shared between operators to ensure all interests are met and a safe and efficient operation can be realized.**

***Index Terms*—Bayesian Networks (BN), Air Traffic Flow Management (ATFM), Airport Arrivals, Probability Analysis, Sensitivity Analysis, Amsterdam Airport Schiphol (AAS)**

I. Introduction

In recent years, the complexity of the Air Traffic Management system has increased due to an increase in aircraft movements and passenger movements [1]. This impacts several stakeholders in the aviation industry. First, for Air Traffic Control (ATC) it becomes more difficult to ensure safe operations. Second, airlines suffer from delays which for some lead to missed connections for passengers. And third, airports like London Heathrow and AAS are operating at their operational limits, which ultimately induces delays for both departures and arrivals. To anticipate the predicted growth in air traffic in Europe, EUROCONTROL implemented an ATFM system with the goal to match demand with the available capacity for en-route sectors and airports in Europe, to ensure safe operation and to prevent Air Traffic Controllers from unexpected high workloads [2]. ATFM is an extensive and complex process, which is initialized several months before a flight takes place when airlines can file flight plans. Based on the filed flight plans, EUROCONTROL can get a good estimate of the traffic situation and hence, a good indication of when certain ATC sectors or airports can get congested. During planning, which ranges from months before the flight up to the day of operation, the aim is to identify and address bottlenecks in the European air transportation network. Flight plans are adjusted to accommodate for the existing bottlenecks, however, as the system is subject to change, it is often the case that even on the day of operation ATFM delay is issued to ensure a safe and efficient operation.

When ATFM delay is issued for a flight, EUROCONTROL expects that a flight will encounter en-route delays or delays at the destination airport if it were to fly according to the flight plan. Such scenarios can lead to additional flight time when a flight has to avoid a certain sector, or it can lead to airborne holding at the airport when it cannot land due to high traffic demand or other reasons. As both scenarios lead to additional fuel burn and inefficient situations like holding, ATFM delay is most often issued at the departure airport. Instead of taking off at the Estimated Take-Off Time (ETOT), a flight is assigned Calculated Take-Off Time (CTOT), which is a later take-off time with a -5 minute to a +10 minute window in which the flight is allowed to be at the runway for take-off [3].

This research will focus on the Airport ATFM delay, which is the ATFM delay issued at departure because of reasons at or around the arrival airport of a flight. This can be due to traffic congestion at the Estimated Time of Arrival (ETA) of a flight, but there are many other reasons such as industrial actions or ATC staffing. Recent years have shown that AAS is the airport in the European air transportation system with the highest number of Airport ATFM delay. The year 2019 even showed numbers twice as high as the second airport in terms of

*MSc student, †Supervisor TU Delft, ‡Supervisor Air Traffic Control the Netherlands, §Supervisor Amsterdam Airport Schiphol.

Airport ATFM delay minutes [4]. Because of the complexity of the network, but also the complexity of AAS itself, it is difficult to find the main reason for this Airport ATFM delay other than the breakdown presented by EUROCONTROL. EUROCONTROL uses 16 ATFM delay codes. Over 2018 and 2019, 60% of the total airport ATFM delay was due to Weather and 37% of the total airport ATFM delay was due to Aerodrome Capacity. This research focuses on the latter, the ATFM Aerodrome Capacity delay, which accounts for 614608 minutes for 2018 and 2019. The ATFM Aerodrome Capacity delay can be operationally improved, whereas weather delays are difficult to change. Additionally, AAS is the only hub airport in Europe that shows a high ATFM Aerodrome Capacity delay. Providing insights for ATFM Aerodrome Capacity delay could potentially lead to a reduction in delay minutes and a better operation of the airport.

This research aims to find the main reasons contributing to the high Airport ATFM delay and specifically ATFM Aerodrome Capacity delay for AAS. The research objective is formulated as follows. *To get more insights into airport ATFM delay and arrival delay for Amsterdam Airport Schiphol by identifying the conditions that lead to airport ATFM delay or arrival delay, understanding the interactions between operational parameters and identifying the parameters that influence airport ATFM delay and arrival delay the most.* Arrival delay or total in-block delay, is included in the research objective because many flights still arrive on time or even too early despite the high number of airport ATFM delay minutes. As ATFM Aerodrome Capacity delay is a part of the total arrival delay, the interaction between the two delays is interesting to study. The parameters that influence the ATFM Aerodrome Capacity delay and total in-block delay will be studied, as well as the combination of parameters that increase the chance of ATFM Aerodrome Capacity delay or arriving too late. It will also be studied whether a more detailed strategic planning can result in a better predictability of arrival delay and a decrease in ATFM Aerodrome capacity delay. Finally, the parameters that can be changed in the operation of AAS to decrease the ATFM Aerodrome Capacity delay are discussed as well as future methods to decrease this delay.

A Bayesian Network (BN) will be used to provide the insights for AAS. A BN is a probabilistic graphical model that shows the dependencies between variables. For example, it can be used to find dependencies that were previously unknown and it can give insights into what combination of operational variables lead to ATFM Aerodrome Capacity delay.

First, related work looking into ATFM delay is presented in section II. More insights into the current operation of AAS are presented in section III. Here, the scope of the research is also presented. The methodology behind a BN and how the BN is created is presented in section IV and section V respectively. The results giving more insights into ATFM Aerodrome Capacity delay are presented in section VI and a further discussion is presented in section VII. Finally, the conclusions of this research and recommendations for future studies are presented in section VIII.

II. Related Work

With the increase of air traffic worldwide, the demand for ATFM systems has increased. ATFM is about balancing demand and available capacity. This section will first present an overview of ATFM related research and possible solutions presented in the literature. Secondly, this section will motivate the use of a BN to investigate the ATFM delay for AAS.

A. ATFM Delay Studies

ATFM is a complex process, which involves multiple stakeholders and spans over a time period of several months. Additionally, the execution of a flight includes multiple stakeholders as well, such as en-route ATC of the countries a flight crosses. This introduces stochasticity in the air transportation system, where one approach may not pose a solution for the overall problem. This section will first introduce several methods used in literature to assess ATFM delay.

1) Strategic Planning: In Europe, strategic planning starts 6 months before a flight departs up to a few days. 6 months in advance, airlines are allowed to file flight plans to EUROCONTROL. At this stage, it is difficult to create a profile that matches the exact day of operation. However, as it can be beneficial to have a detailed traffic profile far in advance, decision support tools are created to support the strategic planning phase. Several studies look at the concept of strategic planning, for example to introduce a decision support tool that includes capacity, airport geometry and ATC capacity [5]. Weather remains a very influential parameter for delay, which is included in the decision support tool by Zhang et al. [6]. Optimization techniques such as Mixed-Integer Linear Programming (MILP) are often applied to minimize congestion, delays [7] or even to decrease uncertainty along waypoints of a flight plan [8], which leans more towards 4D planning. Changing the strategic airport planning might decrease the need for airport ATFM delay.

During strategic planning at AAS landing slots are issued in 20-minute windows. Within this window uncertainty exists about when a flight will actually arrive, but closer to the day of operation more detail is applied. Nonetheless, the question arises whether a smaller window during strategic planning, for example 10 minutes, could decrease the airport ATFM delay for AAS as it could result in a better distribution of arriving traffic.

2) 4D Planning and Trajectory Based Operations: 4D planning aims at knowing the 3D position of a flight over time. This way the predictability of a flight could be increased. A concept for 4D gate-to-gate planning was presented by Jonge [9], where airlines should focus on a required time of arrival. This requires good communication between all stakeholders in air transportation. In recent years, 4D planning is often combined with MILP or machine learning algorithms to optimize planning. Some studies have the goal to minimize ATFM delay, for example by looking at 4D trajectories during planning [10]. Other studies try to include the human-in-the-loop, by modeling the interaction between airlines and the Network Manager (NM), which is the EUROCONTROL entity that manages the flow in the European network [11]. Machine learning methods show to optimize 4D planning, but while 4D planning and Trajectory Based Operations have the potential to reduce ATFM delay, many are still not accurate enough to model real operations [12].

3) Arrival Sequencing: Arrival sequencing focuses on the final phase of the flight and some include the stochastic behavior of air transportation. Current sequencing often comes down to First-Come First-Served (FCFS). The separation between flights is based on the wake turbulence category of each aircraft and with FCFS the sequence can be such that the runway throughput is not maximized. However, altering the arrival sequence can affect multiple flights, so the overall delay has to be minimized as well. Arrival sequencing is also combined with machine learning algorithms in [13], [14], but such studies do not always include stochasticity. Including the stochastic behavior of the system could give a better representation of real operations, which is covered in queuing theory. Queuing theory applied to airport arrivals, models aircraft arriving at an airport according to a certain probability distribution and are handled according to the same or another probability distribution. Many different queuing models are presented in literature which all try to model a different and ideally a more realistic approach [15]–[17]. Most of these studies show to improve the arrival sequence by minimizing delays compared to actual operation. This could mean that an airport could increase its nominal arrival throughput resulting in fewer ATFM delays. However, changing the arrival sequences from FCFS to something different can be difficult for ATC, as most controllers work according to the FCFS principle.

4) Complex Systems: The air transportation system and its subsystems are very complex. There are different stakeholders and operators, which is also the case for AAS. Complexity Science or Complex Network Theory (CNT) can be used to find connections and interactions in a complex system, which can also be applied to transportation systems. In CNT, graph theory is often used to show the variables of a system and the dependencies between them. Complexity science is used to investigate air transportation, to study matters such as uncertainty and emergent behavior [18]. It can be used to find the interaction between variables, but in other studies it is also used to study the resilience of the system. Again machine learning algorithms are used, for example to study the restorative performance after ATFM delay [19]. Network Theory is also applied to ATM to get more insights into the overall system [20]. As is presented in [18], there are many ways to get a detailed understanding of complex systems, among which are Bayesian Networks (BNs).

B. Bayesian Networks

In complex systems, it is often not one variable that leads to degradation of the system, but rather a combination of variables that results in degradation. BNs represent the variables in a system and their causal relationships, or conditional probabilities, through graph theory. The interaction between these variables is always one-directional, resulting in a Directed Acyclic Graph (DAG). In a DAG all edges have one direction and no nodes or variables are visited more than once [21]–[23]. The creation of a BN does require knowledge from the system to establish the dependencies between variables. However, BNs can also be created using a data-driven approach or a hybrid approach through Structure Learning when the BN structure is unknown. This will be explained in section IV. A BN assumes that every variable is conditionally independent of all its non-descendants, given all parents of this variable [24].

Several studies used a BN to investigate air transportation. Some focus on airlines, where complicated systems for aircraft, crew, passengers and luggage all have to work together. BNs have proven to provide more insights into such systems [25], [26]. Rodríguez-Sanz et al. [27] present a study to investigate departure delay for airports. A BN including 51 variables showed good performance for departure delay prediction, and it proved to be insightful to find the main contributors for departure delay. This BN was created using operational data. Creating BNs from data can be a computationally intense process. Some studies show that combining a learning algorithm with the Structure Learning algorithm can decrease computational time and result in better departure delay prediction [28]. Rodríguez-Sanz et al. [29] present a study that uses a BN to get a better understanding of arrival delay for airports. The focus in this study is on arrival delay and airport congestion, the latter is expressed as the percentage of capacity used. The BN in this study showed good performance for arrival delay predictions and is finally used to assess the reliability of the system.

BNs show to be useful in modeling real operations in air transportation systems, including subsystems such as airlines and airports, and are useful decision support tools under uncertainty and with complex relations between variables. BNs are also able to find main drivers behind delay types. The reason for using a BN to address the ATFM aerodrome capacity delay and arrival delay for AAS is further elaborated in section III. The methodology will be further discussed in section IV.

III. Problem understanding

To provide a better understanding of the problem of ATFM Aerodrome Capacity delay for AAS, it is important to have a good understanding of what it is and what might cause it.

Over the time period of 2018 and 2019, 37% of the total airport ATFM delay minutes for AAS were due to Aerodrome Capacity reasons. Every instance ATFM regulations are issued, the arrival capacity of AAS is reduced and ATFM delay is assigned to some flights. In this period, 60% of all regulations is due to Aerodrome Capacity reasons. So, 60% of the ATFM regulations make up 37% of the total ATFM delay. EUROCONTROL's description of Aerodrome Capacity delay is as follows: *"Reduction in declared or expected capacity due to the degradation or non-availability of infrastructure at an airport. e.g. Work in Progress, shortage of aircraft stands, etc. Or when demand exceeds expected aerodrome capacity"*

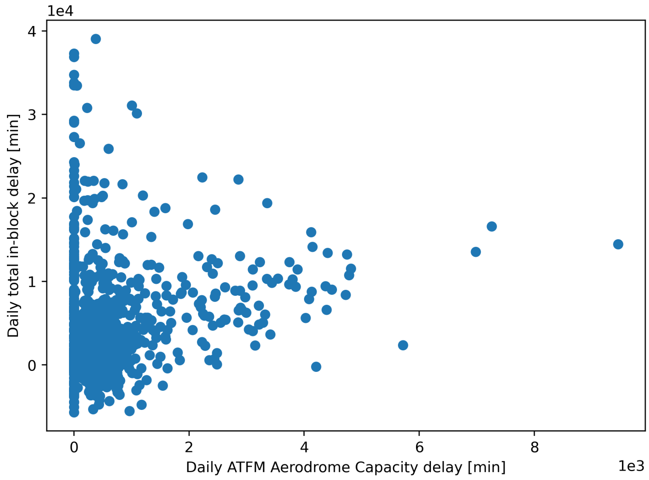


Figure 1: Daily ATFM Aerodrome Capacity delay vs. Daily total in-block delay 2018-2019

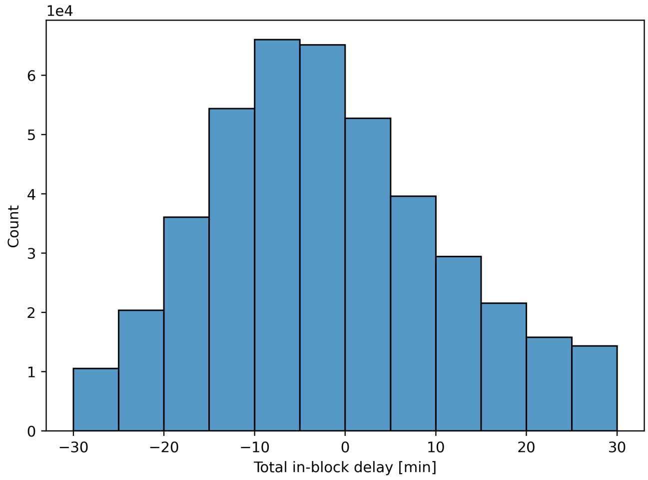


Figure 2: Total in-block delay distribution over 2018 and 2019 for AAS

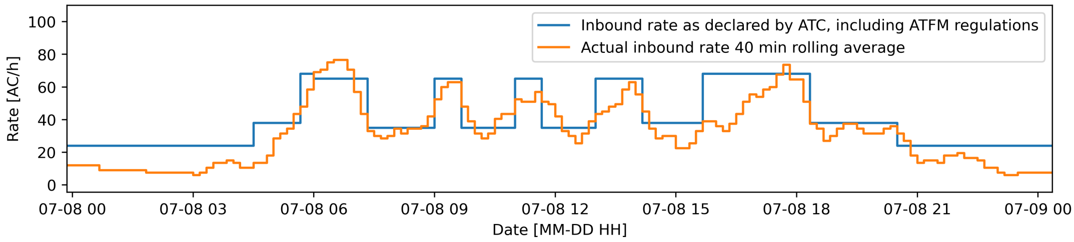
[30]. This is a wide range of reasons and not very conclusive. Therefore additional analyses are made on operational data from AAS, Air Traffic Control the Netherlands (LVNL) and EUROCONTROL to get a better understanding of the operation. It is important to note that ATFM delay can only be issued for intra-European flights, as EUROCONTROL only controls the traffic in the EU region. An inbound intercontinental flight will never encounter ATFM delay from EUROCONTROL. Two brief analyses are presented to give more insights into delays and operational conditions for AAS.

1) ATFM Aerodrome Capacity delay and total in-block delay: One would expect that an airport with many minutes of ATFM Aerodrome Capacity delay, would have a poor performance in terms of total in-block delay, the delay when the aircraft arrives at the gate. When comparing the total ATFM Aerodrome Capacity delay minutes and the total in-block delay minutes over 2018 and 2019 per day, a relationship can be seen that presents some interesting insights. In fig. 1 it can be seen that there are some days where the ATFM Aerodrome Capacity delay is high, but the total in-block delay is low, and vice versa, but there are also days when both delays are high or low. From fig. 1, no clear relationship between ATFM Aerodrome Capacity delay and total in-block delay can be seen, which is unexpected. When looking at the total in-block delay distribution in fig. 2, it can be seen that most of the traffic arrives between -15 and +5 minutes of total arrival delay. This indicates that a lot of traffic arrives on time or slightly early. It could be the case that most of the ATFM Aerodrome Capacity delay issued is absorbed during a flight, by either flying faster, asking for directs to waypoints to make the route shorter or by airlines using schedule buffers.

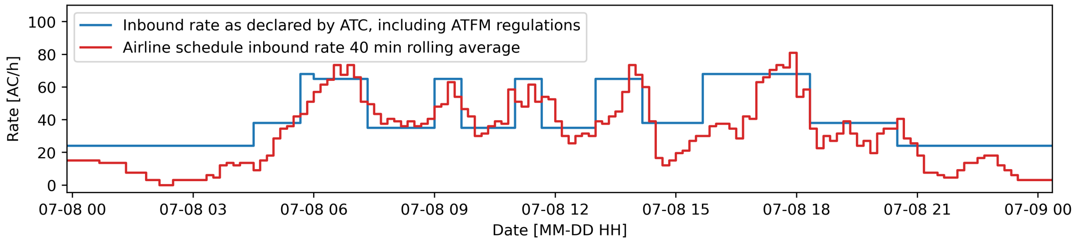
2) Scheduled, initial and actual arrivals: Comparing the landing schedule, demand and actual arrivals for AAS provides an interesting view. During an inbound peak, the nominal capacity of AAS is 68 aircraft per hour. However, when Aerodrome Capacity regulations are issued, this is often lowered to 65 aircraft per hour, indicating that less traffic can be handled and hence, delays are issued. A day at AAS has 5 inbound peaks and 6 outbound peaks to separate the departing and arriving traffic. In fig. 3, the inbound traffic for AAS on a day can be observed. Fig. 3a presents the actual inbound traffic load in orange compared to the declared arrival capacity in blue. Fig. 3b presents the inbound traffic load according to the flight schedules in red, again compared to the declared capacity in blue. Lastly, fig. 3c presents the inbound traffic load on that day if no ATFM Aerodrome Capacity delay was issued in green, compared to the declared arrival capacity in blue. To give an accurate but smooth representation of the inbound traffic, a rolling average is taken from a ± 20 minute window for every 10 minutes for the actual arriving traffic, the scheduled arriving traffic and the traffic if no ATFM Aerodrome Capacity delay was issued. These values are also multiplied by 6 to compare it to the capacity in *AC/h*.

During an inbound peak the traffic load increases, as expected. However, what sometimes happens is that the traffic starts increasing before the inbound peak started, meaning that the available capacity is exceeded, as can be seen in fig. 3a during the first and third inbound peak. It can be seen that on this particular day, the 8^{th} of July 2019, the available capacity in the inbound peak is sometimes exceeded and the traffic is not evenly distributed in the inbound peaks, leaving some capacity unused. This day had a total of 1286 ATFM Aerodrome Capacity delay minutes. Even though this amount of ATFM Aerodrome Capacity delay is not considered much, the inbound traffic still exceeds the declared capacity.

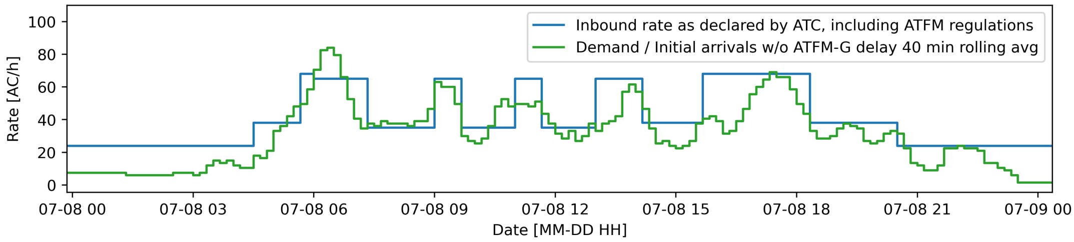
To get a sense of where the demand comes from, fig. 3b presents the airline schedules. A fairly uneven distribution can be seen in the inbound peaks with some capacity imbalances. It is also interesting to see what the inbound traffic would have looked like if no ATFM Aerodrome Capacity delay was issued for this day. Assuming no flights had Aerodrome Capacity delay and were able to arrive at AAS without any disturbances, it can be seen in fig. 3c that the first inbound peak would have



(a) Actual inbound traffic per 10 minutes with a rolling average over a ±20 minute window compared to the declared arrival capacity



(b) Scheduled inbound traffic per 10 minutes with a rolling average over a ±20 minute window compared to the declared arrival capacity



(c) Inbound traffic without ATFM Aerodrome Capacity delay per 10 minutes with a rolling average over a ±20 minute window compared to the declared arrival capacity

Figure 3: Actual, scheduled and initial arrivals compared to the declared capacity

had serious capacity issues and that the third inbound peak would have had quite some flights arriving too early. This is partly mitigated by assigning Aerodrome Capacity delay as can be seen in by the actual arriving traffic in fig. 3a, but it differs a lot when compared to the schedules in fig. 3b. Although this only illustrates one day of operations, it gives an idea of the differences between the scheduled arrival times and actual arrival times. Fig. 3 shows the effect of ATFM Aerodrome Capacity delay, in this case flattening the traffic in the first inbound peak which could have resulted in a more disrupted operation. Nonetheless, the declared capacity is still exceeded in the first inbound peak and the traffic could be distributed better within the inbound peaks, indicating that possibly more ATFM Aerodrome Capacity delay should have been issued or other measures should have been taken.

Many variables have been compared to the ATFM Aerodrome Capacity delay such as daily arrivals, early arrivals and weather, yet none showed a strong correlation. As was stated in section II, in a complex system it is often not one variable that leads to degradation of the system, but rather a combination of multiple variables. A thorough analysis showed no variables had a strong relationship to ATFM Aerodrome Capacity delay, stressing the complexity of ATFM Aerodrome Capacity delay. To find the combination of variables that lead to the disruption, the relations between variables need to be found. A stochastic approach could provide insights from a different angle. This can be achieved by applying a Bayesian Network. Thus, a BN will be created as this has the potential to create more insights into the reasons for Aerodrome Capacity delay for AAS. Additionally, it was found that while Aerodrome Capacity delay is issued often, many flights still arrive early or on time. Hence, this research will also focus on the total in-block delay to study this interaction.

IV. Bayesian Network

This section will discuss the methodology used in this study. It discusses the theory behind Bayesian Networks, Structure Learning and how it will be applied to find the operational conditions of interest. At the end of this section, a conceptual framework is presented as the outline of the model creation.

A. *Bayesian Network*

Section II briefly touched upon the subject of Bayesian Networks. BNs are DAGs with nodes that represent the variables and edges that represent conditional probabilities between two nodes. Every variable is conditionally independent of all its non-descendants, given the parents of this variable. In fig. 4 a simple representation of a BN can be seen, in this BN x_3 and x_4 are the parents of x_5. Over a BN a joint probability

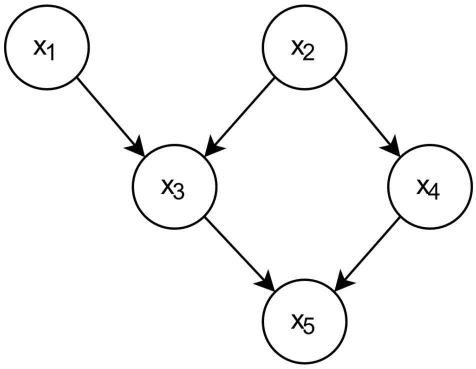


Figure 4: Bayesian Network example

distribution can be found using eq. (1) [22]. In the case of the BN in fig. 4 this results in eq. (2).

$$P(x_1, x_2, ..., x_n) = P(x_n|x_{n-1}, ..., x_1) \cdots P(x_3|x_2, x_1)P(x_2|x_1)P(x_1) \quad (1)$$

$$P(x_1, x_2, x_3, x_4, x_5) = P(x_5|x_4, x_3)P(x_4|x_2)P(x_3|x_2, x_1)P(x_2)P(x_1) \quad (2)$$

In a BN, every variable has its own probability distribution. To know which variables influence each other, expert knowledge is necessary to create the structure. The number of possible BN structures grows super-exponentially with the number of variables, which makes it difficult to create models by hand for a large number of variables [31]. However, there are also data-driven methods to establish the structure of a BN when the structure is unknown.

B. Structure Learning

Structure Learning or Structural Learning (SL) aims at finding the BN structure from a data set through an algorithm. Several algorithms or scoring functions have been developed over time, among which the K2 scoring function. This algorithm is also available in the Python package *pgmpy* which is used for this research [32]. Many studies find that the K2 algorithm performs best for large data sets and for finding the best model structure to represent the data [33]–[36]. As this research makes use of a large data set, the K2 algorithm will be used in combination with a Hill-Climbing algorithm to perform SL.

The K2 algorithm is a Bayesian Scoring function that computes the posterior probability distribution and is aimed at maximizing this value, it maximizes the probability that BN *B* represents dataset *T*, so *P(B|T)*. The K2 score is defined in eq. (3).

$$K2(B, T) = log(P(B)) + \sum_{i=1}^{n} \sum_{j=1}^{q_i} \left(log \left(\frac{(r_i - 1)!}{(N_{ij} + r_i - 1)!} \right) + \sum_{k=1}^{r_i} log(N_{ijk}!) \right) \quad (3)$$

Instead of looking for linear or exponential relationships between variables, the algorithm looks at occurrences between possible parent configurations q_i, with occurrences where variable x_i takes on state k. A parent configuration is a possible combination of parents, where every parent takes on a specific state. If the state of one parent changes it is a different parent configuration. So for variable i there can be a parent configuration j, the occurrences of parent configuration j for variable i are denoted by N_{ij}. This does not include the state of variable i itself. If variable i were to take state k every time for possible parent configuration j, N_{ijk} is equal to N_{ij}. That would mean that N_{ijk} for every other state ($\neq k$) of variable i equals zero, because $N_{ij} = \sum_{k=1}^{r_i} N_{ijk}$. Because of the factorial in the last factor of eq. (3), a parent configuration for which variable i always takes state k, results in a higher score compared to a scenario where for the same parent configuration, variable i takes on each of its states equally often. All states of variable i are denoted by r_i, and n denotes all variables in the data set. New edges are added to the model if these increase the current model score. This process continues until no more edges can be added, the score can no longer be increased or until the maximum number of parents per node, if specified, is reached. For Bayesian Scoring functions, a uniform distribution is assumed resulting in a constant value for $log(P(B))$, which is then removed [33], [36].

SL is the purely data-driven way of finding the model structure, this study will make use of a hybrid method, where an initial DAG is created from expert knowledge which serves as the foundation for the SL algorithm. Additionally, a so-called *blacklist* is defined that included relations between variables that may never be added.

C. Inference and Variable Elimination

In a BN, evidence can be entered for any variable which will change the probability of the states other variables might take in the model, also the parents of the variable. This concept can be used to study how the probability distribution of for example the total in-block delay changes, given the evidence that it is a flight from a network carrier. Or one could study the ATFM Aerodrome Capacity delay given the evidence of certain operational conditions [23]. Such inference or queries can take different forms and can be calculated using Variable Elimination (VE). In the inference query, one can specify evidence for certain variables and define the variables of interest, which could mean variables are left that are neither evidence or of interest and have to be eliminated. When looking at fig. 4 it could be the case that x_2 and x_3 are the variables that are neither evidence or of interest. Eliminating variables can be done by summing over the variables one wants to eliminate. Using the rule for conditional probabilities in eq. (4) an example can be found for the BN in fig. 4. Say one is interested in finding the probability for x_1, given x_4 and x_5, $P(x_1|x_4, x_5)$. This can be rewritten using eq. (5), now $P(x_1, x_4, x_5)$ can be found which is done by summing out variables x_2 and x_3 as is presented in eq. (6) [37]. Summing over the variables that are not of interest yields real numbers hence at the end of eq. (6) only a function of the variables of interest is left. By normalizing the values for $P(x_1, x_4, x_5)$, $P(x_1|x_4, x_5)$ can be found. This is a simple example, but when the number of variables in a BN increases, this method becomes increasingly difficult and computationally intense.

$$P(A|B) = \frac{P(A, B)}{P(B)} \tag{4}$$

$$P(x_1|x_4, x_5) = \frac{P(x_1, x_4, x_5)}{P(x_4, x_5)} \tag{5}$$

$$\begin{aligned}
P(x_1, x_4, x_5) &= \sum_{x_2,x_3} P(x_1, x_2, x_3, x_4, x_5) \qquad (6)\\
&= \sum_{x_2,x_3} P(x_5|x_4, x_3)P(x_4|x_2)P(x_3|x_2, x_1)P(x_2)P(x_1)\\
&= P(x_1)\sum_{x_3} P(x_5|x_4, x_3)\sum_{x_2} P(x_4|x_2)P(x_3|x_2, x_1)P(x_2)\\
&= P(x_1)\sum_{x_3} P(x_5|x_4, x_3)\lambda_{x_2}(x_4, x_3, x_1)\\
&= P(x_1)\lambda_{x_3}(x_5, x_4, x_1)
\end{aligned}$$

D. *Conceptual framework*

Getting to the final version of the BN is a step-wise and iterative approach that is presented in fig. 5. The first step of getting to the model is to acquire data. Data from AAS, LVNL, KNMI and EUROCONTROL is combined from which several interesting variables have been defined to use in the model. Next, the baseline model is constructed based on expert knowledge, this is validated by experts from the industry as well. Before moving on to SL, first a blacklist has to be defined, which is done through manually inspecting and identifying relationships that are not allowed to be added in the model. Using this, in combination with the baseline model, SL can be applied to find new relationships and a model that best represents the data. The edges in this model have to be validated, if there are edges that are illogical these are added to the blacklist and the SL process has to be executed again. Once all edges are validated, based on expert knowledge, the final model is found. The data has to be fitted on this model to establish the conditional probabilities between the variables, after which the model can be used for inference and variable elimination, and to find the results.

V. Model

Section II and section IV provided insights in the methodology behind BNs. This section discusses the construction of the baseline model and the final model. First, information regarding the data and the assumptions are presented. This is followed by the baseline model, structure learning, verification and validation of the model.

A. *Data acquisition and variables*

Before constructing the model, relevant data is gathered. By combining arrival data of almost 500000 arrivals over 2018 and 2019 from AAS, LVNL and EUROCONTROL, many interesting data points can be found. For the model 28 variables are identified. As some of these variables are continuous variables, these are discretized either manually or divided into equal-sized bins based on occurrence. From the EUROCONTROL data only the ATFM Aerodrome Capacity delay is taken as this is the only form of ATFM delay of interest for this research. An overview of the variables and their discretization can be seen in Appendix A. In Appendix A the time resolution of the variables can be seen, for example the *arrival congestion index* is calculated for every 10 minutes. It is also stated if and how far in advance the variables are known. There are a few variables that need further explanation.

Cloud density: This value is an indicator of how cloudy it is. It does not address the cloud base or visibility, it simply grades the skies from being completely clear (0) to fully cloudy (9).

Meteo conditions: This value represents the meteorological conditions and includes horizontal and vertical visibility. The last value in the discretization, *BZO*, indicates very limited visibility.

Actual arrival congestion index: For every 10 minutes, the percentage of capacity used is calculated. The capacity changes accordingly with ATFM regulations. It is assumed that if the declared capacity is exceeded, that ATC has a high workload.

Scheduled arrival congestion index - 20 minute window: This value is similar to the *actual arrival congestion index*, but in this case it is the percentage of nominal capacity used according to the arrival schedule, so the congestion index according to planning. Instead of 10 minutes, this value is calculated every 20 minutes as AAS issues strategic landing slots based on 20-minute windows. These windows are fixed and are in the form of [09:00h-09:20h, 09:20h-09:40h, 09:40h-10:00h, etc.]. It is expected that if the 20-minute window is decreased to for example a 10-minute window, that this could possibly lead to a decrease in ATFM Aerodrome Capacity delay [38] and a better predictability of arriving traffic. As the official strategic planning data is unavailable, it is assumed that this value is similar to the actual arrival schedule, which was confirmed by experts from AAS.

Heavies in the mix: For every 10 minutes the percentage of aircraft from the wake turbulence category *heavy* or *super heavy* in the arrival sequence is calculated. More heavy aircraft means that aircraft have to keep a larger distance to the leading aircraft which could result in a decrease in arrival throughput.

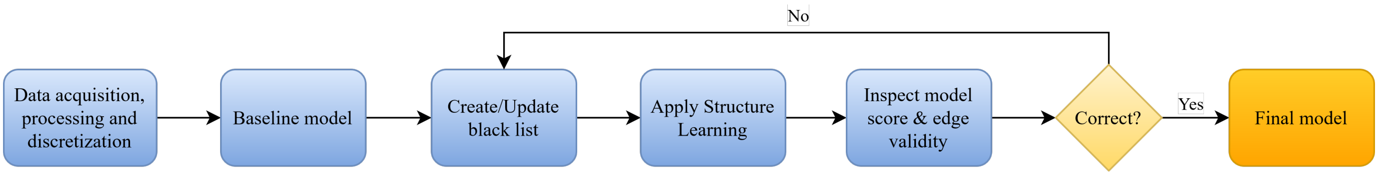


Figure 5: Conceptual framework

Daily number of arrivals: The daily number of arrivals is the number of flights that actually arrived that day. It is assumed that the total number of flights that will arrive that day is known in the morning, also on days with many cancellations.

Runway configuration type: Over 2018 and 2019, 122 unique runway configurations were used. For computational reasons, the categorical variable *runway configuration type* is introduced with only 9 states.

Estimated schedule buffer: Sometimes even though ATFM Aerodrome Capacity delay, or some other form of ATFM delay, is issued, a flight still arrives on time or even too early. One explanation for this could be that airlines use schedule buffers, where additional time is added to anticipate possible delays and to make sure passengers can still arrive on time, which is important for a hub airport like AAS [3]. The buffers are unknown, but an estimation can be made. By assuming that a schedule buffer is never smaller than 0 and never larger than 100 minutes, and by only looking at flights with less than 30 minutes of total in-block delay, the value can be estimated. This is done by using eq. (7), where the initial time of arrival can be found by subtracting the ATFM Aerodrome Capacity delay and FIR delay from the Actual Time of Arrival (ATA), this is the time the flight would have arrived were it not delayed. By subtracting the initial time of arrival from the Schedule Time of Arrival (STA), a schedule buffer can be found. This value also includes any other reason why a flight arrives early, such as flying faster, tailwind or directs.

$$\begin{aligned} \textit{Schedule buffer estimate} = STA - (ATA - \\ \textit{ATFM Aerodrome Capacity delay} - \textit{FIR delay}) \end{aligned} \tag{7}$$

Total in-block delay: The value is defined as the difference between actual arrival time at the gate and the scheduled arrival time at the gate. This value includes ATFM Aerodrome Capacity delay, FIR delay, taxi time and other delays possibly encountered during the operation of a flight.

ATFM Aerodrome Capacity delay: The data used for the model is data per flight. So, the operational conditions are used at the ATA of a flight, as over small time windows the conditions do not differ much. However, this assumption can have an influence on the operational conditions that lead to ATFM Aerodrome Capacity delay because, if a flight is assigned for example 10 minutes of ATFM Aerodrome Capacity delay, it would initially have arrived 10 minutes before its current ATA. The conditions at this initial time of arrival are the conditions that lead to the ATFM Aerodrome Capacity delay, assuming that the ETA that EUROCONTROL uses for ATFM delay matches the initial arrival time of a flight. To see the effect of this assumption, the operational conditions are compared between the ATA and the initial arrival time of every flight that was issued ATFM Aerodrome Capacity delay in Appendix C. There are two main implications of this assumption. First, the heavies in the mix seem slightly underestimated, 6% of the flights with ATFM Aerodrome capacity delay would have encountered a higher number of heavies in the mix. Secondly, 3.5% of all flights that have been issued AFTM Aerodrome Capacity delay would otherwise have arrived during a departure peak but are pushed back to consecutive arrival peak.

B. Baseline model

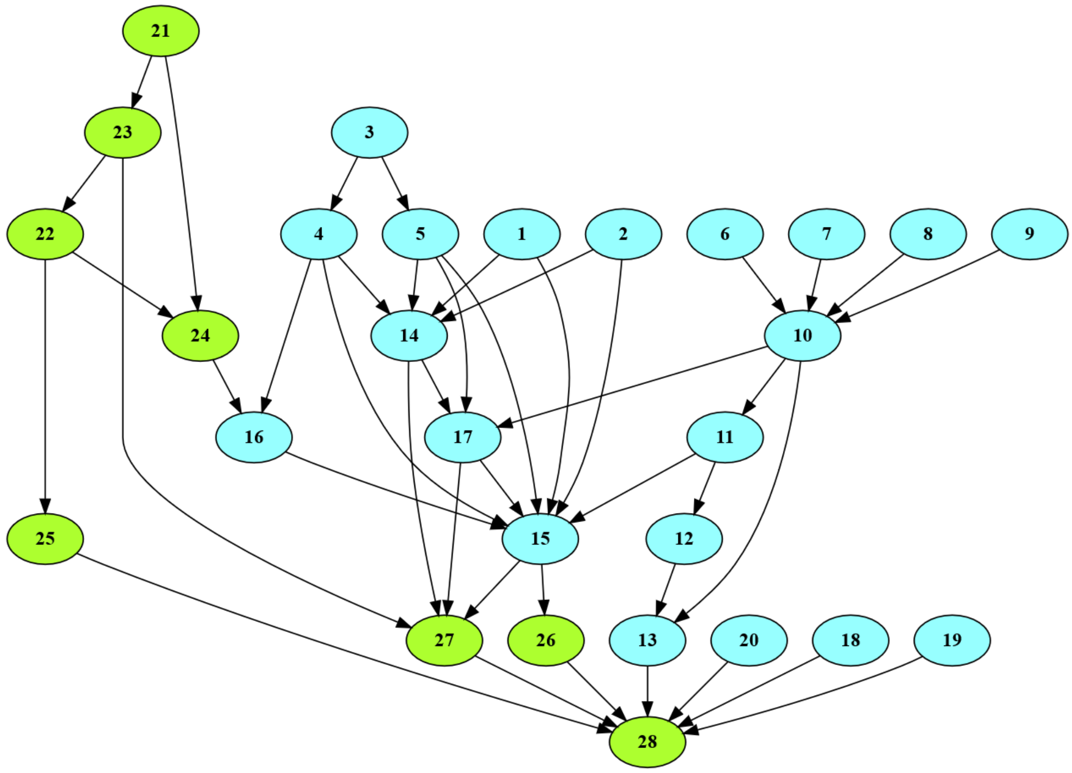
The baseline model can be seen in fig. 6. This model is constructed using expert knowledge. The nodes displayed in blue are the nodes that represent the operational conditions at AAS such as the runway configuration or arrival congestion index. The nodes displayed in green are the flight-specific variables, such as departure airport and total in-block delay.

The ATFM Aerodrome Capacity delay is believed to be influenced by the scheduled arrival congestion index (as this could give an estimation of how congested it will be), the actual arrival congestion index (this value shows the capacity used), the declared rate (under ATFM regulations the arrival rate for AAS is often lowered) and lastly, by the departure continent of a flight (as EUROCONTROL only has jurisdiction over its member states).

The total in-block delay is believed to be influenced by the parameters that make up part of the delay, so the ATFM Aerodrome Capacity delay, FIR delay, taxi time and the estimated schedule buffer. Additionally, it is believed that the total in-block delay is influenced by the cumulative delay throughout the day, so cumulative delayed flights and cumulative delay minutes, as well as the total number of flights that will arrive that day.

C. Structure learning

The baseline model provides a knowledge based foundation for further exploration of causality between variables. Before applying the SL algorithm, first a blacklist is defined. A blacklist defines all edges that the SL algorithm is not allowed to add, for example, the actual arrival congestion index does not influence what month it is, as the month is a time variable. But the other way around, the month of the year could influence the actual arrival congestion index, as it is often busier in the summer season. The complete blacklist can be



Number	Variable
1	Month number
2	Day of the week
3	Hour of the day
4	Moment of the day
5	Inbound peak number
6	Wind direction
7	Average wind speed
8	Cloud density
9	Meteo conditions
10	Runway configurations
11	Runway configurations type
12	Landing runway
13	Taxi time
14	Scheduled arrival congestion index - 20 minute window
15	Actual arrival congestion index
16	Heavies in the mix
17	Declared arrival rate
18	Cumulative delay minutes since start of the first inbound peak
19	Cumulative delayed flights (>15 minutes) since start of the first inbound peak
20	Daily number of arrivals
21	Departure airport
22	Airline type
23	Continent
24	Wake turbulence category
25	Estimated schedule buffer
26	FIR delay
27	ATFM Aerodrome Capacity delay
28	Total in-block delay

Figure 6: BN Baseline Model

found in Appendix A, it contains 441 edges. If every node were to be connected to every other node, all 28 nodes would have 27 outgoing edges because the edges are directional. This results in $28 * 27 = 756$ possible edges. Subtracting the edges in the blacklist and the edges of the baseline model twice, because of the directional property of a DAG, it leaves the algorithm with a search space of 229 edges that could be added.

Ideally, one would apply SL for the entire data set. However on a data set incorporating almost 500000 flights this becomes vastly computationally heavy. Yet, a larger data set is preferred as taking a small random sample from the data set could lead to a one-off variable combination and hence, false findings for causal relationships. Using an iterative approach, it was found that defining a maximum number of parents is computationally advantageous and hence provides the opportunity to use a large data set. Defining a maximum number of parents allows for a maximum data set size of roughly 150 days of arrivals. The K2 scores per model specification are shown in table I. It can be seen that compared to the baseline model, the SL model has an increased score. Above a maximum number of 7 parents, no additional edges are added to the model, so the score is not increased. Hence, the best model is the one where the maximum number of parents equals 7, resulting in a score of -13140641. The maximum number of parents above 7 is interesting, as the actual arrival congestion index in the baseline model already has 7 parent variables. So the value of maximum parents above 7 shows whether or not the actual arrival congestion index needs more parents to increase the score, this is also the case for total in-block delay.

The final model can be seen in fig. 7. The final model is further discussed in section VI.

Table I: Overview Structure Learning models and Scores

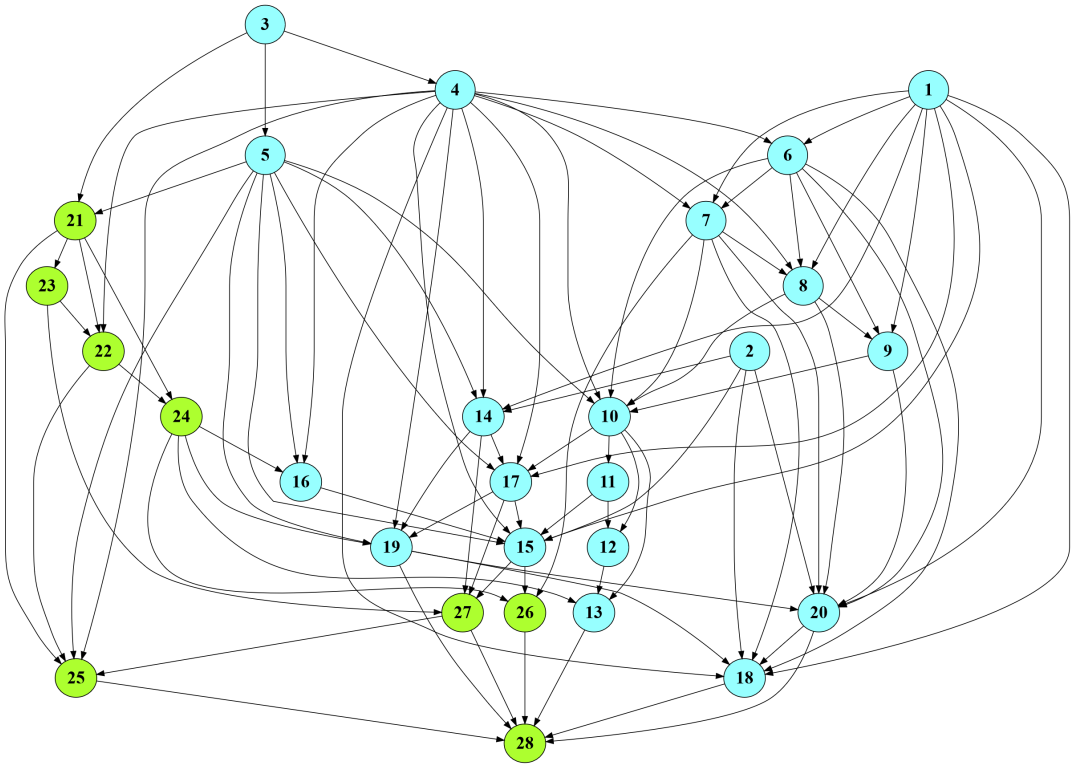
Model specifications	**K2 score**
Baseline model	$-15.57 \cdot 10^6$
Structure Learning, maximum parents = 5	$-13.32 \cdot 10^6$
Structure Learning, maximum parents = 6	$-13.18 \cdot 10^6$
Structure Learning, maximum parents = 7	$-13.14 \cdot 10^6$
Structure Learning, maximum parents = 8	$-13.14 \cdot 10^6$

D. *Verification*

Verification of the model is performed throughout the research. The main thing to look for in verifying the BN, is to see whether the model responds as expected for certain input variables. For example, a flight with a large estimated schedule buffer, is expected to have a high chance of arriving too early. The verification is done through a sensitivity analysis, which is also part of the results, that can be found in section VI.

E. *Validation*

Validating the BN is performed in multiple steps. In Appendix A, it is shown that the number of blacklist edges is high, so it is easy to miss one as these have to be defined



Number	Variable
1	Month number
2	Day of the week
3	Hour of the day
4	Moment of the day
5	Inbound peak number
6	Wind direction
7	Average wind speed
8	Cloud density
9	Meteo conditions
10	Runway configurations
11	Runway configurations type
12	Landing runway
13	Taxi time
14	Scheduled arrival congestion index - 20 minute window
15	Actual arrival congestion index
16	Heavies in the mix
17	Declared arrival rate
18	Cumulative delay minutes since start of the first inbound peak
19	Cumulative delayed flights (>15 minutes) since start of the first inbound peak
20	Daily number of arrivals
21	Departure airport
22	Airline type
23	Continent
24	Wake turbulence category
25	Estimated schedule buffer
26	FIR delay
27	ATFM Aerodrome Capacity delay
28	Total in-block delay

Figure 7: BN Structure Learning Model

manually. So after the SL algorithm finds the model structure, it has to be visually inspected whether all relations added to the model are logical. This is cross-validated with experts from the industry, both from AAS and LVNL.

The BN is trained on real operational data. Validation is often done using predictions. For this research, the data set is split into 3 different parts. First, 3 days are chosen with a different number of ATFM Aerodrome Capacity delay and total in-block delay minutes. The reason for choosing 3 specific days is that for a stochastic system such as an airport, it is possible to look at the predictions per flight but also at the delay distribution throughout the day. A morning flight that arrives for example from Asia, will not always have the same amount of delay, as there are still many other variables during the operation of a flight that influence the delay. The data used to train the model is 95% of the remaining data and the other 5% can be used for predictions.

Predicting delays is not the main goal of this research, so both the predictions on a flight by flight basis as well as the distributions over a day of operation are compared. Two types of predictions are compared, first the stochastic predictions based on the predicted probability distribution, and second the Maximum a Posteriori (MAP) predictions, which will always pick the variable state with the highest probability according to the predicted probability distribution, also when the differences are small. The predictive accuracy of these three days is presented in table II. The predictive performance of the ATFM Aerodrome Capacity delay is high, often around 90% except for the predictions on the day with high ATFM Aerodrome Capacity delay minutes. The predictive performance of the total in-block delay is poor, sometimes slightly below 50%, but the predictability seems to be higher on days with a high number of total in-block delay minutes. Appendix D presents the predicted and actual delay distributions over these three days. MAP predictions show somewhat higher predictive performance as a stochastic prediction chooses a value based on the probability distribution hence, a value of 30% actually has a 30% chance of being chosen, which is not the case with MAP predictions if another value is higher. However, when looking at a day of operations, the stochastic predictions show a better delay distribution for both ATFM Aerodrome Capacity delay and total in-block delay compared to the MAP predictions as can be seen in Appendix D. So while the predictive performance of the total in-block delay on a flight by flight basis for both MAP and stochastic predictions is low, a day of operations can be accurately modeled by using stochastic predictions.

For 1000 randomly chosen flights, the MAP predictions show an average predictive accuracy of 50% for the total in-block delay and 90% for ATFM Aerodrome Capacity delay. The stochastic predictions show a predictive accuracy of 37% for the total in-block delay and 84% for ATFM Aerodrome Capacity delay, but again a good delay distribution. In 75% of the cases for total in-block delay and in more than 93% of the cases for ATFM Aerodrome Capacity delay, the predictions are only one bin off.

Table II: Predictive accuracy of the Bayesian Network

			MAP predictions		**Stochastic predictions**	
Day	Total in-block delay	ATFM Aerodrome Capacity delay	Total in-block delay	ATFM Aerodrome Capacity delay	Total in-block delay	ATFM Aerodrome Capacity delay
21-12-2018	High	Low	72%	94%	50%	87%
23-07-2019	Low	Low	59%	96%	43%	89%
13-09-2019	Low	High	48%	56%	40%	54%

VI. Results

The results section discusses four aspects. First, it discusses the final model and the parameters that influence the ATFM Aerodrome Capacity delay and total in-block delay. Secondly, the operational conditions that lead to an increased chance of ATFM Aerodrome Capacity delay or an increased chance of arriving too late are looked into. After this, the sensitivity of some parameters is looked into to see which parameters have the most influence on the ATFM Aerodrome Capacity delay or total in-block delay. Finally, it is studied whether decreasing the window size for strategic planning from 20 minutes to 10 minutes increases the predictability of the total in-block delay for the BN.

A. Parameters of influence

The final BN is presented in fig. 7, the operational variables of AAS are displayed in blue and the flight specific variables in green. This model has 91 edges compared to the 43 edges in the baseline model. SL finds variable relations which were previously unknown or at least thought to have little effect, such as the edge between wake turbulence category and taxi time. It also shows that the ATFM Aerodrome Capacity delay seems to influence the estimated schedule buffer, and the same goes for the departure airport of a flight.

It is remarkable to see that the two main variables of interest, ATFM Aerodrome Capacity delay and total in-block delay are not influenced by any other variables than the ones defined in the baseline model. For the ATFM Aerodrome Capacity delay this could be explained by one of the earlier findings where hardly any correlation between ATFM Aerodrome Capacity delay and other variables could be found.

B. Operational conditions

To find the operational conditions that could potentially lead to an increased chance of the two delay types, queries are created with evidence for several operational variables. The operational conditions consist of a combination of the following variables:

- Month number
- Day of the week
- Hour of the day
- Day moment
- Inbound peak number
- Meteo conditions
- Runway configuration
- Runway configuration type
- Scheduled arrival congestion index
- Actual arrival congestion index
- Heavies in the mix
- Declared arrival rate
- Cumulative delay since the start of the first inbound peak
- Cumulative delayed flights since the start of the first inbound peak
- Daily number of arrivals

Using this evidence, the queries are created where the probability distributions for ATFM Aerodrome Capacity delay and total in-block delay are inspected. As random sampling for every variable could lead to impossible variable combinations, for example for hour of the day and day moment, random samples are drawn from all unique combinations of the evidence variables. This results in a little over 73000 unique operational conditions. Before diving into the details regarding the operational conditions, first the overall probability distributions of the ATFM Aerodrome Capacity delay and total in-block delay must be inspected to find the values for which the chance of any of the two delay types is considered high. When looking at fig. 8, it can be seen that on average the probability of 0 minutes ATFM Aerodrome Capacity delay is high, namely 93%. This distribution can be explained as there is never an operational scenario where all arriving flights will have ATFM Aerodrome Capacity delay. For this reason, the conditions where the probability of 0 to 10 minutes of ATFM Aerodrome Capacity delay is equal to or higher than 10% is looked into, as this is already considered much higher than the average (3.3%). For the total in-block delay in fig. 9 it can be seen that the probability distribution is more evenly distributed on average. On average the probability of arriving too late, more than 15 minutes, is 22%. Hence, the conditions where the chance of arriving too late is considered high are the conditions where the chance of arriving more than 15 minutes late is at least 30%. A flight that is more than 15 minutes late is officially considered as a late arrival.

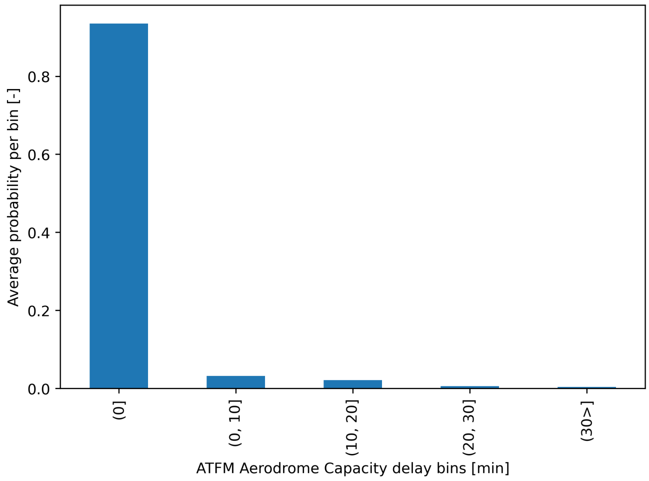


Figure 8: Average probability distribution of ATFM Aerodrome Capacity delay over 4594 operational conditions

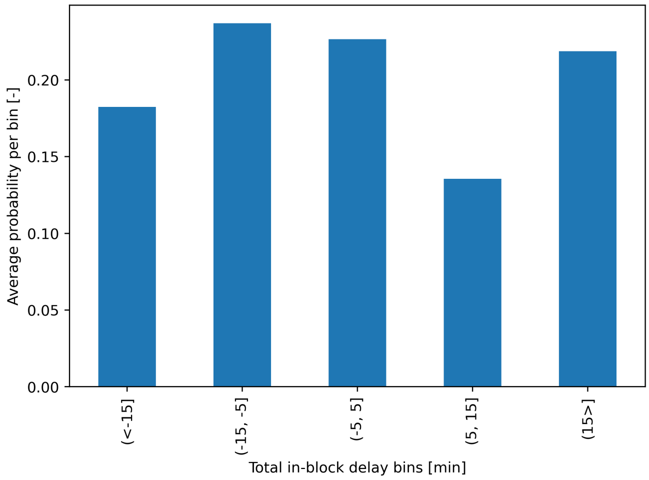


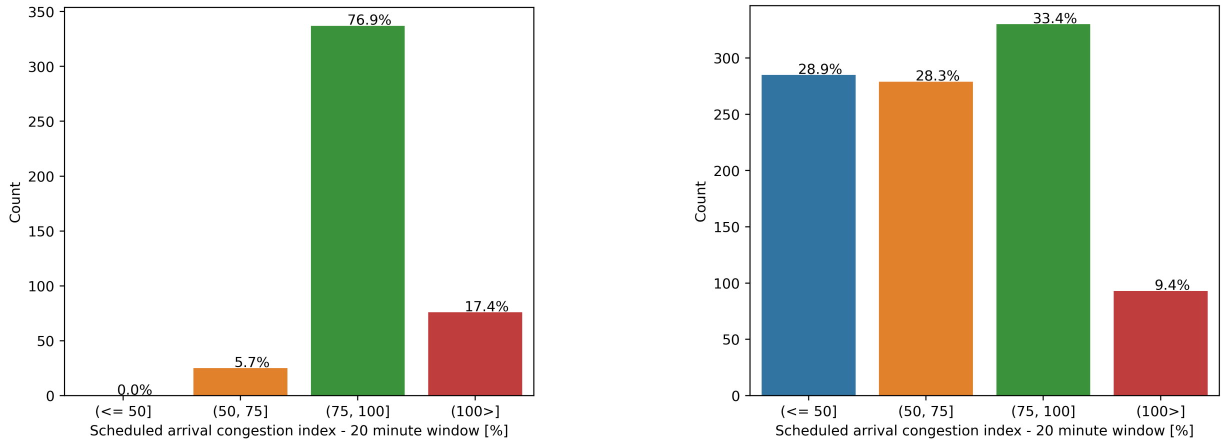
Figure 9: Average probability distribution of Total In-Block delay over 4594 operational conditions

For the results 4594 operational conditions are modeled. Out of these conditions, 438 conditions have an increased chance of ATFM Aerodrome Capacity delay and 987 conditions have an increased chance of arriving more than 15 minutes late. This part will focus on the parameters that stand out. Side by side comparisons are made between the conditions that result in a higher chance of ATFM Aerodrome Capacity delay and the conditions that could result in a higher chance of arriving too late.

Scheduled arrival congestion index: In fig. 10 the difference in the scheduled arrival congestion index for the two conditions can be seen. As the total number of operational conditions differs, both the count and the percentages are presented in all figures. What can be seen in more than 75% of the observed conditions, is when the chance of ATFM Aerodrome Capacity delay is high, the scheduled arrival congestion index is often between 75% and 100%. For a high chance of arriving too late, this is not the case, as a high chance of arriving too late happens under all scheduled arrival congestion indices and even slightly less for conditions where the scheduled arrival congestion index exceeds 100%.

Actual arrival congestion index: When looking at the actual arrival congestion index, a shift compared to the scheduled arrival congestion index can be observed. Analyzing the conditions where the chance of ATFM Aerodrome Capacity delay is high, it can be seen that the scheduled arrival congestion index is often between 75% and 100%. However, when looking at the actual arrival congestion index in fig. 11, this value is often higher than 100% indicating that the declared capacity is exceeded. Again, aircraft that arrive too late occur under all arrival congestion indices, although an increase for the value of over 100% can be observed compared to the scheduled arrival congestion index. It is important to note that the scheduled arrival congestion index spans across a 20-minute window, which is used during strategic planning at AAS, whereas the actual arrival congestion index spans across a 10-minute window to add more detail.

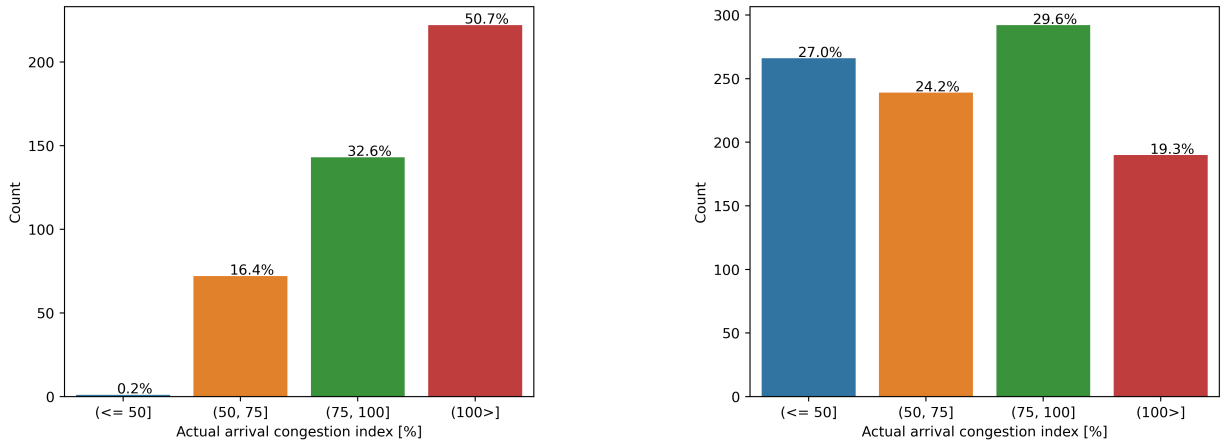
Heavies in the mix: It is interesting to see what the traffic mix looks like, as more heavy aircraft could reduce the arrival throughput in arrival sequencing. What can be seen in fig. 12, is when the chance of having either of the two delays, there are often only 11% heavy aircraft in the mix or less for every 10 minutes. Nonetheless, it must be noted that when the chance of ATFM Aerodrome Capacity delay is high, 51% of the occurrences show less than 11% heavy aircraft in the traffic mix. This indicates that in almost half of the occurrences with a high chance of ATFM Aerodrome Capacity delay, there are more than 11% heavy aircraft in the mix. When the chance of arriving more than 15 minutes late is high, only 27% of the occurrences show more than 11% heavy aircraft in the mix. More heavy aircraft could decrease the arrival throughput due to larger separation during landing. Most intercontinental flights which are heavy aircraft arrive in the morning, but are not subject to ATFM delays.



(a) Conditions with a high chance of ATFM Aerodrome Capacity delay

(b) Conditions with a high chance of high total in-block delay

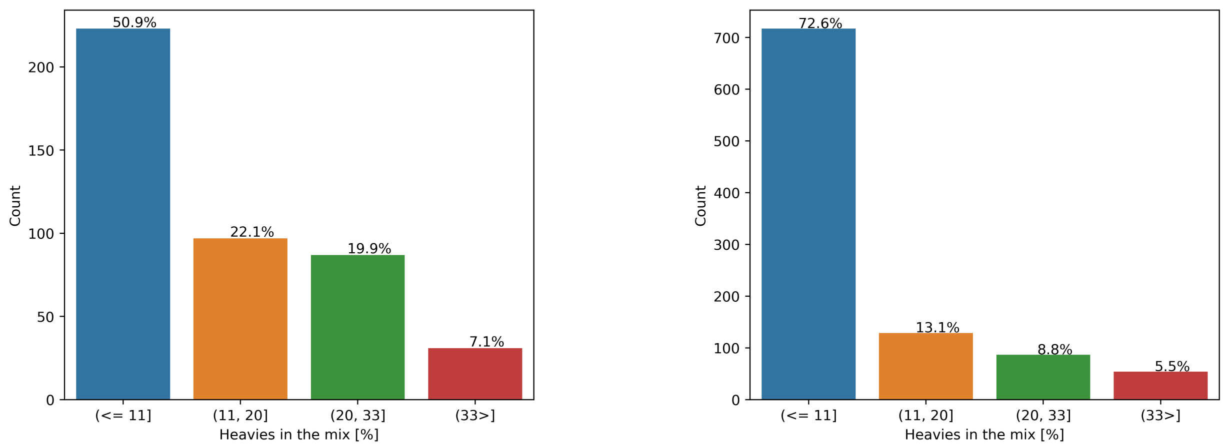
Figure 10: Comparison of the scheduled arrival congestion index - 20 minute window



(a) Conditions with a high chance of ATFM Aerodrome Capacity delay

(b) Conditions with a high chance of high total in-block delay

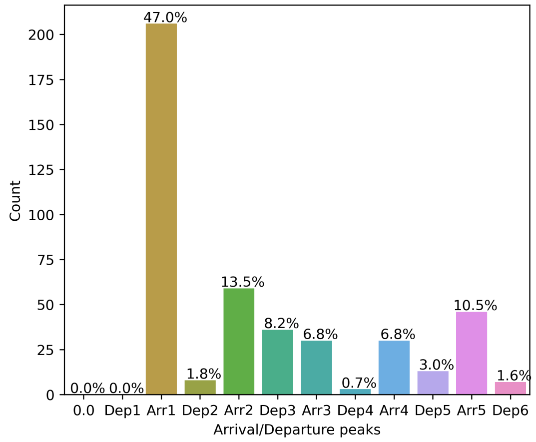
Figure 11: Comparison of the actual arrival congestion index



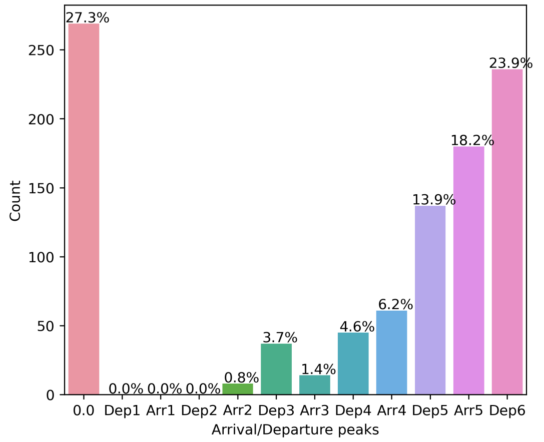
(a) Conditions with a high chance of ATFM Aerodrome Capacity delay

(b) Conditions with a high chance of high total in-block delay

Figure 12: Comparison of the heavy aircraft in the traffic mix

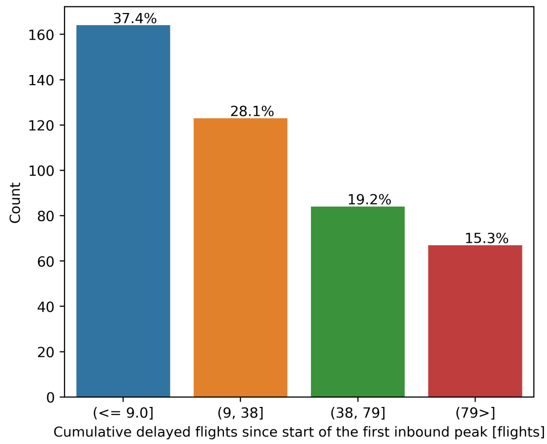


(a) Conditions with a high chance of ATFM Aerodrome Capacity delay

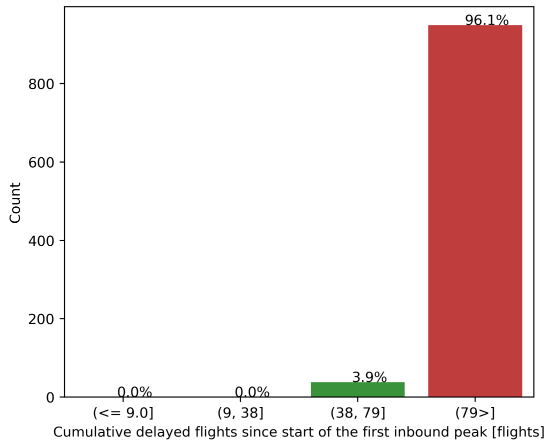


(b) Conditions with a high chance of high total in-block delay

Figure 13: Comparison of the arrival or departure peaks

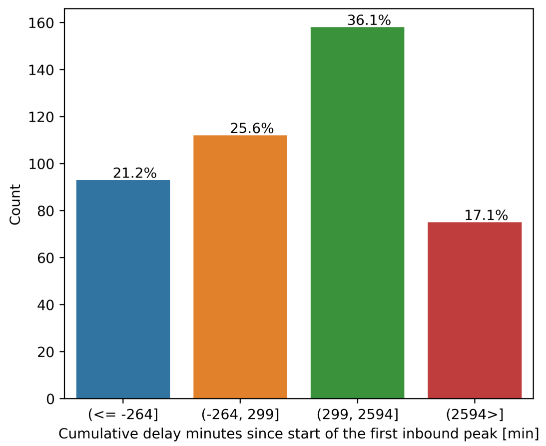


(a) Conditions with a high chance of ATFM Aerodrome Capacity delay

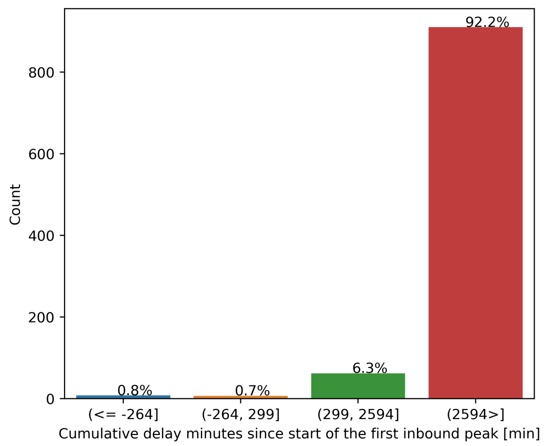


(b) Conditions with a high chance of high total in-block delay

Figure 14: Comparison of the cumulative delayed flights



(a) Conditions with a high chance of ATFM Aerodrome Capacity delay



(b) Conditions with a high chance of high total in-block delay

Figure 15: Comparison of the cumulative delay minutes

Inbound peaks: When looking at the departure or arrival peaks under conditions of an increased chance of ATFM Aerodrome Capacity delay or an increased chance of arriving too late, a large difference can be seen. From fig. 13 it can be seen that a high chance of ATFM Aerodrome Capacity delay often occurs in the first inbound peak of the day, whereas a high chance of arriving too late is often either in the last inbound or outbound peak, or in peak 0 which is an off-peak or during the night. Interestingly enough, it seems that even though the first inbound peak occurs most often when the chance of ATFM Aerodrome Capacity delay is high, the first inbound peak never occurs when the chance of arriving too late is high. This seems counter-intuitive, as one would expect the ATFM Aerodrome Capacity delay leads to total arrival delay as well.

Cumulative delay: Finally, when looking at the cumulative delayed flights throughout the day and the cumulative delay minutes throughout the day, some large differences can be observed as well. What can be seen in fig. 14, is that when the chance of ATFM Aerodrome Capacity delay is high, often only 9 flights or less arrived too late. When the chance of arriving too late is high, this is often the other way around. It seems that when many flights arrived too late, the chance of arriving too late is high as well. Something similar can be seen in fig. 15. However when the chance of ATFM Aerodrome Capacity delay is high, there is often some positive cumulative delay. When again looking at the conditions where the chance of arriving too late is high, the cumulative delay minutes are often in the highest bin, again indicating a disrupted operation. The negative values for cumulative delay minutes indicate flights arriving early.

A comparison of all variables listed in the beginning of this section can be found in Appendix B.

C. Sensitivity analysis

With 28 variables in the Bayesian Network, it is interesting to investigate the sensitivity of some of these with respect to the ATFM Aerodrome Capacity Delay and total in-block delay. Again, similar operational conditions as for the previous results are used as evidence, but now some flight-related variables are added to the evidence such as airline type and estimated schedule buffers. Keeping the operational conditions constant, all possible states of the variable of interest are used to find the effect of changing only one variable. By doing this for multiple operational conditions, the average effect of changing the variable can be found. The same thing can be done for the operational variables, however, no additional variables have to be added to the operational conditions. This section also serves as a verification of the model.

For every variable discussed in this section, 40 different operational conditions are simulated after which the average is taken over the probability of the different states for ATFM Aerodrome Capacity delay and total in-block delay. In the figures that follow, every color adds up to 100%, for example in fig. 16 it can be seen that if the estimated schedule buffer is between 0 and 10 minutes (blue), there is a 40% chance that the flight will arrive more than 15 minutes late, a 20% chance that the flight will arrive with +5 to +15 minutes of delay, a 25% chance that the flight will arrive with -5 to +5 minutes of delay, almost a 10% chance that the flight will arrive with -15 to -5 minutes of delay and almost a 5% chance that the flight will arrive with -15 minutes of delay or earlier, summing up to 100%.

Estimated schedule buffer: The estimated schedule buffer as defined in section V is expected to strongly influence the total in-block delay, it could potentially nullify the ATFM Aerodrome Capacity delay issued on departure. The results shown in fig. 16, are as expected. For high values of the estimated schedule buffer, the probability of arriving 15 minutes early or more significantly increases. Even with a schedule buffer of 10 to 20 minutes, the chances of arriving between -15 and +5 minutes sum up to 83%. Only those flights with a schedule buffer between 0 and 10 minutes, show a high chance of arriving too late, 40% on average. This parameter seems very sensitive towards total in-block delay. While the BN after using SL showed a relationship between ATFM Aerodrome Capacity delay and the estimated schedule buffer, no strong effects on the Aerodrome Capacity delay can be seen by changing the estimated schedule buffer (fig. 17). Nonetheless, it seems as if a flight with an estimated schedule buffer above 10 minutes has a slight increase in the probability of having ATFM Aerodrome Capacity delay.

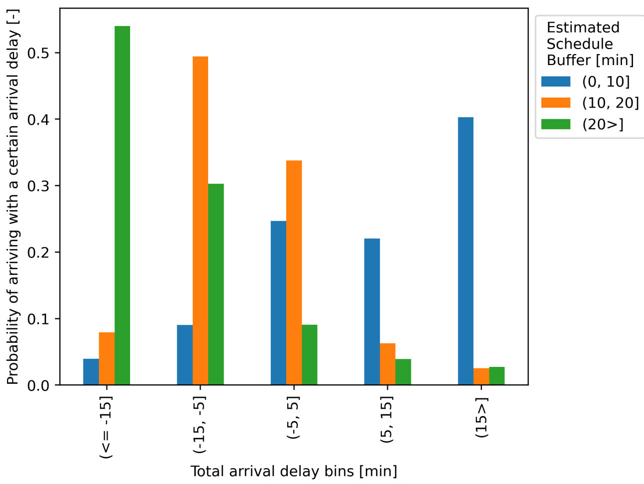


Figure 16: Sensitivity of estimated schedule buffer with respect to total in-block delay

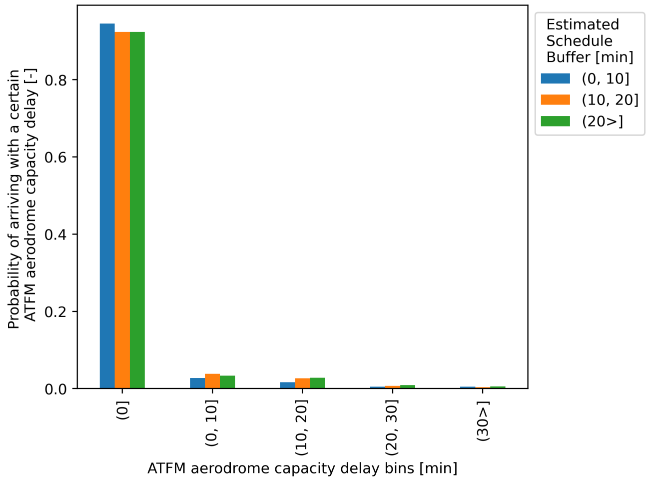


Figure 17: Sensitivity of estimated schedule buffer with respect to ATFM Aerodrome Capacity delay

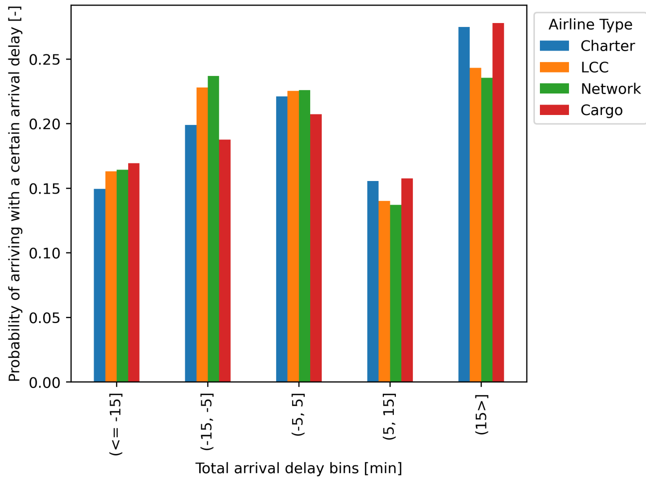


Figure 19: Sensitivity of airline type with respect to total in-block delay

Airline type: From the sensitivity analysis it was found that a Low-Cost Carrier (LCC) or a Network carrier have a slightly higher chance of ATFM Aerodrome capacity delay when compared to the other airline types as can be seen in fig. 18, but the differences are small, less than 5%. LCC and Network carriers also have a slightly higher chance of arriving between -15 and +5 minutes when compared to Charter and Cargo airlines as can be seen in fig. 19. The differences for every total in-block delay bin are small, it does not seem like there is one airline type that often arrives earlier or later than another.

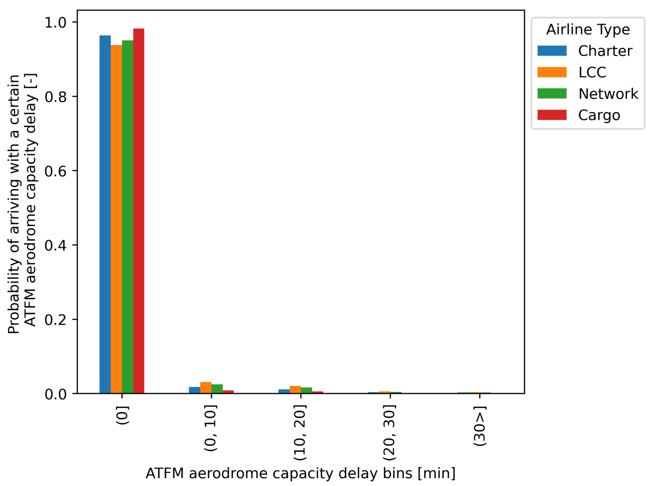


Figure 18: Sensitivity of airline type with respect to ATFM Aerodrome Capacity delay

Taxi time and Landing runway: There are two variables that are both flight specific and operational. Taxi time and landing runway differ per flight, but strongly depend on the operational conditions at AAS. It is expected that landing at runway *18R* for example, leads to a higher taxi time and hence a higher in-block delay compared to other runways. Similarly, a high taxi time is expected to result in a higher total in-block delay. For the landing runways, only the top 4 most used landing configurations are used to zoom in on the most used landing runways. The most used landing configurations are: *Landing: 18R/18C - Take-off: 18L*, *Landing: 18R/18C - Take-off: 24*, *Landing: 06/36R - Take-off: 36L* and *Landing: 36R/36C - Take-off: 36L*. From fig. 20 it can be seen that the landing runway of a flight does not strongly influence whether or not a flight has ATFM Aerodrome Capacity delay. When looking at the sensitivity towards the total in-block delay in fig. 21, it can be observed that the runway with the highest probability of arriving with -5 minutes of delay or more, compared to the other runways, is when aircraft land on runway *18R*. The location of runway *18R* is quite far from the terminal, hence the taxi time is large. When comparing this to runway *06* or *36R* it can be seen that the probability of arriving late is much lower, a landing on runway *06* or *36R* sums up to a probability of 53% for both runways individually, of arriving with -5 minutes of delay or less. Landing on these runways allows a flight to exit the runway and almost immediately be at the gate. In terms of taxi time, as expected, no strong relationship was found with ATFM Aerodrome Capacity delay. When looking at the sensitivity of taxi time with respect to the total in-block delay, it can be seen that for a longer taxi time, the chance of arriving too late is higher, and vice versa (fig. 22). On average, a taxi time of over 12 minutes yields a probability of 25% of arriving more than 15 minutes late, and a taxi time of 5 minutes or less yields a probability of 29% of arriving 15 minutes or more ahead of time.

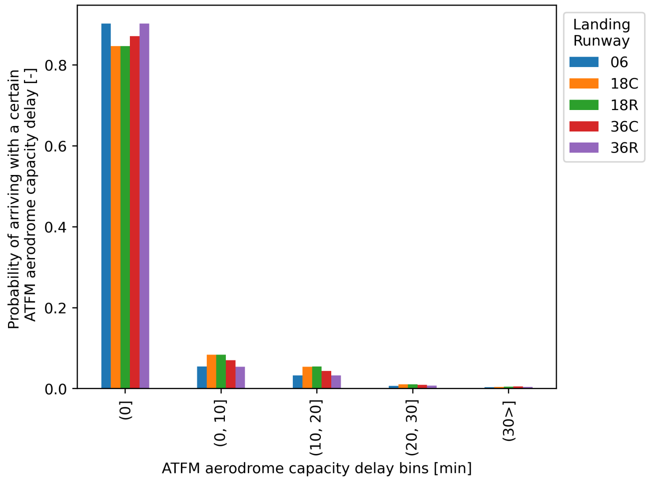


Figure 20: Sensitivity of landing runway with respect to ATFM Aerodrome Capacity delay

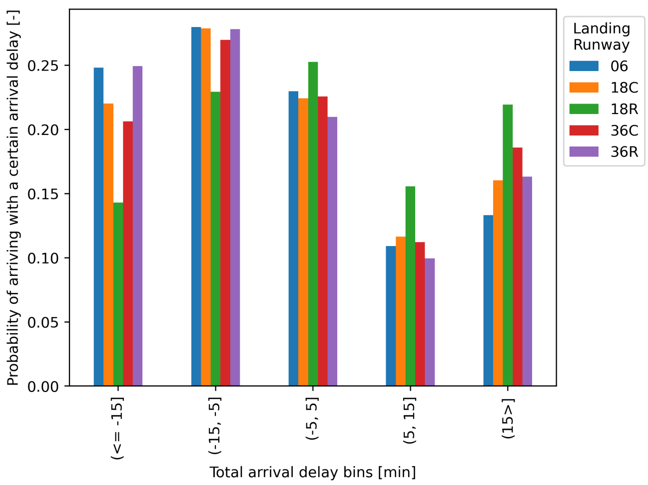


Figure 21: Sensitivity of landing runway with respect to total in-block delay

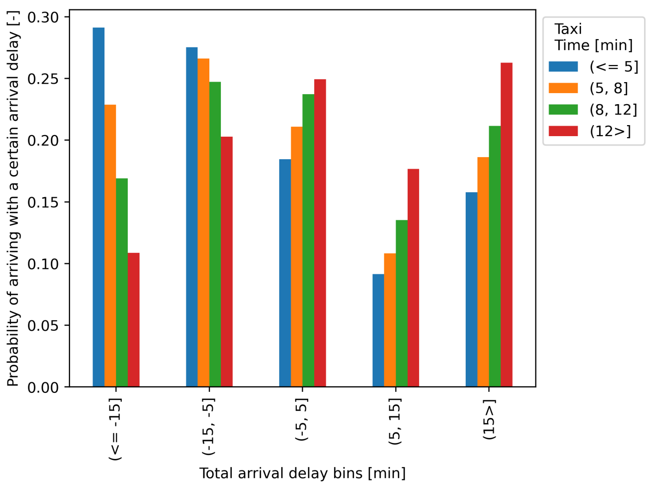


Figure 22: Sensitivity of taxi time with respect to total in-block delay

Arrival congestion indices: In the previous section it was found that the scheduled arrival congestion index and the actual arrival congestion index are often high when the chance of ATFM Aerodrome Capacity delay is high. Therefore, the sensitivity of these two values is also studied. The two arrival congestion indices are also modeled for the most used runway configurations to test the effects under common operations. Very little effect is observed in the total in-block delay when changing either of the two arrival congestion indices. However, a strong effect is observed when testing the sensitivity towards the ATFM Aerodrome Capacity delay. First, when looking at the scheduled arrival congestion index, it can be seen in fig. 23 that as the scheduled arrival congestion index becomes larger, so does the probability of ATFM Aerodrome Capacity delay. A scheduled arrival congestion index of over 100% yields a 9% probability of having 0 to 10 minutes of ATFM Aerodrome Capacity delay on average. An even stronger effect can be seen for the actual arrival congestion index in fig. 24, where an actual arrival congestion index of over 100% yields a probability of 13% of having 0 to 10 minutes of ATFM Aerodrome Capacity delay. This shows that the percentage of capacity used seems to relatively strongly influence the probability of ATFM Aerodrome Capacity delay.

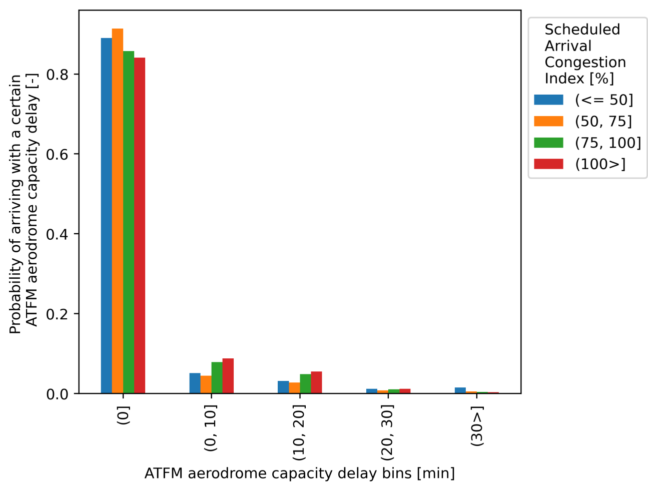


Figure 23: Sensitivity of scheduled arrival congestion index with respect to ATFM Aerodrome Capacity delay

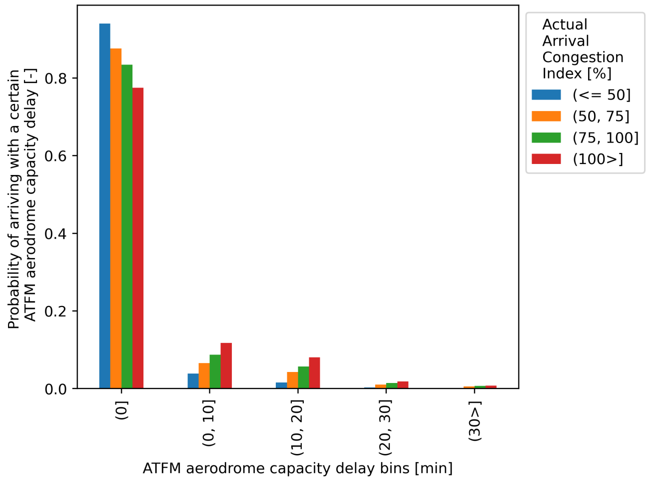


Figure 24: Sensitivity of actual arrival congestion index with respect to ATFM Aerodrome Capacity delay

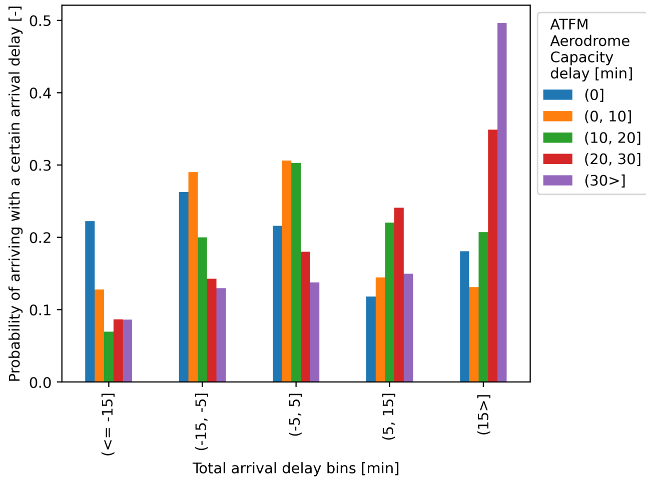


Figure 25: Sensitivity of ATFM Aerodrome Capacity delay with respect to total in-block delay

ATFM Aerodrome Capacity delay: The relationship between the ATFM Aerodrome Capacity delay and total in-block delay has not been found yet. Hence, sensitivity analysis is performed on how changing the ATFM Aerodrome Capacity delay changes the probability distribution of the total in-block delay. The results can be seen in fig. 25. What can be seen, is that for high amounts of ATFM Aerodrome Capacity delay, 20 minutes or more, the probability of arriving more than 15 minutes late is highest. However, with an ATFM Aerodrome Capacity delay between 20 and 30 minutes, there is still only a 35% chance of arriving more than 15 minutes late. This indicates that the chance is still 65% of arriving with less than 15 minutes of delay. With 0 to 10 minutes of ATFM Aerodrome Capacity delay, the probability of arriving between -15 and +5 minutes of delay is the highest. Even with 10 to 20 minutes of ATFM Aerodrome Capacity delay, the bin with the highest probability of 30% is -5 to +5 minutes of delay. The chance of actually arriving late given an amount of ATFM Aerodrome Capacity delay, is relatively small. With more than 30 minutes of ATFM Aerodrome Capacity delay, one would expect that the probability of arriving more than 15 minutes late is high, but it is still only 49%. Fig. 25 shows that ATFM Aerodrome Capacity delay does not have to result in a late arrival, it seems that it is often absorbed by applying schedule buffers, or by pilot actions.

D. Changing the scheduled arrival congestion index window

A relatively simple study was performed to see whether providing the scheduled arrival congestion index in a smaller window could increase the predictive performance of total in-block delay in the model. It is believed that a better predictability of the traffic could lead to a decrease in ATFM Aerodrome Capacity delay. This is done by modeling predictions using a part of the validation data, and by modeling predictions on that same data, where the scheduled arrival congestion index is substituted with the value that is calculated for every 10 minutes, instead of every 20 minutes. The 20 minute values and 10 minute values are only equal in 38% of the cases, the values for the 10 minute window shows strong fluctuations indicating that while the traffic might fit the 20 minute window, it is concentrated in the first or second half of the window.

Only MAP predictions are used, as the stochastic predictions are difficult to compare with each other due to the stochasticity. For 500 predictions, decreasing the resolution for the scheduled arrival congestion index showed no improvements in predicting the total in-block delay.

VII. Discussion

This section discusses the results presented in section VI as well as the limitations of the study.

A. Operational conditions

Combining the operational conditions presented in section VI, it can be seen that the circumstances with an increased chance of ATFM Aerodrome Capacity delay and the circumstances with an increased chance of arriving with a high total in-block delay differ. It was found that ATFM Aerodrome Capacity delay mainly concentrates in the first inbound peak, when the arrival congestion index according to schedule is high but does not exceed the nominal capacity. However, during the operation, the actual arrival congestion index often exceeds 100%, indicating that too many aircraft arrive compared to the declared capacity. Additionally, there often seem to be more heavy aircraft in the traffic mix as many heavy aircraft arrive in the morning, but this intercontinental traffic is not subject to ATFM Aerodrome Capacity delay. During these operations, there are often not many delayed flights as it is still the first inbound peak and hence, the number of cumulative delay minutes is relatively low. Nonetheless, it often takes on values above 300 minutes, the second highest bin. This indicates that while not many flights were more than 15 minutes late, the official definition of arriving late, some flights do arrive a few minutes late according to schedule. These findings fit the description of the ATFM Aerodrome Capacity delay according to EUROCONTROL, when the demand exceeds the expected aerodrome capacity. However, the expected aerodrome capacity, the actual arrival congestion index, is often still exceeded despite the delays.

When combining the operational conditions that could result in a high total in-block delay, it was observed that these mainly occur late in the afternoon or evening, in all possible scheduled arrival congestion indices and actual arrival congestion indices. Thus, it seems this is influenced less by the percentage of capacity used. Additionally, sometimes there are fewer heavy aircraft when compared to the conditions for an increased chance of ATFM Aerodrome Capacity delay, which could be explained by the fact that most heavy aircraft arrive in the morning. Most interestingly, the chance of arriving too late is high when the cumulative delayed flights and cumulative delay minutes are high. It seems that due to delay propagation, there are days when the operation at AAS is so disrupted that one delayed flight leads to more delayed flights, and by the end of the day the cumulative delay has grown so high that all arrivals are pushed back in time. This could also explain why the high chance of arriving too late often occurs in the final two departure peaks, the fifth and sixth outbound peak. Due to delay propagation, traffic could be pushed out of the arrival peak. During a departure peak, the arrival capacity is significantly lowered, which could lead to issues when flights suddenly arrive outside of the inbound peak.

B. Sensitivity analysis

By looking at the sensitivity of relevant parameters, it was found that the parameters that influence ATFM Aerodrome Capacity delay the most are the scheduled arrival congestion index and the actual arrival congestion index. The latter can be explained by the fact that ATFM regulations result in a reduction in declared capacity which affects the actual arrival congestion index. For the scheduled arrival congestion index, it seems that ATFM aerodrome capacity delay is often issued when the scheduled capacity is close to the 100% limit, which could indicate that a slight disruption can result in the capacity being exceeded.

The total in-block delay is influenced by some other parameters. The parameters that are sensitive towards total in-block delay are the estimated schedule buffer, the taxi time and hence the landing runway of a flight. The airline type does not show significant changes with respect to the total in-block delay. The reason for the estimated schedule buffer to influence the total in-block delay in such a significant manner, could be because the buffers are unknown to AAS, EUROCONTROL and LVNL. As it is unknown, EUROCONTROL could issue ATFM Aerodrome Capacity delay to a flight, but this might have no effect on the total in-block delay if a flight has a schedule buffer. The landing runway and hence the taxi time of a flight are unknown to an airline beforehand, so if a flight is assigned to land a runway *18R*, this flight could have to taxi for 15 minutes. Airlines not knowing whether or not a flight will land at runway *18R*, which strongly depends on the weather as well, could lead to airlines applying more schedule buffers to mitigate this uncertainty. Because of the hub function of AAS, arriving on time is important, especially for the network carriers with transfer passengers. This focus on arriving on time, could lead to a vicious cycle where larger buffers lead to more ATFM delay, which in turn will lead to even larger buffers.

One of the most interesting metrics is the sensitivity between the ATFM Aerodrome Capacity delay and total in-block delay. It shows what was expected, namely that having ATFM Aerodrome Capacity delay does not have to result in arriving too late. It could be the case that because of a lack of information from all parties, ATFM Aerodrome Capacity delay does not work as intended. Something that could possibly happen in the first inbound peak, is that according to the scheduled arrival congestion index, 75% to 100% of the capacity will be used. However, it could be expected that the traffic situation will still become congested, hence regulations are issued by EUROCONTROL, resulting in a reduction of the declared capacity and an emergence of ATFM Aerodrome Capacity delay for some flights. Because of a reduction in declared capacity, the scheduled arrival congestion index will suddenly exceed the 100% capacity limit. However, due to the ATFM Aerodrome Capacity delay, the traffic is spread out over time as some flights are delayed, causing the actual arrival congestion index to be lowered below the 100% limit. Theoretically, this concept works. However, if flights have schedule buffers in place because delays from EUROCONTROL are expected, traffic could still arrive at the same time at AAS as was scheduled. This means that in reality, the traffic is not spread out but still arrives more or less according to schedule, due to which the actual arrival congestion index still exceeds 100%, the thing that ATFM delay was trying to prevent. This does not necessarily happen to all flights that get ATFM Aerodrome Capacity delay, but fig. 25 still shows that the chance of a high total in-block delay remains small for high numbers of ATFM Aerodrome Capacity delay.

C. Changing the scheduled arrival congestion index window

A possible solution to reduce the ATFM Aerodrome Capacity delay is through strategic planning. Predicting the total in-block delay with a smaller resolution for the scheduled arrival congestion index, showed no improvements in the predictive performance of the model. This small case study was performed to understand whether a smaller window during strategic planning, could result in a better predictability of the model. For the total in-block delay, it was found that the scheduled arrival congestion index is not a sensitive parameter. This could explain why the predictions showed no changes, as it hardly changes the probability of arriving with a different amount of total in-block delay. When comparing this to real operations, changing the window during strategic planning from 20 minutes to 10 minutes, would give a better idea of the traffic distribution over the hour and possibly a different arrival schedule. But, if there is one thing this study showed, it is that it remains very hard to predict the total in-block delay of a flight and hence, what time a flight actually arrives. Changing the strategic planning window to 10 minutes would give a better idea of the arriving traffic in theory, but in practice this could also result in more flights arriving outside of their strategic planning window, as the window is smaller and total in-block delay predictions remain difficult.

D. Limitations

In this study, several assumptions are made that limit this study and its results. First, the discretization of the variables is done in quite large steps. This is mainly for computational reasons, however, adding more bins could potentially provide more detail in the model, especially for the ATFM Aerodrome Capacity delay and total in-block delay.

The predictive performance of the total in-block delay of this model is low. The predictions have not been the main focus of this research, but if the model were to be used for delay predictions, possibly additional information such as en-route ATC delays is necessary. The predictions make use of the conditional probability distributions found from fitting the operational data to the model. As this data comes directly from operational data, it is not necessarily the model that performs poor predictions, it also shows that given the information available, predicting the total in-block delay is difficult. Nonetheless, the stochastic predictions showed accurate representations of delay distribution over a day of operation.

Operationally, this study is limited to the exact moments in time that a flight arrives. Hence, it cannot model the interactions that happen during the transition from an inbound to an outbound peak. During such a situation, it could be the case that the arrival throughput is still high, which could have an effect on the departure throughput. This is also why AAS sometimes operates with 4 runways, 2 for landings and 2 for departures, which is unwanted because of noise regulations.

To study the true impact of the strategic planning window size, additional research is necessary. This research briefly tried to find the effect of decreasing the window size, but this showed no changes. The scheduled arrival congestion index was calculated for every 10 minutes instead of every 20 minutes, but the actual arrival schedule stayed the same. Nonetheless a discrepancy was found that showed that most of the traffic arrives in the first or second half of the 20 minute window. The model does not mimic the airlines filing flight plans and AAS issuing landing slots with the slot coordinator. To find the effect of the strategic planning window size, and to see whether a smaller window could lead to a different arrival schedule, the interaction between airlines and airport needs to be modeled, and how it is used over time to construct the final arrival schedule. Human interaction is important in this decision process.

The final limitation, is also regarding the human decision process. This model showed the operational conditions at AAS that increase the probability of issuing ATFM Aerodrome Capacity delay. However, someone has to decide whether regulations will be put in place or not. Choosing to apply regulations could even differ per Air Traffic Controller (ATCo). Additionally, only one reason for ATFM delay can be filed, but in reality it could be the case that there are Aerodrome Capacity issues as well as weather issues for example. The decision process of choosing to regulate or not and for what reason would be interesting to study as well.

VIII. Conclusions & Recommendations

This research aims to find the operational conditions at Amsterdam Airport Schiphol that lead to an increased chance of ATFM Aerodrome Capacity delay. Additionally, the conditions that result in a high chance of arriving more than 15 minutes late have been studied. This problem is assessed by using a Bayesian Network.

A preliminary analysis found no correlations between ATFM Aerodrome Capacity delay and other operational variables. Hence, the first part of this research aims at finding causal relationships between operational variables. First, a baseline model is constructed using expert knowledge from the industry. After the baseline model is constructed, Structure Learning is applied to find additional relationships between variables. Many edges are added between seasonal variables such as the month and weather conditions, but the operational conditions at Schiphol also seem to strongly influence one another. The Structure Learning algorithm showed no additional relations with respect to the ATFM Aerodrome Capacity delay and total in-block delay, other than the ones defined in the baseline model.

Using the Bayesian Network, the operational conditions that result in an increased chance of ATFM Aerodrome Capacity delay or total in-block delay are studied. The conditions that lead to an increased chance of ATFM Aerodrome Capacity delay most often occur under a scheduled arrival congestion index of 75% - 100% and an actual arrival congestion index of over 100%. Most often it occurs during the first inbound peak under conditions where the cumulative delay is low and in half of the occurrences where the chance of ATFM Aerodrome Capacity delay is high, the percentage of heavy aircraft in the mix is higher than the median of 11%.

The operational conditions that result in an increased chance of arriving more than 15 minutes late, look somewhat different. It occurs under all values of the scheduled and actual arrival congestion indices. A high chance of arriving more than 15 minutes late often occurs at the end of the day, during the last landing or departure peak, or during the night. The chance of arriving more than 15 minutes late is strongly increased when the cumulative delay is high, indicating strong delay propagation. This time in only 27% of the occurrences, the percentage of heavy aircraft in the mix is higher than 11%.

The operational conditions when the chance of ATFM Aerodrome Capacity delay is high and when the chance of arriving more than 15 minutes late is high, differ a lot from one another. Both show seasonal effects where the delays occur more often during the summer season, but other than the months and weather conditions, there are few similarities between these operational scenarios.

A sensitivity analysis has been performed that, among others, looked into the relation between ATFM Aerodrome Capacity delay and total in-block delay. It was found that having an ATFM Aerodrome Capacity delay of 20 to 30 minutes, results in a 35% chance of arriving more than 15 minutes late, and that an ATFM Aerodrome Capacity delay of more than 30 minutes, results in a 49% chance of arriving more than 15 minutes late on average.

This research also aimed to investigate whether decreasing the window size during strategic planning from 20 to 10 minutes could increase the arrival delay predictions. Changing the scheduled arrival congestion index window in the Bayesian Network showed no improvement in the predictive performance of the total arrival delay. Additional research into the effects of changing this window from 20 to 10 minutes, or even smaller, is recommended. It could potentially lead to an arrival schedule that is a closer representation of the actual arrivals on the day of operation and hence, reduces the ATFM Aerodrome Capacity delay necessary. This could be combined with a decision support tool, such as a Bayesian Network, for which a high predictive performance would be beneficial. Increasing the predictive performance of the Bayesian Network in this research could be achieved by adding other variables that influence a flight.

The main conclusion of this study is that ATFM Aerodrome Capacity delay issued on departure for an inbound flight to Amsterdam Airport Schiphol, has a relatively small chance of resulting in a late arrival. Many flights seem to absorb the ATFM Aerodrome Capacity delay during the flight, either by airlines applying schedule buffers in the flight plan or through pilot actions. The goal of ATFM delay is to prevent ATC from unexpected high workload, but if the ATFM delay is absorbed, this could still result in situations where for example airborne holding is necessary, which could have been prevented if the traffic actually flew according to schedule. If Schiphol wants to reduce its Airport ATFM delay minutes, it should mainly focus on the first inbound peak, on the scheduled planning and on the capacity declaration in the morning. However, the question remains whether Schiphol can reduce the Airport ATFM delay minutes by itself. If EUROCONTROL and Schiphol keep operating with a lack of information, for example regarding schedule buffers, ATFM delay is issued without knowing whether it will have an effect or not. Over 2018 and 2019, Schiphol shows the highest number of Airport ATFM delay minutes in Europe, yet most of the traffic arrives on time or slightly ahead of time. The biggest concern for the airlines is arriving on time, especially for the network carriers. To increase the predictability of the traffic, schedule buffers could be reduced, which is only attractive for the airlines if it can be guaranteed that a flight arrives on time. 4D planning could pose a solution for such a centralized system, however, the day of operation is always subject to change especially with schedule buffers. This is why more research into the effects of schedule buffers is necessary. Schiphol and LVNL could possibly look into arrival sequencing for the first inbound peak, to see whether the arrival throughput can be increased when there are more heavy aircraft in the traffic mix. Overall, more information should be shared between airlines, airports and ATC regarding schedule buffers and required arrival times to closer match the arrival schedule with the actual arrivals. This way, the operation can be optimized and delays can be minimized, which will ultimately improve the journey of the passenger.

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II
Scientific Paper Appendices

A

Model Variables & Blacklist

Table A.1: Bayesian Network Variables and Discretization

	Variable	**Time resolution**	**Known in advance**	**Unit**	**Discretization**
1	Month number	-	Yes	-	-
2	Day of the week	-	Yes	-	-
3	Hour of the day	-	Yes	UTC	-
4	Moment of the day	-	Yes	-	[Morning (06:30h - 13:00h), Afternoon (13:00h - 18:00h), Evening (18:00h - 22:30h), Night (22:30h - 06:30h)] (CET)
5	Inbound peak number	-	Yes	-	-
6	Wind direction	Hour	Few hours	Degrees	[0-110, 110-170, 170-270, 270-360]
7	Average wind speed	Hour	Few hours	Knots	[$\leq$10, 10-20, 20-30, 30>]
8	Cloud density	Hour	Few hours	-	[$\leq$2, 2-8, 8-9]
9	Meteo conditions	Actual	Few hours	-	[Good, Marginal, BZO]
10	Runway configurations	Actual	Few hours	-	-
11	Runway configuration type	Actual	Few hours	-	[South landing, North landing, South departure, North departure, South 4 runways, North 4 runway, South off peak, North off peak, other]
12	Landing runway	-	Few hours	-	-
13	Taxi time	Actual	No	Minutes	[$\leq$5, 5-8, 8-12, 12>]
14	Scheduled arrival congestion index - 20 minute window	20 minutes	Few days	Percentage	[$\leq$50, 50-75, 75-100, 100>]
15	Actual arrival congestion index	10 minutes	Few hours	Percentage	[$\leq$50, 50-75, 75-100, 100>]
16	Heavies in the mix	10 minutes	Few hours	Percentage	[$\leq$11, 11-20, 20-33, 33>]
17	Declared arrival rate	Actual	Few hours	Aircraft/hour	[$\leq$32, 32-36, 36-38, 38-60, 60-65, 65-68, 68>]
18	Cumulative delay minutes since start of the first inbound peak	Actual	No	Minutes	[$\leq$(-264), (-264)-299, 299-2594, 2594>]
19	Cumulative delayed flights (>15 minutes) since start of the first inbound peak	Actual	No	Flights	[$\leq$9, 9-38, 38-79, 79>]
20	Daily number of arrivals	Daily	Day of operation	Flights	[$\leq$648, 648-698, 698-738, 738>]
21	Departure airport	-	Yes	-	-
22	Airline type	-	Yes	-	[Charter, LCC, Network, Cargo]
23	Continent	-	Yes	-	-
24	Wake turbulence category	-	Yes	-	[Medium, Heavy, Super heavy]
25	Estimated schedule buffer	-	No	Minutes	[$\leq$10, 10-20, 20>]
26	FIR delay	-	No	Minutes	[$\leq$5, 5-10, 10-20, 20>]
27	ATFM Aerodrome Capacity delay	-	No	Minutes	[0, 0-10, 10-20, 20-30, 30>]
28	Total in-block delay	-	No	Minutes	[$\leq$-15, (-15)-(-5), (-5)-5, 5-15, 15>]

Table A.2: Blacklist

Airline type → Scheduled arrival congestion index - 20 minute window	Total in-block delay → Cloud density
Airline type → Actual arrival congestion index	Total in-block delay → Runway configuration
Airline type → Average wind speed	Total in-block delay → Runway configuration type
Airline type → Cloud density	Total in-block delay → Continent
Airline type → Runway configuration	Total in-block delay → Moment of the day
Airline type → Runway configuration type	Total in-block delay → Day of the week
Airline type → Moment of the day	Total in-block delay → Declared arrival rate
Airline type → Day of the week	Total in-block delay → Departure airport
Airline type → Declared arrival rate	Total in-block delay → Heavies in the mix
Airline type → Departure airport	Total in-block delay → Hour of the day
Airline type → FIR delay	Total in-block delay → Inbound peak number
Airline type → Heavies in the mix	Total in-block delay → Landing runway
Airline type → Hour of the day	Total in-block delay → Meteo conditions
Airline type → Inbound peak number	Total in-block delay → Month
Airline type → Landing runway	Total in-block delay → Wind direction
Airline type → Meteo conditions	Total in-block delay → Wake turbulence category
Airline type → Month	Departure airport → Scheduled arrival congestion index - 20 minute window
Airline type → Daily number of arrivals	Departure airport → Actual arrival congestion index
Airline type → Taxi time	Departure airport → Average wind speed
Airline type → Wind direction	Departure airport → Cloud density
Scheduled arrival congestion index - 20 minute window → Airline type	Departure airport → Runway configuration
Scheduled arrival congestion index - 20 minute window → Average wind speed	Departure airport → Runway configuration type
Scheduled arrival congestion index - 20 minute window → Cloud density	Departure airport → Moment of the day
Scheduled arrival congestion index - 20 minute window → Continent	Departure airport → Day of the week
Scheduled arrival congestion index - 20 minute window → Total in-block delay	Departure airport → Declared arrival rate
Scheduled arrival congestion index - 20 minute window → Departure airport	Departure airport → FIR delay
Scheduled arrival congestion index - 20 minute window → Heavies in the mix	Departure airport → Hour of the day

Table A.2 continued from previous page

Scheduled arrival congestion index - 20 minute window → Hour of the day	Departure airport → Inbound peak number
Scheduled arrival congestion index - 20 minute window → Landing runway	Departure airport → Landing runway
Scheduled arrival congestion index - 20 minute window → Meteo conditions	Departure airport → Meteo conditions
Scheduled arrival congestion index - 20 minute window → Estimated schedule buffer	Departure airport → Month
Scheduled arrival congestion index - 20 minute window → Taxi time	Departure airport → Taxi time
Scheduled arrival congestion index - 20 minute window → Wind direction	Departure airport → Wind direction
Scheduled arrival congestion index - 20 minute window → Wake turbulence category	FIR delay → Airline type
Actual arrival congestion index → Airline type	FIR delay → Scheduled arrival congestion index - 20 minute window
Actual arrival congestion index → Scheduled arrival congestion index - 20 minute window	FIR delay → Average wind speed
Actual arrival congestion index → Average wind speed	FIR delay → Cloud density
Actual arrival congestion index → Cloud density	FIR delay → Runway configuration
Actual arrival congestion index → Runway configuration	FIR delay → Runway configuration type
Actual arrival congestion index → Continent	FIR delay → Continent
Actual arrival congestion index → Departure airport	FIR delay → Moment of the day
Actual arrival congestion index → Heavies in the mix	FIR delay → Day of the week
Actual arrival congestion index → Hour of the day	FIR delay → Departure airport
Actual arrival congestion index → Meteo conditions	FIR delay → Heavies in the mix
Actual arrival congestion index → Estimated schedule buffer	FIR delay → Hour of the day
Actual arrival congestion index → Wind direction	FIR delay → Inbound peak number
Actual arrival congestion index → Wake turbulence category	FIR delay → Landing runway
ATFM Aerodrome Capacity delay → Airline type	FIR delay → Meteo conditions
ATFM Aerodrome Capacity delay → Average wind speed	FIR delay → Month

Table A.2 continued from previous page

ATFM Aerodrome Capacity delay → Cloud density	FIR delay → Daily number of arrivals
ATFM Aerodrome Capacity delay → Runway configuration	FIR delay → Estimated schedule buffer
ATFM Aerodrome Capacity delay → Runway configuration type	FIR delay → Taxi time
ATFM Aerodrome Capacity delay → Moment of the day	FIR delay → Wind direction
ATFM Aerodrome Capacity delay → Day of the week	FIR delay → Wake turbulence category
ATFM Aerodrome Capacity delay → Departure airport	Heavies in the mix → Airline type
ATFM Aerodrome Capacity delay → Heavies in the mix	Heavies in the mix → Scheduled arrival congestion index - 20 minute window
ATFM Aerodrome Capacity delay → Hour of the day	Heavies in the mix → Average wind speed
ATFM Aerodrome Capacity delay → Inbound peak number	Heavies in the mix → Cloud density
ATFM Aerodrome Capacity delay → Landing runway	Heavies in the mix → Runway configuration
ATFM Aerodrome Capacity delay → Meteo conditions	Heavies in the mix → Runway configuration type
ATFM Aerodrome Capacity delay → Month	Heavies in the mix → Continent
ATFM Aerodrome Capacity delay → Daily number of arrivals	Heavies in the mix → Moment of the day
ATFM Aerodrome Capacity delay → Taxi time	Heavies in the mix → Day of the week
ATFM Aerodrome Capacity delay → Wind direction	Heavies in the mix → Departure airport
ATFM Aerodrome Capacity delay → Wake turbulence category	Heavies in the mix → Inbound peak number
Average wind speed → Airline type	Heavies in the mix → Landing runway
Average wind speed → Scheduled arrival congestion index - 20 minute window	Heavies in the mix → Meteo conditions
Average wind speed → Scheduled arrival congestion index - 20 minute window	Heavies in the mix → Month
Average wind speed → Continent	Heavies in the mix → Estimated schedule buffer
Average wind speed → Moment of the day	Heavies in the mix → Wind direction
Average wind speed → Day of the week	Heavies in the mix → Wake turbulence category
Average wind speed → Departure airport	Hour of the day → Airline type

Table A.2 continued from previous page

Average wind speed → Heavies in the mix	Hour of the day → Scheduled arrival congestion index - 20 minute window
Average wind speed → Hour of the day	Hour of the day → Actual arrival congestion index
Average wind speed → Inbound peak number	Hour of the day → ATFM Aerodrome Capacity delay
Average wind speed → Month	Hour of the day → Average wind speed
Average wind speed → Estimated schedule buffer	Hour of the day → Cloud density
Average wind speed → Wind direction	Hour of the day → Runway configuration
Average wind speed → Wake turbulence category	Hour of the day → Runway configuration type
Cloud density → Airline type	Hour of the day → Continent
Cloud density → Scheduled arrival congestion index - 20 minute window	Hour of the day → Cumulative delay minutes since start of the first inbound peak
Cloud density → Scheduled arrival congestion index - 20 minute window	Hour of the day → Cumulative delayed flights since start of the first inbound peak
Cloud density → Average wind speed	Hour of the day → Day of the week
Cloud density → Runway configuration type	Hour of the day → Declared arrival rate
Cloud density → Continent	Hour of the day → Total in-block delay
Cloud density → Moment of the day	Hour of the day → FIR delay
Cloud density → Day of the week	Hour of the day → Heavies in the mix
Cloud density → Departure airport	Hour of the day → Landing runway
Cloud density → Heavies in the mix	Hour of the day → Meteo conditions
Cloud density → Hour of the day	Hour of the day → Month
Cloud density → Inbound peak number	Hour of the day → Daily number of arrivals
Cloud density → Month	Hour of the day → Estimated schedule buffer
Cloud density → Estimated schedule buffer	Hour of the day → Taxi time
Cloud density → Wind direction	Hour of the day → Wind direction
Cloud density → Wake turbulence category	Hour of the day → Wake turbulence category
Runway configuration→ Airline type	Inbound peak number → Airline type
Runway configuration→ Scheduled arrival congestion index - 20 minute window	Inbound peak number → Average wind speed
Runway configuration→ Scheduled arrival congestion index - 20 minute window	Inbound peak number → Cloud density
Runway configuration→ Actual arrival congestion index	Inbound peak number → Continent
Runway configuration→ ATFM Aerodrome Capacity delay	Inbound peak number → Moment of the day

Table A.2 continued from previous page

Runway configuration→ Average wind speed	Inbound peak number → Day of the week
Runway configuration→ Cloud density	Inbound peak number → Meteo conditions
Runway configuration→ Continent	Inbound peak number → Month
Runway configuration→ Cumulative delay minutes since start of the first inbound peak	Inbound peak number → Wind direction
Runway configuration→ Cumulative delayed flights since start of the first inbound peak	Inbound peak number → Wake turbulence category
Runway configuration→ Moment of the day	Landing runway → Airline type
Runway configuration→ Day of the week	Landing runway → ATFM Aerodrome Capacity delay
Runway configuration→ Total in-block delay	Landing runway → Average wind speed
Runway configuration→ Departure airport	Landing runway → Cloud density
Runway configuration→ FIR delay	Landing runway → Runway configuration
Runway configuration→ Heavies in the mix	Landing runway → Continent
Runway configuration→ Hour of the day	Landing runway → Moment of the day
Runway configuration→ Inbound peak number	Landing runway → Day of the week
Runway configuration→ Meteo conditions	Landing runway → Departure airport
Runway configuration→ Month	Landing runway → Heavies in the mix
Runway configuration→ Daily number of arrivals	Landing runway → Hour of the day
Runway configuration→ Estimated schedule buffer	Landing runway → Meteo conditions
Runway configuration→ Wind direction	Landing runway → Month
Runway configuration→ Wake turbulence category	Landing runway → Estimated schedule buffer
Runway configuration type → Airline type	Landing runway → Wind direction
Runway configuration type → Scheduled arrival congestion index - 20 minute window	Landing runway → Wake turbulence category
Runway configuration type → Average wind speed	Meteo conditions → Airline type
Runway configuration type → Cloud density	Meteo conditions → Scheduled arrival congestion index - 20 minute window
Runway configuration type → Continent	Meteo conditions → Average wind speed
Runway configuration type → Moment of the day	Meteo conditions → Cloud density
Runway configuration type → Day of the week	Meteo conditions → Runway configuration type

Table A.2 continued from previous page

Runway configuration type → Departure airport	Meteo conditions → Continent
Runway configuration type → Heavies in the mix	Meteo conditions → Moment of the day
Runway configuration type → Hour of the day	Meteo conditions → Day of the week
Runway configuration type → Inbound peak number	Meteo conditions → Departure airport
Runway configuration type → Meteo conditions	Meteo conditions → Heavies in the mix
Runway configuration type → Month	Meteo conditions → Hour of the day
Runway configuration type → Estimated schedule buffer	Meteo conditions → Inbound peak number
Runway configuration type → Wind direction	Meteo conditions → Landing runway
Runway configuration type → Wake turbulence category	Meteo conditions → Month
Continent → Scheduled arrival congestion index - 20 minute window	Meteo conditions → Wind direction
Continent → Average wind speed	Meteo conditions → Wake turbulence category
Continent → Cloud density	Month → Airline type
Continent → Runway configuration	Month → Runway configuration
Continent → Runway configuration type	Month → Runway configuration type
Continent → Moment of the day	Month → Continent
Continent → Day of the week	Month → Moment of the day
Continent → Declared arrival rate	Month → Day of the week
Continent → FIR delay	Month → Departure airport
Continent → Heavies in the mix	Month → Hour of the day
Continent → Hour of the day	Month → Inbound peak number
Continent → Inbound peak number	Month → Landing runway
Continent → Landing runway	Month → Wake turbulence category
Continent → Meteo conditions	Daily number of arrivals → Airline type
Continent → Month	Daily number of arrivals → Scheduled arrival congestion index - 20 minute window
Continent → Taxi time	Daily number of arrivals → Average wind speed
Continent → Wind direction	Daily number of arrivals → Cloud density
Cumulative delay minutes since start of the first inbound peak → Airline type	Daily number of arrivals → Continent

Table A.2 continued from previous page

Cumulative delay minutes since start of the first inbound peak → Scheduled arrival congestion index - 20 minute window	Daily number of arrivals → Moment of the day
Cumulative delay minutes since start of the first inbound peak → Average wind speed	Daily number of arrivals → Day of the week
Cumulative delay minutes since start of the first inbound peak → Cloud density	Daily number of arrivals → Departure airport
Cumulative delay minutes since start of the first inbound peak → Continent	Daily number of arrivals → Hour of the day
Cumulative delay minutes since start of the first inbound peak → Cumulative delayed flights since start of the first inbound peak	Daily number of arrivals → Inbound peak number
Cumulative delay minutes since start of the first inbound peak → Moment of the day	Daily number of arrivals → Meteo conditions
Cumulative delay minutes since start of the first inbound peak → Day of the week	Daily number of arrivals → Month
Cumulative delay minutes since start of the first inbound peak → Departure airport	Daily number of arrivals → Wind direction
Cumulative delay minutes since start of the first inbound peak → Heavies in the mix	Daily number of arrivals → Wake turbulence category
Cumulative delay minutes since start of the first inbound peak → Hour of the day	Estimated schedule buffer → Scheduled arrival congestion index - 20 minute window
Cumulative delay minutes since start of the first inbound peak → Inbound peak number	Estimated schedule buffer → Average wind speed
Cumulative delay minutes since start of the first inbound peak → Meteo conditions	Estimated schedule buffer → Cloud density
Cumulative delay minutes since start of the first inbound peak → Month	Estimated schedule buffer → Runway configuration
Cumulative delay minutes since start of the first inbound peak → Daily number of arrivals	Estimated schedule buffer → Runway configuration type
Cumulative delay minutes since start of the first inbound peak → Estimated schedule buffer	Estimated schedule buffer → Continent
Cumulative delay minutes since start of the first inbound peak → Wind direction	Estimated schedule buffer → Moment of the day
Cumulative delay minutes since start of the first inbound peak → Wake turbulence category	Estimated schedule buffer → Day of the week
Cumulative delayed flights since start of the first inbound peak → Airline type	Estimated schedule buffer → Departure airport
Cumulative delayed flights since start of the first inbound peak → Scheduled arrival congestion index - 20 minute window	Estimated schedule buffer → Hour of the day

Table A.2 continued from previous page

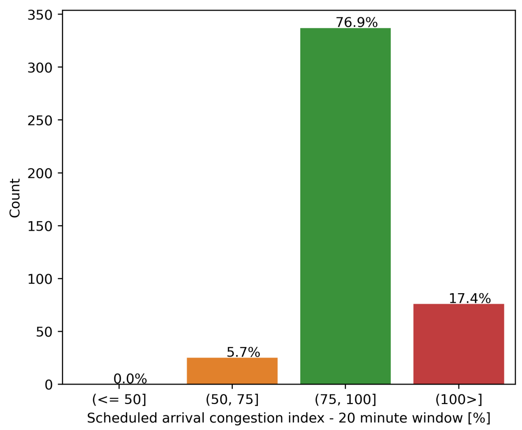
Cumulative delayed flights since start of the first inbound peak → Average wind speed	Estimated schedule buffer → Inbound peak number
Cumulative delayed flights since start of the first inbound peak → Cloud density	Estimated schedule buffer → Landing runway
Cumulative delayed flights since start of the first inbound peak → Continent	Estimated schedule buffer → Meteo conditions
Cumulative delayed flights since start of the first inbound peak → Moment of the day	Estimated schedule buffer → Month
Cumulative delayed flights since start of the first inbound peak → Day of the week	Estimated schedule buffer → Taxi time
Cumulative delayed flights since start of the first inbound peak → Departure airport	Estimated schedule buffer → Wind direction
Cumulative delayed flights since start of the first inbound peak → Heavies in the mix	Taxi time → Airline type
Cumulative delayed flights since start of the first inbound peak → Hour of the day	Taxi time → Scheduled arrival congestion index - 20 minute window
Cumulative delayed flights since start of the first inbound peak → Inbound peak number	Taxi time → Average wind speed
Cumulative delayed flights since start of the first inbound peak → Meteo conditions	Taxi time → Cloud density
Cumulative delayed flights since start of the first inbound peak → Month	Taxi time → Runway configuration type
Cumulative delayed flights since start of the first inbound peak → Estimated schedule buffer	Taxi time → Continent
Cumulative delayed flights since start of the first inbound peak → Wind direction	Taxi time → Day of the week
Cumulative delayed flights since start of the first inbound peak → Wake turbulence category	Taxi time → Departure airport
Moment of the day → Day of the week	Taxi time → Heavies in the mix
Moment of the day → Inbound peak number	Taxi time → Hour of the day
Moment of the day → Month	Taxi time → Meteo conditions
Day of the week → Average wind speed	Taxi time → Month
Day of the week → Cloud density	Taxi time → Estimated schedule buffer
Day of the week → Runway configuration	Taxi time → Wind direction
Day of the week → Runway configuration type	Taxi time → Wake turbulence category
Day of the week → Moment of the day	Wind direction → Airline type
Day of the week → Hour of the day	Wind direction → Scheduled arrival congestion index - 20 minute window
Day of the week → Inbound peak number	Wind direction → Continent

Table A.2 continued from previous page

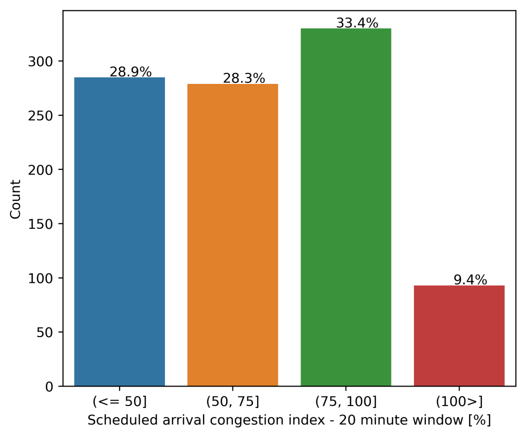
Day of the week → Landing runway	Wind direction → Day of the week
Day of the week → Meteo conditions	Wind direction → Departure airport
Day of the week → Month	Wind direction → Heavies in the mix
Day of the week → Wind direction	Wind direction → Hour of the day
Day of the week → Wake turbulence category	Wind direction → Inbound peak number
Declared arrival rate → Airline type	Wind direction → Month
Declared arrival rate → Average wind speed	Wind direction → Estimated schedule buffer
Declared arrival rate → Cloud density	Wind direction → Wake turbulence category
Declared arrival rate → Runway configuration	Wake turbulence category → Airline type
Declared arrival rate → Continent	Wake turbulence category → ATFM Aerodrome Capacity delay
Declared arrival rate → Moment of the day	Wake turbulence category → Average wind speed
Declared arrival rate → Day of the week	Wake turbulence category → Cloud density
Declared arrival rate → Departure airport	Wake turbulence category → Runway configuration
Declared arrival rate → Heavies in the mix	Wake turbulence category → Runway configuration type
Declared arrival rate → Hour of the day	Wake turbulence category → Moment of the day
Declared arrival rate → Landing runway	Wake turbulence category → Day of the week
Declared arrival rate → Meteo conditions	Wake turbulence category → Departure airport
Declared arrival rate → Month	Wake turbulence category → Hour of the day
Declared arrival rate → Estimated schedule buffer	Wake turbulence category → Inbound peak number
Declared arrival rate → Wind direction	Wake turbulence category → Landing runway
Declared arrival rate → Wake turbulence category	Wake turbulence category → Meteo conditions
Total in-block delay → Airline type	Wake turbulence category → Month
Total in-block delay → Scheduled arrival congestion index - 20 minute window	Wake turbulence category → Estimated schedule buffer
Total in-block delay → Actual arrival congestion index	Wake turbulence category → Wind direction
Total in-block delay → Average wind speed	

B

Operational Conditions Comparison

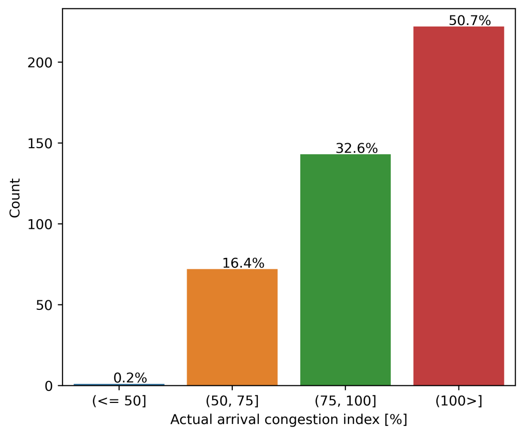


(a) Conditions with a high chance of ATFM Aerodrome Capacity delay

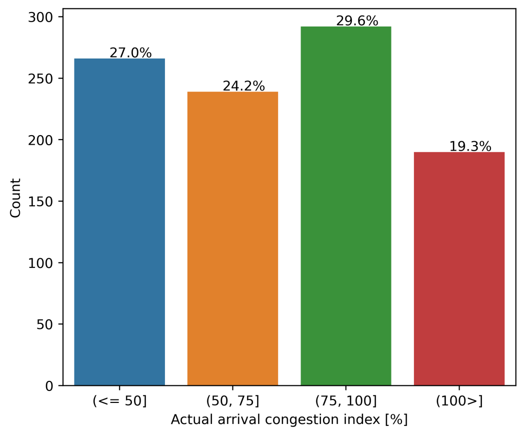


(b) Conditions with a high chance of high total in-block delay

Figure B.1: Comparison of the scheduled arrival congestion index - 20 minute window

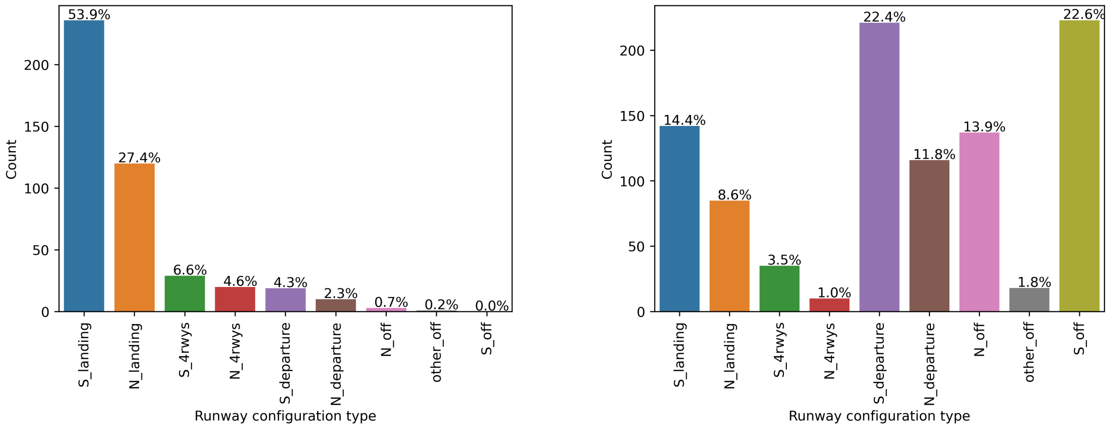


(a) Conditions with a high chance of ATFM Aerodrome Capacity delay



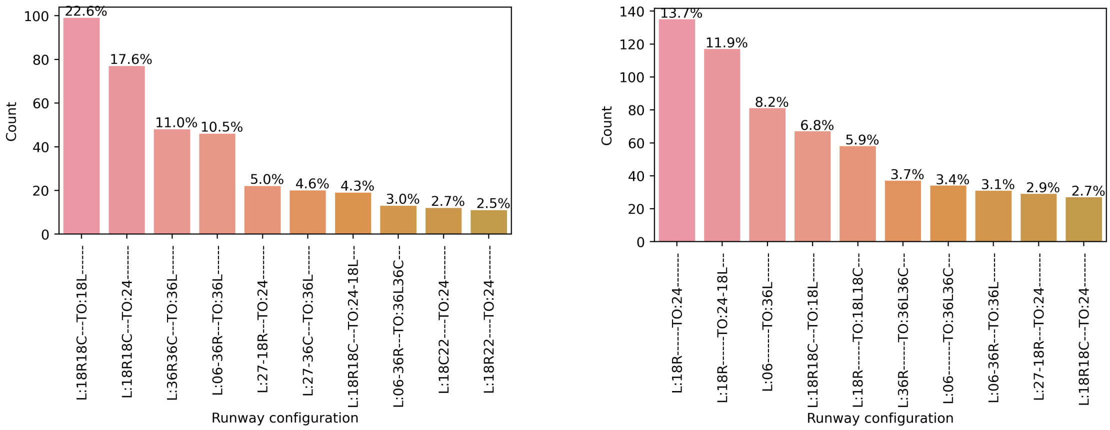
(b) Conditions with a high chance of high total in-block delay

Figure B.2: Comparison of the actual arrival congestion index



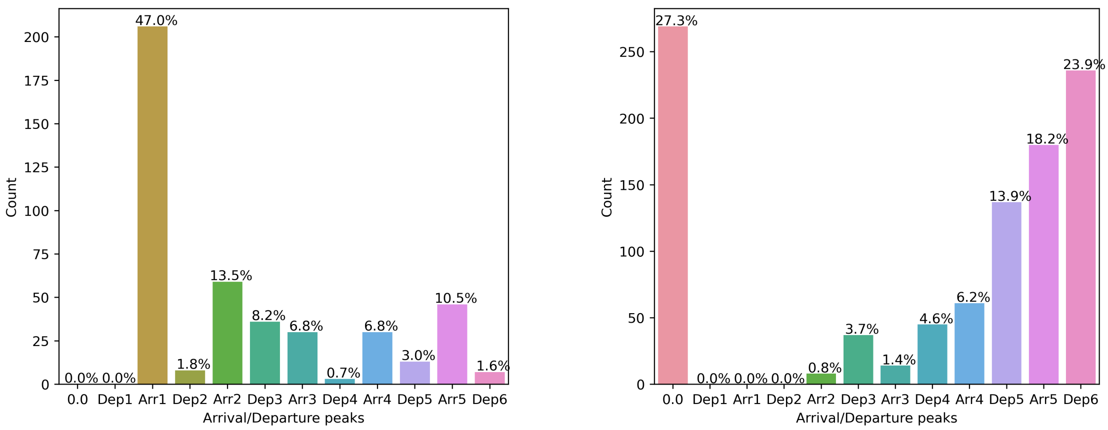
(a) Conditions with a high chance of ATFM Aerodrome Capacity delay (b) Conditions with a high chance of high total in-block delay

Figure B.3: Comparison of the runway configuration types



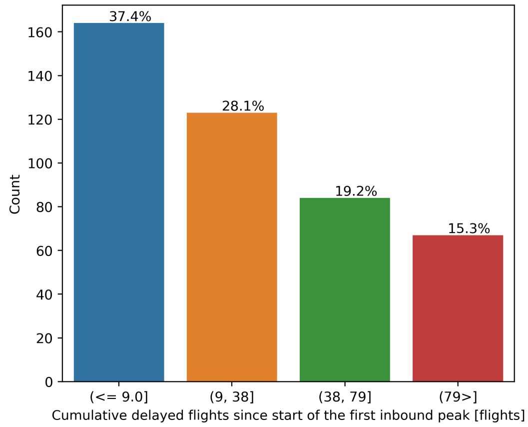
(a) Conditions with a high chance of ATFM Aerodrome Capacity delay (b) Conditions with a high chance of high total in-block delay

Figure B.4: Comparison of the runway configurations

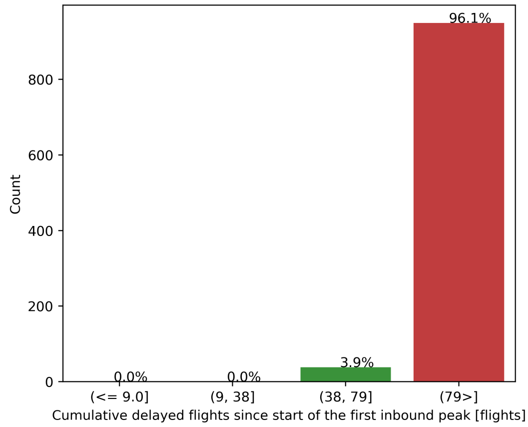


(a) Conditions with a high chance of ATFM Aerodrome Capacity delay (b) Conditions with a high chance of high total in-block delay

Figure B.5: Comparison of the arrival or departure peaks [0=Off-peak/Night]

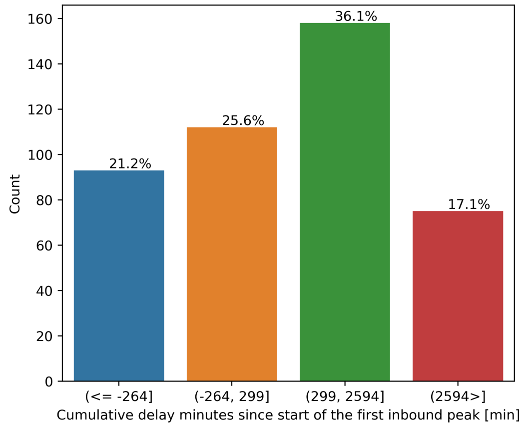


(a) Conditions with a high chance of ATFM Aerodrome Capacity delay

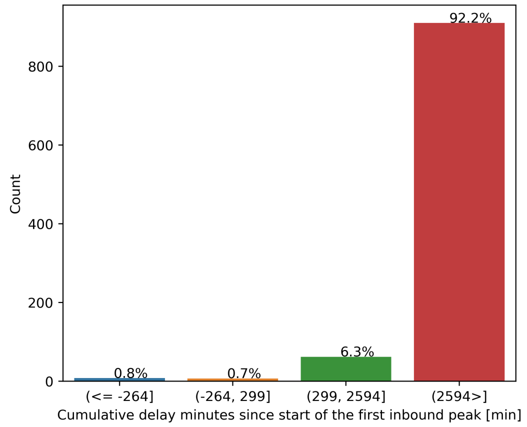


(b) Conditions with a high chance of high total in-block delay

Figure B.6: Comparison of the cumulative delayed flights

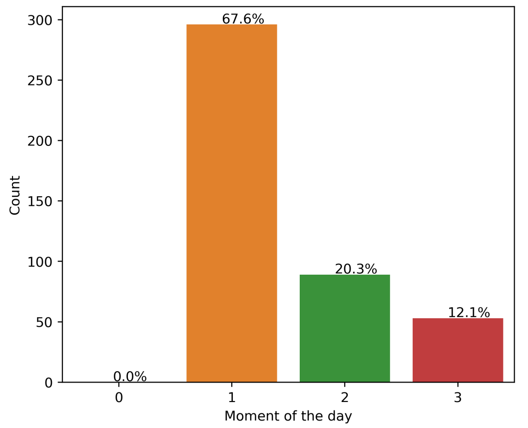


(a) Conditions with a high chance of ATFM Aerodrome Capacity delay

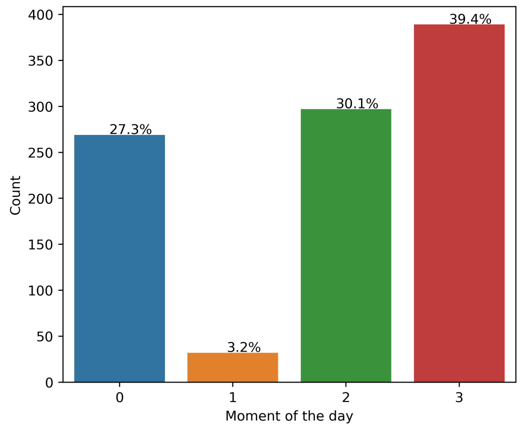


(b) Conditions with a high chance of high total in-block delay

Figure B.7: Comparison of the cumulative delay minutes

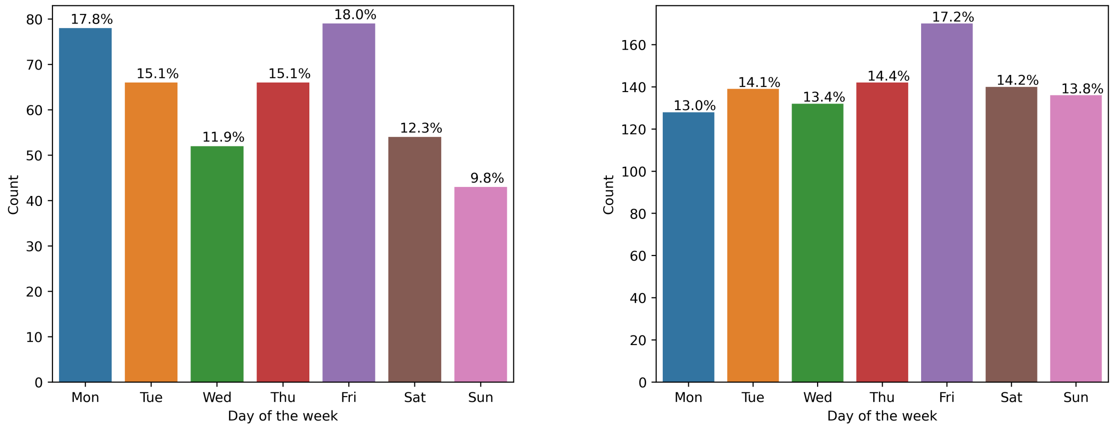


(a) Conditions with a high chance of ATFM Aerodrome Capacity delay



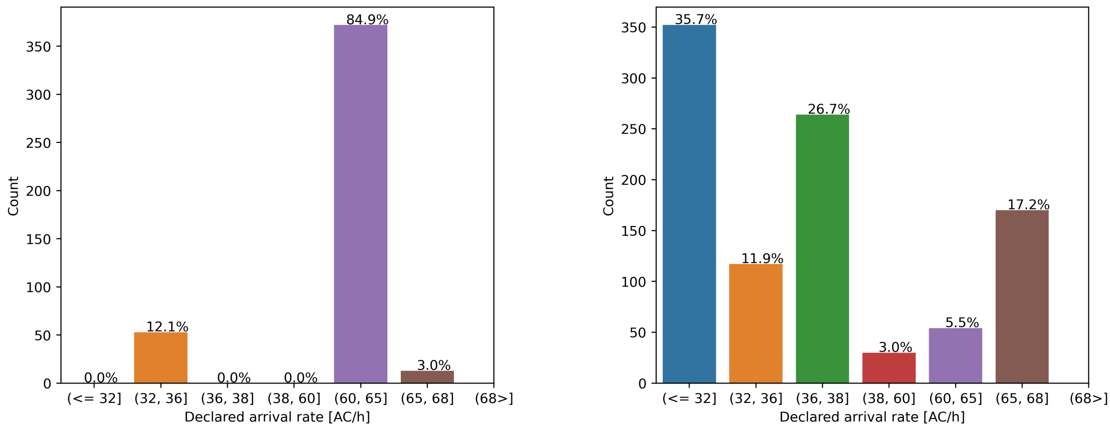
(b) Conditions with a high chance of high total in-block delay

Figure B.8: Comparison of the moment of the day [0=Night, 1=Morning, 2=Afternoon, 3=Evening]



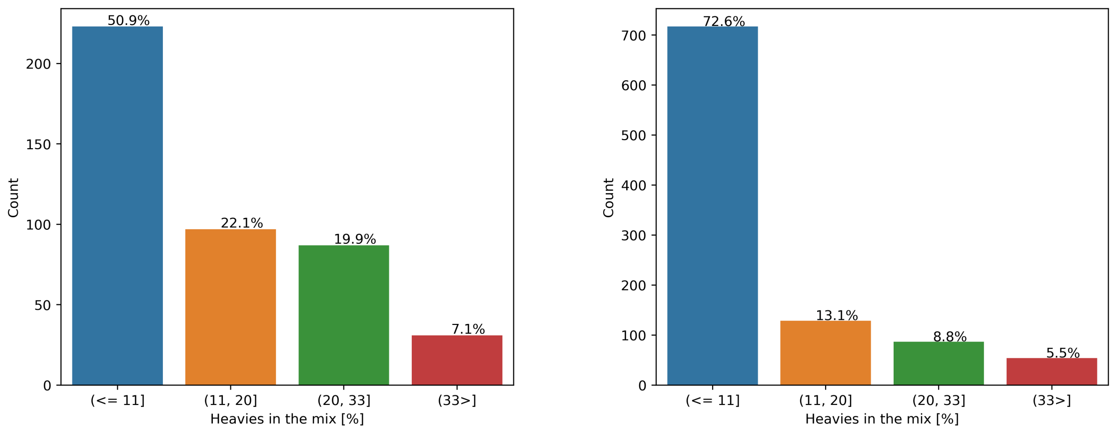
(a) Conditions with a high chance of ATFM Aerodrome Capacity delay (b) Conditions with a high chance of high total in-block delay

Figure B.9: Comparison of the day of the week



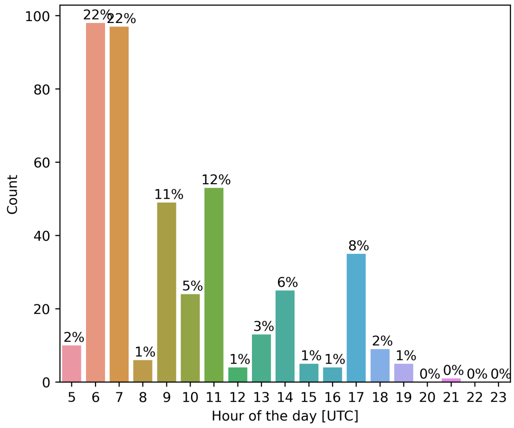
(a) Conditions with a high chance of ATFM Aerodrome Capacity delay (b) Conditions with a high chance of high total in-block delay

Figure B.10: Comparison of the declared arrival rate

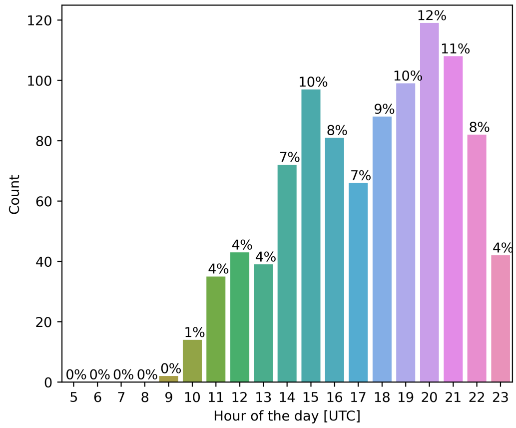


(a) Conditions with a high chance of ATFM Aerodrome Capacity delay (b) Conditions with a high chance of high total in-block delay

Figure B.11: Comparison of the heavy aircraft in the traffic mix

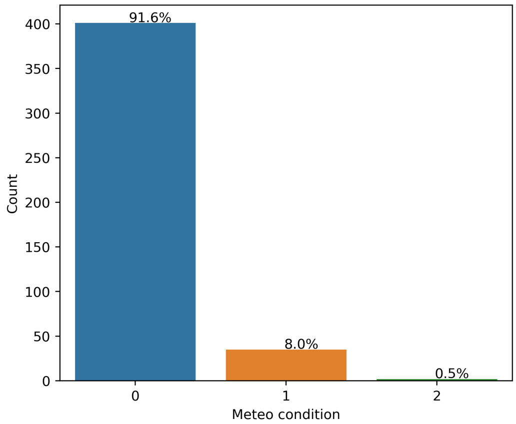


(a) Conditions with a high chance of ATFM Aerodrome Capacity delay

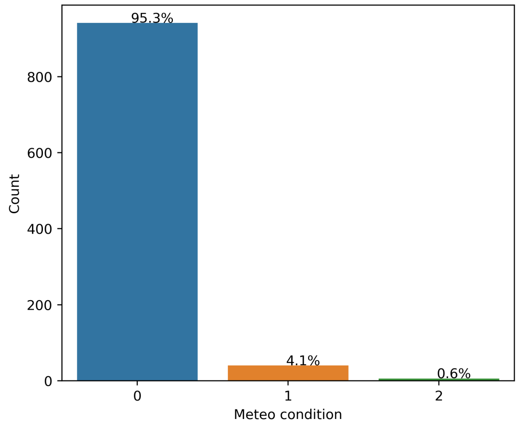


(b) Conditions with a high chance of high total in-block delay

Figure B.12: Comparison of the hour of the day

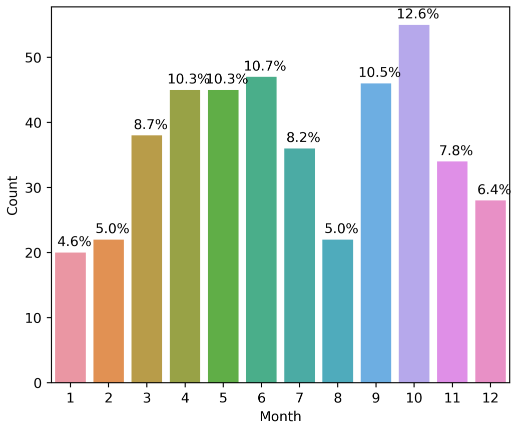


(a) Conditions with a high chance of ATFM Aerodrome Capacity delay

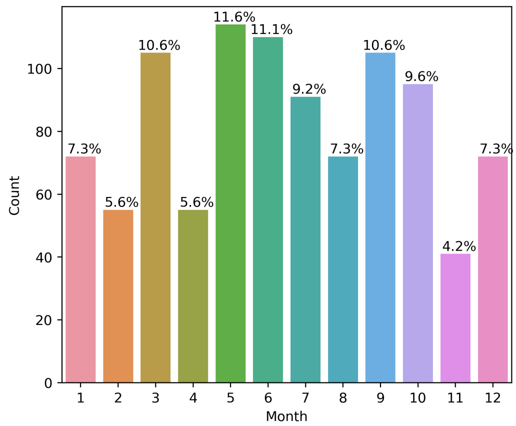


(b) Conditions with a high chance of high total in-block delay

Figure B.13: Comparison of the meteorological conditions [0=Good, 1=Marginal, 2=BZO]

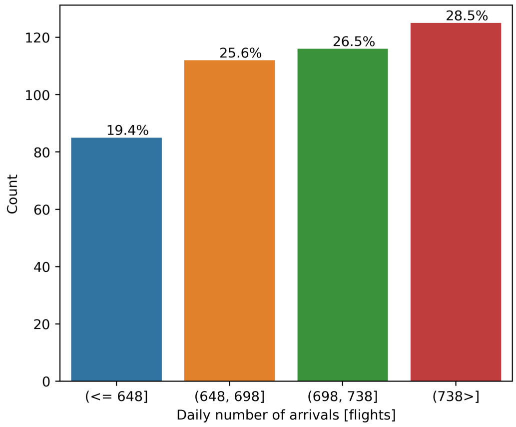


(a) Conditions with a high chance of ATFM Aerodrome Capacity delay

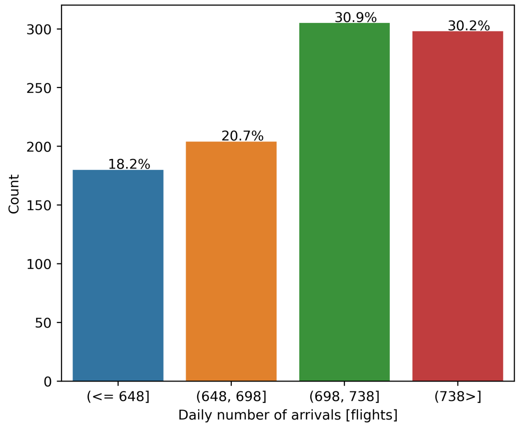


(b) Conditions with a high chance of high total in-block delay

Figure B.14: Comparison of the month of the year



(a) Conditions with a high chance of ATFM Aerodrome Capacity delay



(b) Conditions with a high chance of high total in-block delay

Figure B.15: Comparison of the daily number of arrivals

C
Compare Actual Time of Arrival and Initial Time of Arrival

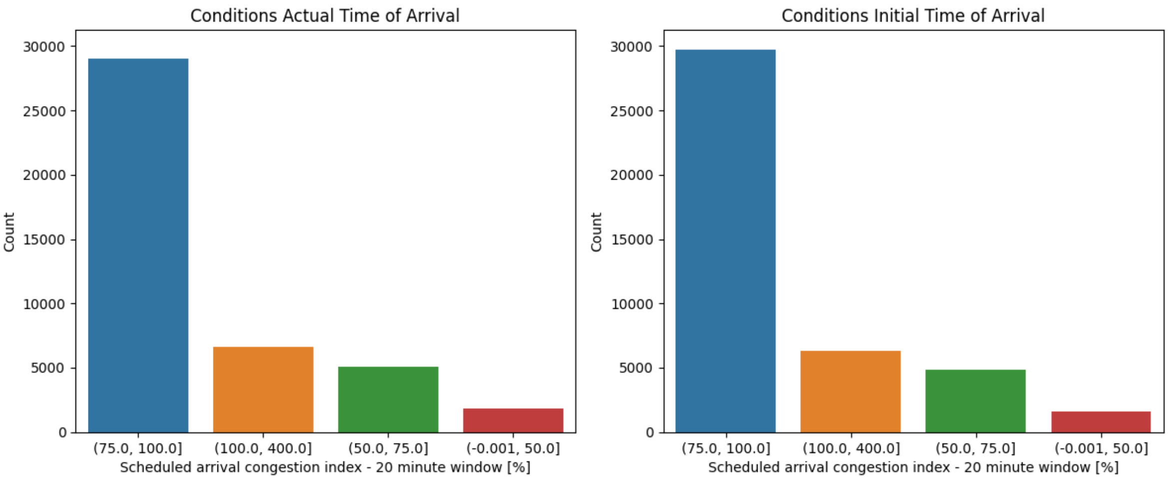


Figure C.1: Scheduled arrival congestion index - 20 minute window

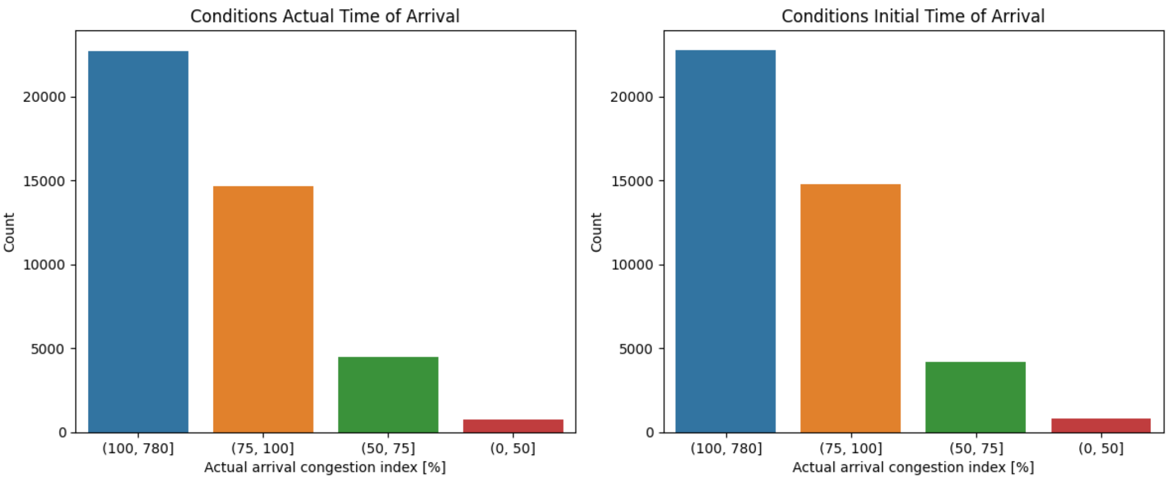


Figure C.2: Actual arrival congestion index

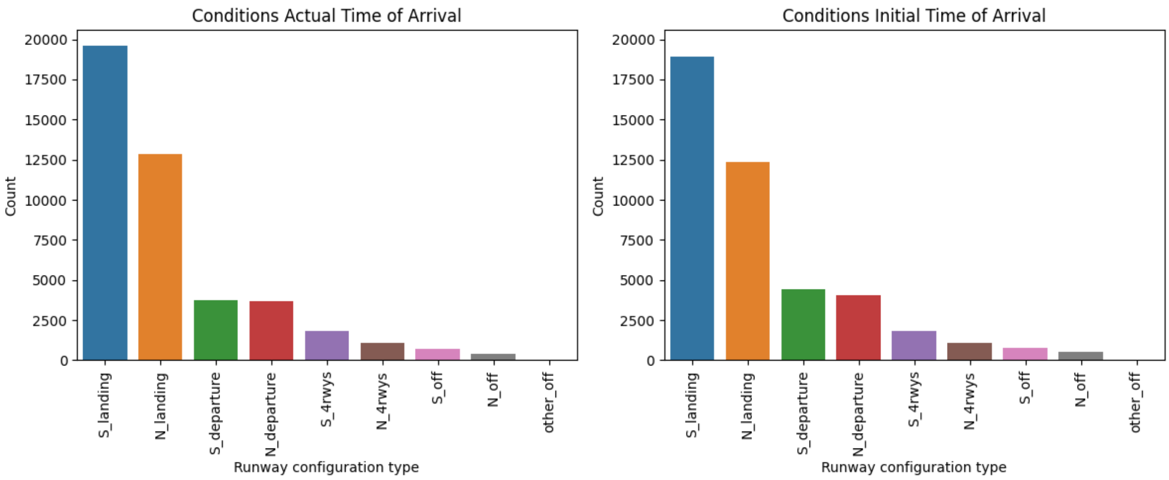


Figure C.3: Runway configuration type

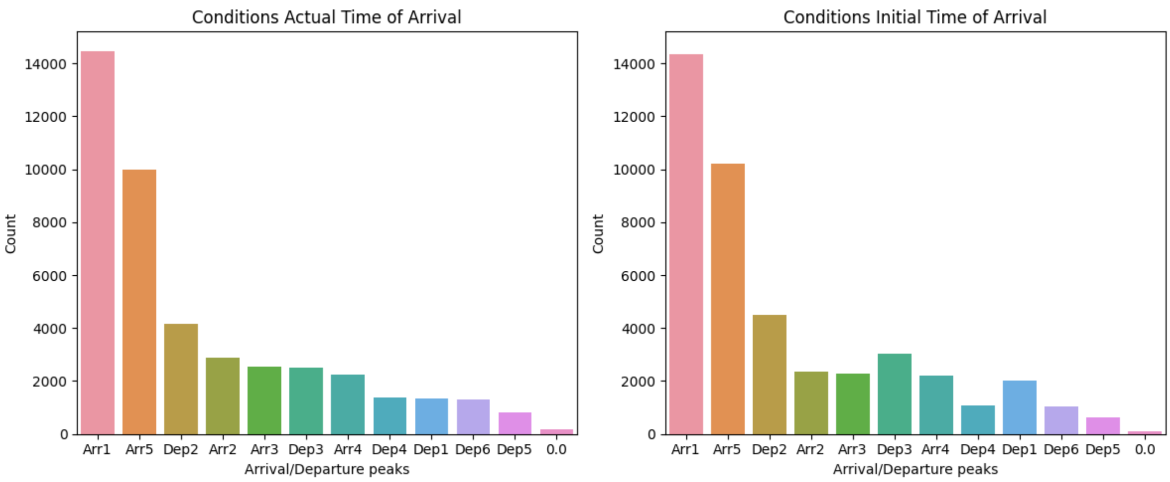


Figure C.4: Depature or arrival peaks [0 = Off-peak/Night]

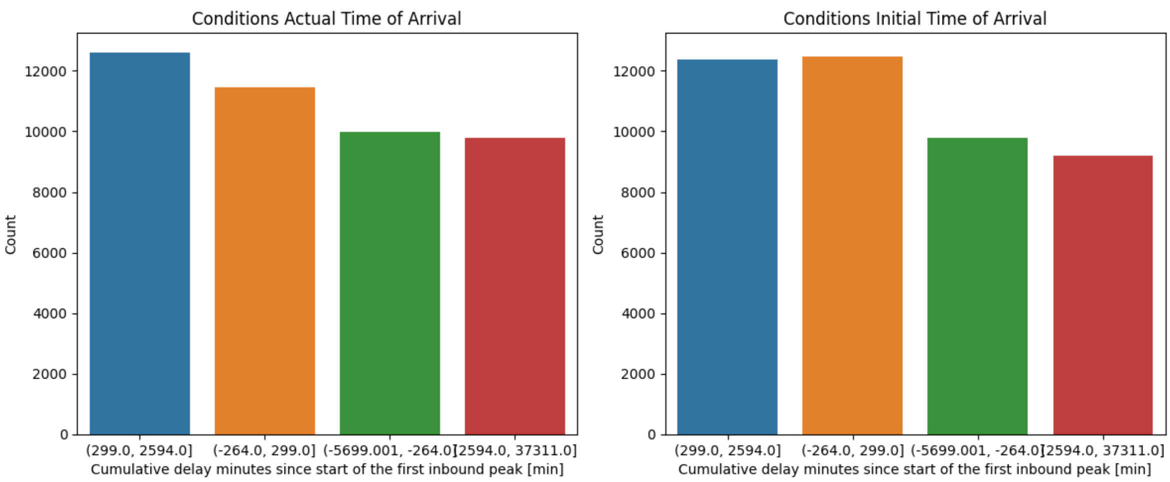


Figure C.5: Cumulative delay minutes

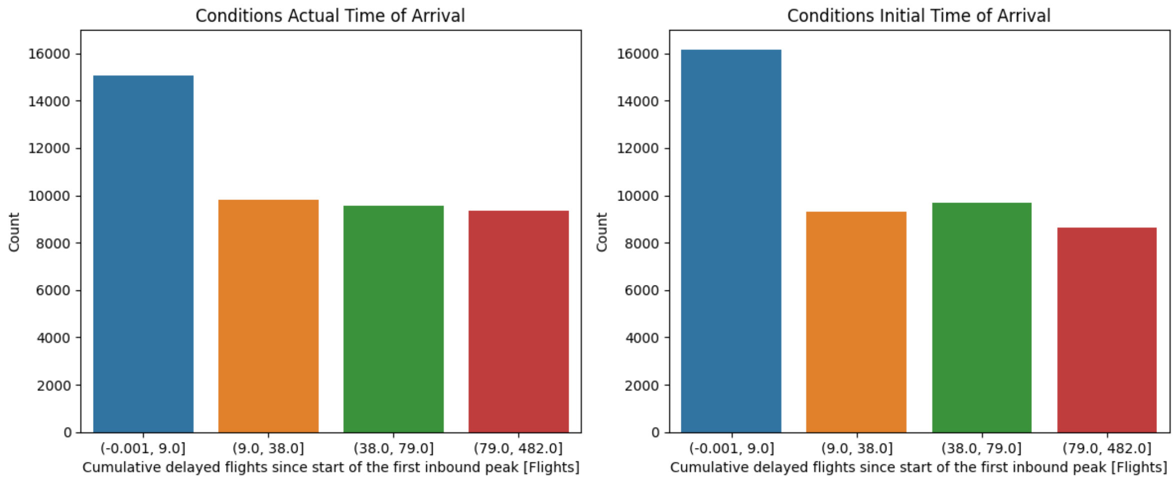


Figure C.6: Cumulative delayed flights

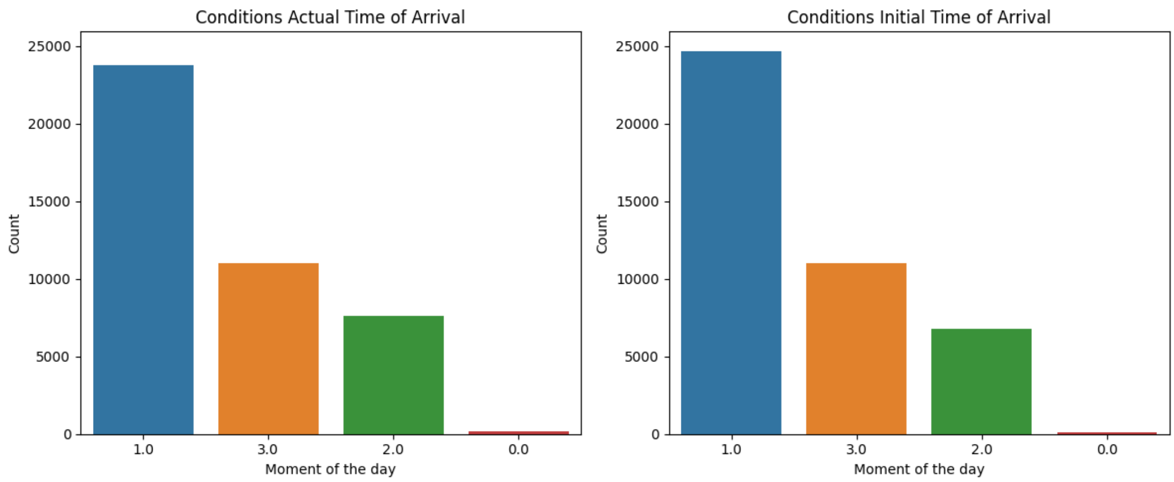


Figure C.7: Moment of the day [0 = Night, 1 = Morning, 2 = Afternoon, 3 = Evening]

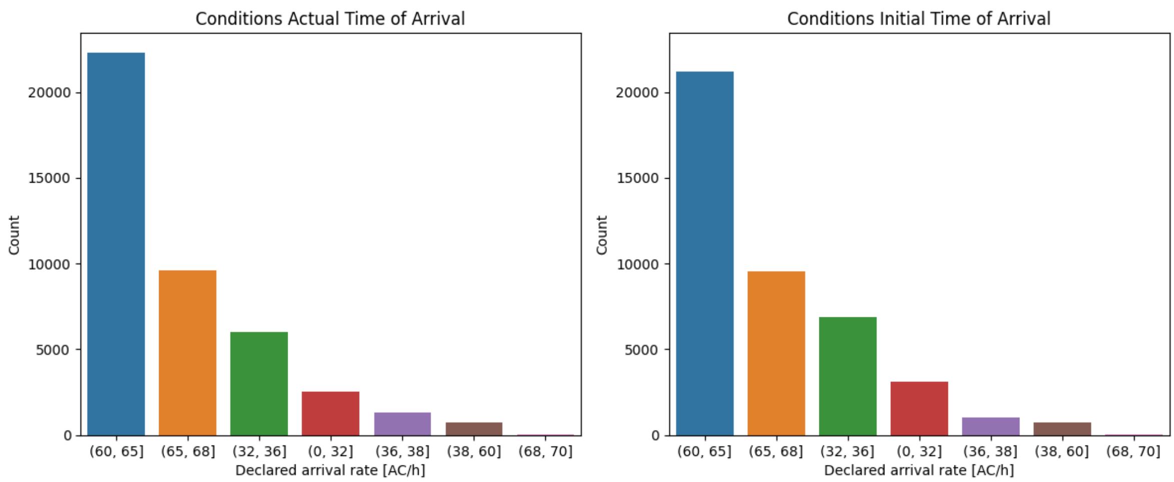


Figure C.8: Declared arrival capacity

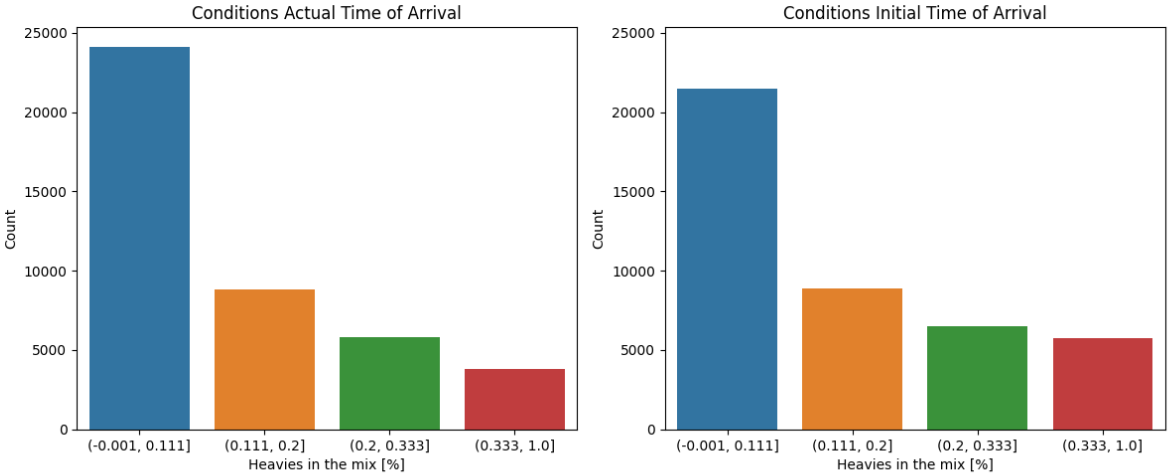


Figure C.9: Heavies in the mix

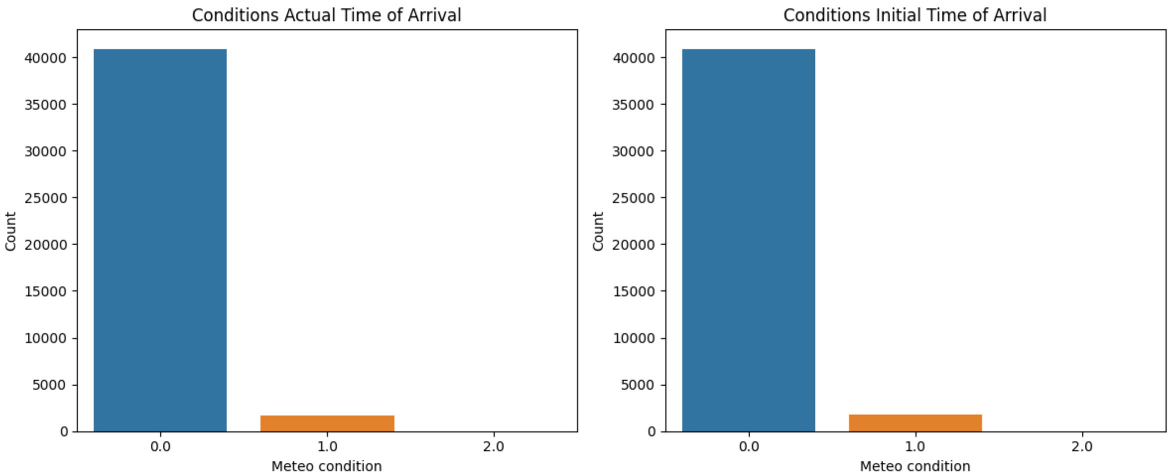
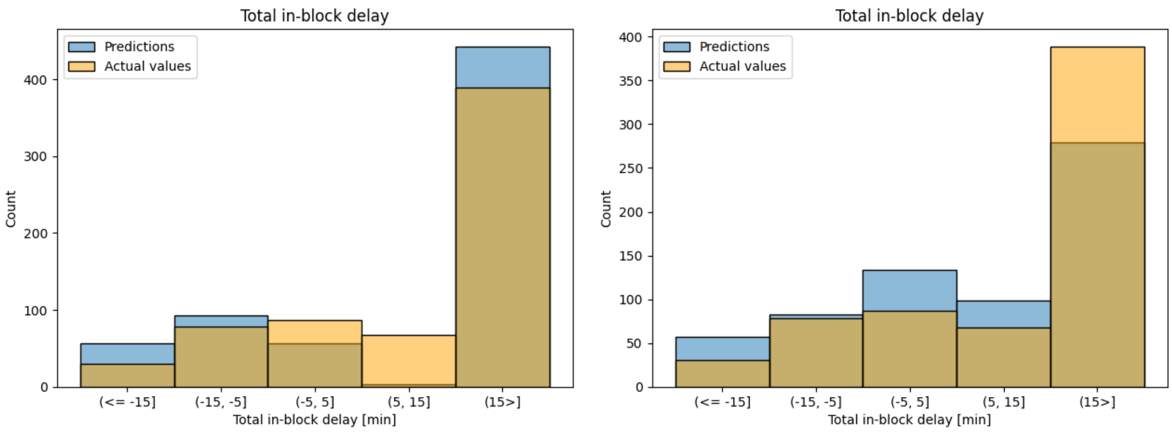


Figure C.10: Meteorological conditions [0 = Good, 1 = Marginal, 2 = BZO]

D

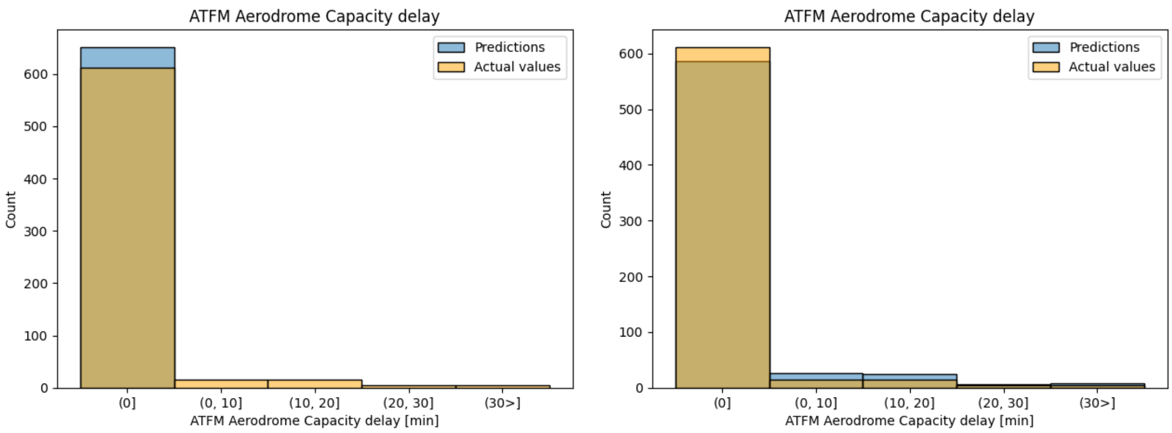
Prediction graphs



(a) MAP predictions

(b) Stochastic predictions

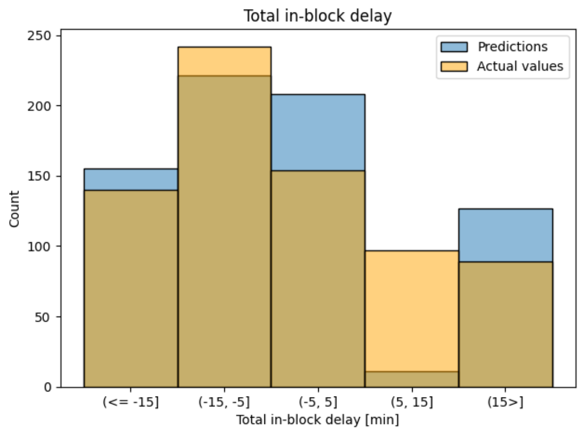
Figure D.1: Total in-block delay prediction for 21-12-2018



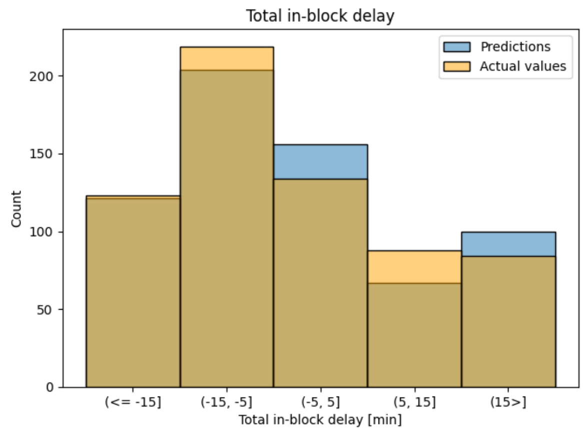
(a) MAP predictions

(b) Stochastic predictions

Figure D.2: ATFM Aerodrome Capacity delay prediction for 21-12-2018

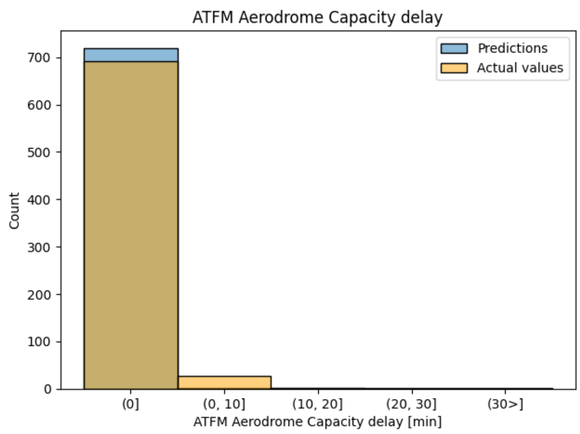


(a) MAP predictions

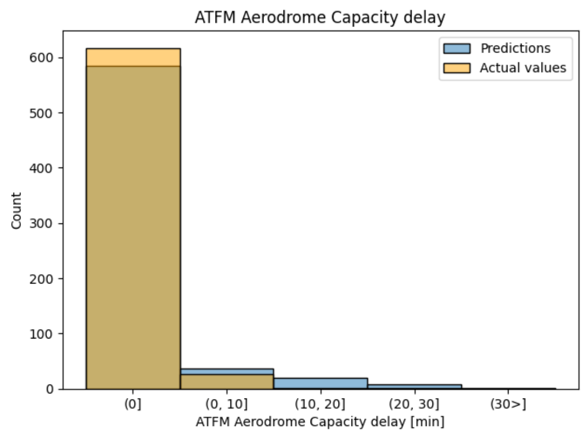


(b) Stochastic predictions

Figure D.3: Total in-block delay prediction for 23-07-2019

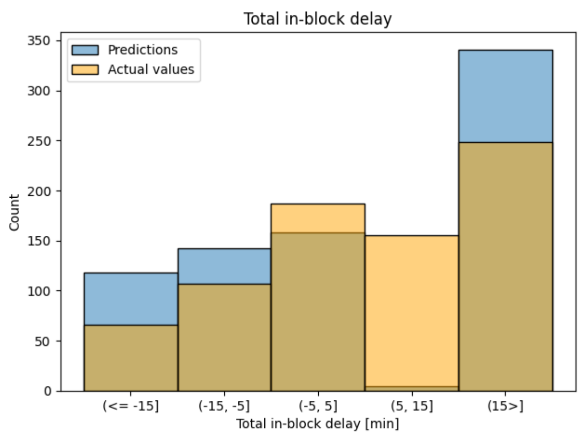


(a) MAP predictions

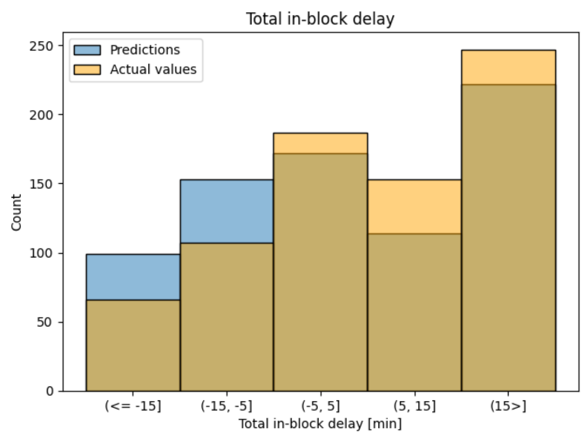


(b) Stochastic predictions

Figure D.4: ATFM Aerodrome Capacity delay prediction for 23-07-2019

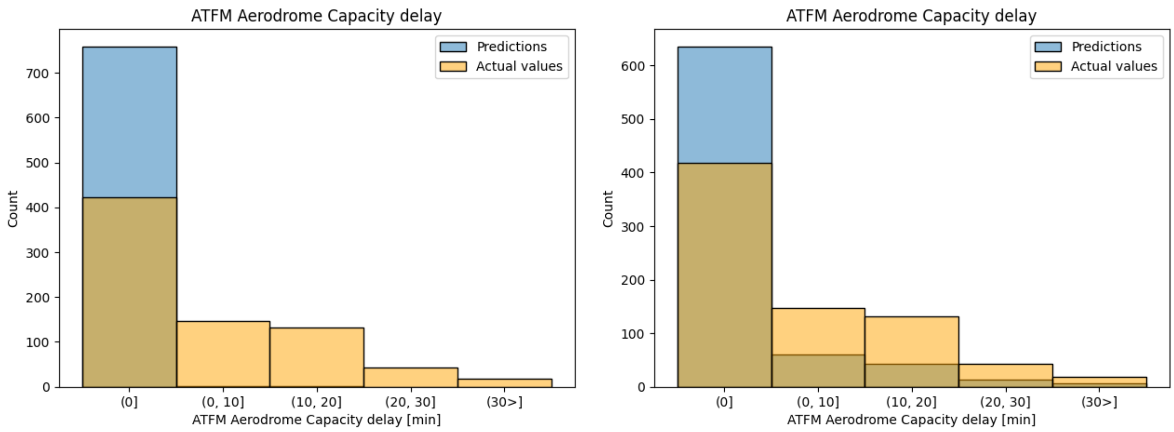


(a) MAP predictions



(b) Stochastic predictions

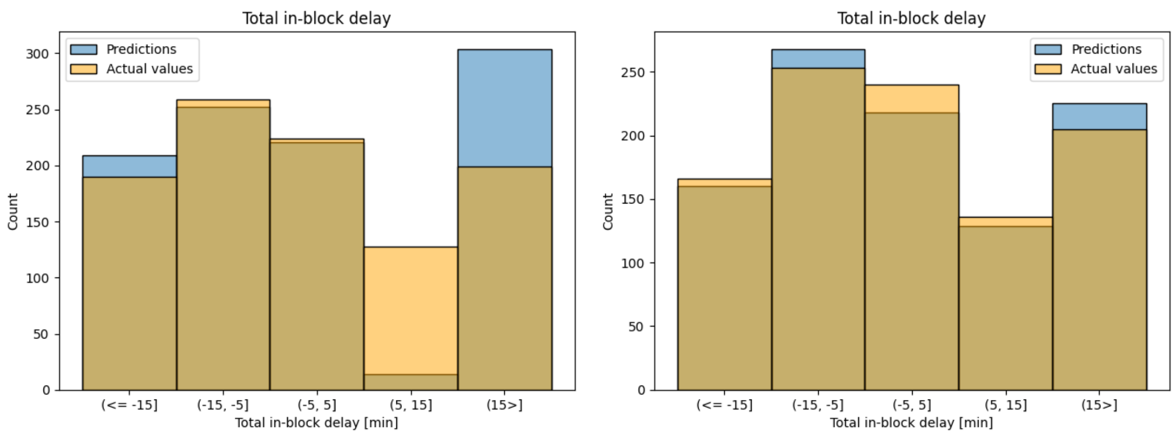
Figure D.5: Total in-block delay prediction for 13-09-2019



(a) MAP predictions

(b) Stochastic predictions

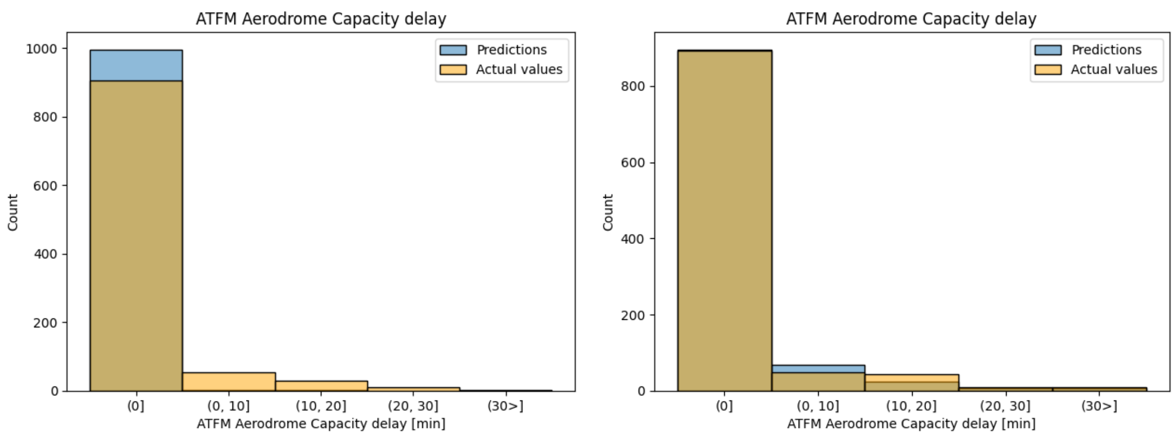
Figure D.6: ATFM Aerodrome Capacity delay prediction for 13-09-2019



(a) MAP predictions

(b) Stochastic predictions

Figure D.7: Total in-block delay 1000 random predictions



(a) MAP predictions

(b) Stochastic predictions

Figure D.8: ATFM Aerodrome Capacity delay 1000 random predictions

III

Preliminary Report [already graded]

1

Introduction

Air transportation networks are complex, there are many interactions between the aircraft, air traffic control and airports and many uncertainties such as weather or other disruptions. Delays can propagate throughout the network, which affects the operations of the airlines and airports, as well as the passengers.

In recent years, the aviation industry has been growing at a fast rate [11]. Due to this, the possibility of having some form of delay due to other traffic has increased. This issue is largely visible at airports, the bottlenecks of the air transportation system. To cope with the issue of growing air traffic and growing congestion, Air Traffic Flow Management (ATFM) was introduced in different places, among which in Europe. In Europe, EUROCONTROL is responsible for issuing ATFM delay such that flights can be operated in a safe manner and with as little delay as possible and to prevent air traffic controllers from unexpected high workloads. When it is expected that at the current take-off time a flight can encounter congestion, either en-route or at the arrival airport, ATFM delay is issued.

With growing air traffic, more airports are operating close to the operational capacity. Amsterdam Airport Schiphol, with 496826 aircraft movements in 2019, is one of these airports [17]. Operating close to the operational capacity can lead to congestion, which again can lead to ATFM delay. Every month, EUROCONTROL releases a network operations report, containing several statistics for the European aviation system. Over the past 3 years, Amsterdam Airport Schiphol has been the airport in Europe with the highest Airport ATFM delay. The statistics for 2019 can be seen in figure 1.1. A little less than half of the airport ATFM delay is classified as Airport Capacity. It is unclear where this delay exactly originates from. This preliminary study is performed to find the reasons for this delay and propose a way to minimize this delay, by creating more insights into the operational conditions for Amsterdam Airport Schiphol and more understanding of the interactions between operational variables. The focus of this study will be on the arrival operation of Amsterdam Airport Schiphol. Currently, during the COVID-19 pandemic, little ATFM delay is issued. However, it is expected that the traffic will grow back to pre-pandemic levels in a couple of years [1]. If nothing changes, similar issues will arise.

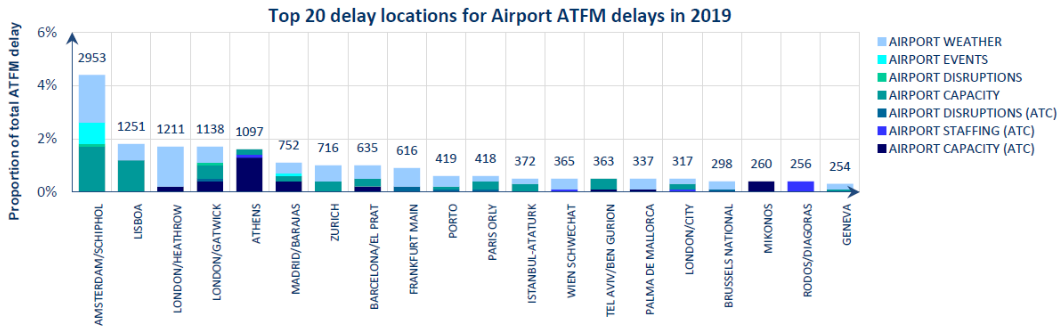


Figure 1.1: Airport ATFM delay 2019 [32]

In this report, a literature review is presented on ATFM, ATFM delay and possible ways to minimize ATFM delay in chapter 2. For a better understanding of the operations at AAS, data analysis is performed and results are presented in chapter 3. By combining the findings from chapter 2 and chapter 3, a research proposal is presented in chapter 4. The conclusion of this report can be found in chapter 5.

2

Literature Review

In recent years, ATFM has become a more important subject in Air Traffic Control. ATFM has been in place for quite some time in Europe and the United States, but with increasing air traffic this topic becomes relevant for Asia and South America as well. ATFM and ATFM delay are complex subjects, as these depend on many operational aspects of aviation. In this chapter, a literature study is presented regarding ATFM and ATFM delay, the history and operational challenges, and several topics are presented that pose interesting solutions to minimize ATFM delay. In this chapter, the focus will be on the European ATFM system, as this system impacts Amsterdam Airport Schiphol.

2.1. Air Traffic Flow Management

ATFM is meant to support the Air Traffic Controllers in successfully and safely executing their task. In Europe in the late sixties (Leal de Matos and Ormerod [42]), and in the United States of America in the early eighties (Weigang et al. [60]), air traffic networks were starting to show congestion. In order to relieve the Air Traffic Controllers from unpredictable high workloads, a solution had to be found. The concept of *flow management* was introduced. Flow management is the effort to match demand with the available capacity by controlling the flow of traffic. This is done through of the Central Flow Management Unit (CFMU), which is a directorate of EUROCONTROL. ATFM has a long history in Europe with several local flow management units, which did not work out. An European Central Data Bank was constructed where all flight data of European flights would be stored. A centralized way of ATFM was put in place in Europe, as congestion problems were increasing. In 1988, the International Civil Aviation Organisation (ICAO), proposed a concept to EUROCONTROL for a centralized ATFM system. The CFMU was eventually based on the concept proposed by ICAO, which consists of a Western and Eastern Central Executive Unit. The CFMU was approved in 1989 and was fully functional by 1996, when all pre-tactical and tactical functions were transferred from the interim systems to the CFMU (Leal de Matos and Ormerod [42]).

The CFMU's main systems are the Initial Flight Plan Processing System, the system that receives the flight plans from the airlines, the Tactical (TACT) system, the Environment Database and the Archives System. The TACT System gets all the necessary data for a flight, to provide information for pre-tactical and tactical planning. It takes demand and capacity into account, ATFM regulations and it allocates departure slots. There is the Environment Database, which contains permanent data such as routes, geographical data, airports and ATC centers. Lastly, there is the Archives System, where all operational data of the past is stored and this data is used to improve the ATFM operations, for strategic planning and pre-tactical planning. Strategic planning starts six months in advance and takes until 2 days before operation, pre-tactical planning is 2 days in advance and tactical planning is on the day of operation (Leal de Matos and Ormerod [42]).

In all parts of the planning aspect, the focus is on identifying the bottlenecks of the network and to try and avoid or solve these, if possible. When the day of operations starts, there are already regulations in place in the TACT system, mainly in the form of slot allocations. TACT allocates these slots automatically based on the flight plans that were filed. When during the day congestion occurs that was not anticipated in the earlier planning phases, the flow manager at the CFMU will have to issue regulations, which can lead to ATFM Delay.

From the CFMU, the Network Manager Operations Centre (NMOC) was evolved. The NMOC is in place since 2020 when it replaced the CFMU [3].

2.2. ATFM Delay

In ATFM, there are several moments during a flight when ATFM delay can be applied. These delays can have different reasons and different magnitudes as well. ATFM delay is defined as the difference between the scheduled departure time of the flight and the actual departure time [59]. This section will provide more detail on the different parts of ATFM delay.

2.2.1. Departure

One of the most common form of ATFM delay happens at departure. All aircraft that take off in Europe, try to do so according to the flight plan. However, it could be the case that the flight will encounter congestion if it departs according to the flight plan. In this case, the flight gets a departure delay in the form of a Calculated Take-Off Time (CTOT), which is a time window in which the aircraft has to be at the runway ready for departure. The window starts 5 minutes before the CTOT and ends 10 minutes after the CTOT, this margin is there for potential taxiway delays or safety issues [59].

During ATFM regulation, it is often the case that the departing aircraft is issued with a later CTOT. The reason for the later CTOT can be due to a crowded en-route sector, or when it is predicted that at the current time of arrival at the destination airport, the airspace at the destination airport will be too crowded leading to additional delay over there. So instead of putting the aircraft in a holding pattern during the flight or having it deviate from the flight trajectory, the aircraft is kept on the ground at the departure airport, which is both safer and better for the environment as the aircraft will not burn any additional fuel. So the delay is issued at the departure airport, while the departure airport is not always the cause of the regulation [59].

Such a slot regulation, or Ground Delay Programs as is used by the FAA in the US (Campanelli et al. [24]), is one of the safest methods of controlling the flow of traffic. The slot delays are assigned by the Network Manager in Brussels.

2.2.2. En-route

Once airborne, there is still the possibility of running into certain delays. Often it is the case that bad weather expected along the flight trajectory. Therefore, flights can be rerouted to avoid these areas. By rerouting a flight, it is important that the rerouting is kept to a minimum such that the cost of the delay remains as low as possible (Bertsimas et al. [21]).

Rerouting strategies are difficult for solving congestion problems, this will most probably affect the other flights in the congested airspace as well. Therefore rerouting is seldom used to solve congestion problems (Lulli and Odoni [45]).

2.2.3. Arrival

ATFM delay is either issued before take-off or in some cases en-route, a flight will not get ATFM delay in the final phase of a flight as the purpose of ATFM is to prevent this. However, the departure delays issued are often because of the arrival airport of that flight. In addition to that, ATFM delay, both at the departure airport and en-route, does affect the arrival time of the flight. Interestingly enough, the number of delayed departures is higher than the amount of delayed arrivals, a gap that is growing larger every year. In 2018, 25% of the ATFM regulation minutes did not affect the arrival punctuality of the flight. More than one-third of the flights with an ATFM delay of 20 minutes, still arrived on time on their destination [59]. Often it is even the case that due to ATFM delay, the flight will actually arrive closer to the scheduled arrival time than without the delay.

This has to do with the airlines. For an airline, it is important that its passengers arrive on time, especially when they have a transfer flight. Hence, airlines are applying schedule buffers to the expected flight time. These schedule buffers make up for the expected delay, such that if delay occurs, the passengers can still arrive on time. The last years the difference in departure delays and arrival delays has been increasing, which could indicate that ever larger schedule buffers are used. The downside of this is that if no ATFM delay is issued, there is the possibility of flights arriving early [59]. Early arrivals can lead to traffic bunching, bunching happens when aircraft arrive at an unexpected time in a congested area. Traffic bunching could lead to the delay of other flights as well, due to which the total delay of the system could increase (Stoltz and Ky [57]).

EUROCONTROL forecasts that in 2040, 16 airports in Europe will be as congested as London Heathrow is today. That will push the network delays up to 20 minutes per flight compared to the 14.7 minutes per flight in 2018. That suggests that airlines might make more use of schedule buffers, which could in turn result in more traffic bunching and other delays as well [59].

2.2.4. ATFM Delay Reasons

Once ATFM delay is issued, a reason is assigned to this delay such that one can track where the delay originates from. The location due to which the regulation is applied is either the arrival airport or en-route. En-route, the most common reasons for ATFM delay in 2019 are weather, ATC staffing and ATC capacity. For arrival ATFM delay, the most common reasons in 2019 are airport capacity and weather [32]. All ATFM Delay Codes can be seen in table 2.1, these codes are used for both en-route delay as well as arrival delay.

Table 2.1: ATFM Delay Codes [5]

Regulation Code	Regulation Name	Regulation Code	Regulation Name
C	ATC Capacity	A	Accident/Incident
S	ATC Staffing	E	Aerodrome Services
I	Industrial Action (ATC)	N	Industrial Action (non-ATC)
T	Equipment (ATC)	NA	Not regulated/Not specified
G	Aerodrome Capacity	O	Other
M	Military Activity	P	Special Event
R	ATC Routeing	D	De-icing
V	Environmental Issues	W	Weather

2.3. Applied Rates

As was explained in section 2.1, the CFMU issues ATFM delay, but how is this translated to the actual operation? Once ATFM delay is issued, this is communicated to the Air Navigation Service Providers (ANSP) at the airport in case of airport delay and to the ANSP en-route in case of en-route delay.

For the airport ATFM delay, inbound traffic is regulated to prevent the workload from becoming too high for the air traffic controllers. These regulations are translated to applied rates at the airport, the number of aircraft that can land per hour. Such regulations have a start and end time and can span over multiple inbound and outbound peaks. Essentially, the nominal capacity of the aerodrome is reduced. Often weather will reduce the nominal capacity by a large amount, whereas aerodrome capacity regulations only decrease the nominal capacity by a few flights [2].

During a day at AAS, there are usually 6 outbound peaks, with mainly departing traffic, and 5 inbound peaks, with mainly arriving traffic. In normal conditions during an outbound peak, 74 departures can be handled and 36 arrivals. With normal conditions during an inbound peak, 68 arrivals can be handled and 38 departures [9].

2.4. Airport ATFM delay

As can be seen from figure 1.1, Amsterdam Airport Schiphol is subject to a lot of airport ATFM delay, much more than any other airport in Europe. As was explained in 2.1, ATFM was first introduced to handle congested airspace. AAS is one of the airports operating close to the operational capacity and with this comes an issue that ATFM could handle as well, which is demand and capacity imbalance.

Demand and capacity imbalance is a recurring topic in many ATFM delay studies. As the system is operating close to its capacity, and capacity is not the same throughout the day, a small disturbance in one flight could already lead to a demand and capacity imbalance at an airport. Coordinated airports, try to balance their traffic by using airport slots, which are time slots in which an aircraft is allowed to land or depart, which are planned during strategic planning up to 6 months in advance (Ivanov et al. [38]). While much effort is put into balancing the demand and capacity of the airport, this remains a difficult task to do months ahead of time. At AAS, flights are issued with a landing slot of 20 minutes during strategic planning. While this should be sufficient months in advance, it remains only an estimate of the traffic that will arrive or depart. This is why strategic planning takes place up to a few days before the flight departs to try and plan the traffic as best as possible.

On the day of operation, despite all the efforts put into planning the flight, there remain many things that can go wrong. The weather can change, crew could be late, the aircraft can have a technical issue or sectors might get congested. Congestion, especially at airports but also en-route, can be a result of traffic bunching. In Stoltz and Ky [57] it is stated that one of the reasons for this is when a CTOT is issued, as an aircraft is allowed to depart 5 minutes before up to 10 minutes after the CTOT, which gives uncertainty in when the flight takes off, hence even more uncertainty when the flight will arrive. These unexpected arrivals could also be due to intercontinental flights, as these are not subject to ATFM regulations. But many things can happen en-route, a pilot could ask for a re-direction to a waypoint, to reduce the flight distance or the pilot could ask to fly faster to make up for the delay issued during departure. Bad weather could occur en-route or a sudden deviation from the intended trajectory. Traffic bunching, especially at an airport, will increase the workload of the air traffic controllers and if the congestion remains airport ATFM delay can be issued. While ATFM regulations are used to create better traffic scenarios with less congestion, the actual operations provide many uncertainties. Stoltz and Ky [57] found that 30% of the ATFM regulations are not strictly followed, which is a high number. Stoltz and Ky [57] propose that better integration of airports into the European air traffic system is necessary, just as was proposed in [59], but at the same time, prevention of traffic bunching should be accessed locally as well.

Demand and capacity imbalance and traffic bunching can be a result of a very congested airport which is subject to disruptions throughout the day due to low predictability of traffic. Many studies focus on improving the predictability of the traffic at an airport as this will most likely decrease the delay at the airport. There are many ways how this problem is approached, for example through changed strategic planning [22, 42, 46], 4D Planning and Trajectory Based Operations (TBO) [28, 39, 63], Arrival Sequencing [23, 36, 40] and machine learning approaches such as Agent-Based Modeling [24, 51] and Bayesian Networks [25, 52, 53, 61].

2.5. Strategic Planning

The definitions do differ slightly, in the United States of America strategic planning is everything up until take-off, but in Europe strategic planning starts six months before the flight up to a few days, after which pre-tactical planning takes over two days before the flight and tactical planning on the day of the flight itself, the European definition is used in this report.

At the start of strategic planning, an ATFM co-ordination meeting takes place. In this meeting, the major bottlenecks of the European airspace are identified, as well as other ATFM issues of the past six months. After this meeting is over, aircraft operators can file flight plans for the upcoming months to the CFMU. As the traffic demand becomes more clear over time, the Standard Routing Scheme is prepared, in which routes are planned and congestion could already be seen and mitigated. According to the flight plans, airport departure and landing slots are issued.

In pre-tactical planning, the congestion problems are identified mainly by looking at historical data and ATFM regulations on the same day of the previous week as well as by inspecting the flight plans. If necessary and possible, capacity is increased by using re-routing of flows and slot allocation regulations.

During tactical planning, CTOT and ground delays are allocated and flights that are predicted to have a high ATFM delay, are prioritized to minimize the delay. The TACT system plays an important role during tactical planning. In this phase, just before the operation of the flight, it is important that the systems provides quick and easy solutions.

As strategic planning takes place up to months in advance of the operation, it is difficult to accomplish a detailed flight plan. Nonetheless, it would be beneficial if the daily operation can be predicted as accurately as possible far in advance. Through strategic planning, this can be done by means of demand forecasts, simulations and optimization techniques (Leal de Matos and Ormerod [42]).

In Stamatopoulos et al. [56] a decision support system is proposed to improve the strategic planning of an airport. By using MACAD a macroscopic airside model was created, in which all parameters are implemented such as capacity, airport geometry and local ATC capacity. Using this model, a few scenarios were simulated with a different number of runways and a different runway configuration. As MACAD showed good approximations of different scenarios at different airports, it could be used during the strategic planning of airport capacity. During 2002 and 2003, an enhanced version of MACAD was applied for several European airports, among which Amsterdam, which showed satisfactory results.

During strategic planning, there are many decision variables that make it difficult to predict ATFM from a strategic level, therefore, studies provide decision support tools, such as in Zhang et al. [64]. In this study, a decision support tool is developed with a focus on the speed at which solutions can be proposed. It does so by doing offline computations on historical data, however the scope of this study is only limited to weather induced delay.

In most strategic planning studies, but other aviation related studies as well, one has to take into account that multiple stochastic processes are happening during a flight. Marceau et al. [46] present a probabilistic model is presented to decrease uncertainty along waypoints of a flight plan. It is a multi-objective evolutionary optimization algorithm that tries to minimize both congestion and delay. For the interaction between variables, a Bayesian Network is created. Now, this study did mainly focus on strategic planning for trajectories and sectors, and not for airport slots, in order to create better flight schedules. It does however show, that from a strategic level, better predictability can be achieved.

Bolić et al. [22] present, a similar study is performed however this study also included airport capacity constraints. It is stated that capacity is usually managed from a tactical perspective, as strategically flight plans are known but not the exact time of operation. Additionally, the information regarding flight routes is also distributed during the tactical phase, leaving ATC almost no time to prepare for possible overcapacity or regulations. By taking the nominal capacities of airports and sectors into account, this paper tries to minimize demand-capacity imbalances from a strategic point of view. A better redistribution of traffic from a strategic level could decrease the number of ATFM regulations during operation. By means of an integer programming model flights are redistributed. The hard constraints of this model are the sector and airport capacities. With only a small percentage of flights that are redistributed, Bolić et al. [22] show promising results for strategic planning as a measure to lower ATFM delay. However, strategic planning will always have uncertainty due to the fact that it does take place months in advance, which is also the main reason why often decision support tools are created and no permanent solutions.

2.6. 4D Planning and Trajectory Based Operations

The general idea behind 4D trajectories is that one knows the exact location of an aircraft at the exact time. This would make it easier to predict when a flight arrives at which waypoint. 4D trajectories can prove a solution for ATFM delay.

In the early days of 4D planning, Jonge [39] presented an approach called *Refined Flow Management* for 4D gate to gate planning. The idea is that an airline plans a required time of arrival, such that the CFMU can provide the capacity with a high accuracy over time and the airline will focus on the arrival punctuality. For the system to work, the information exchange of all different stakeholders in ATM has to be very good.

Recently, 4D trajectories are often combined with Mixed Integer Programming (MIP) or machine learning techniques to optimize the trajectories and make the models more robust to external disturbances such as weather. Dal Sasso et al. [28] combine a multi-objective binary program with 4D trajectories to minimize ATFM delay. Xu et al. [63] present an interesting approach that includes the interacting between network manager and airlines, incorporating the human in the loop. By filing flight plans, possible congestion is observed which is then sent back to the airlines to ask for adjustments after which trajectories are planned. The main focus is on minimizing the costs induced for the airlines by delay. It makes use of a Mixed Integer Linear Programming (MILP) model and results showed to be much better than compared to the current system in French airspace. 4D planning and TBO seem to hold the potential to reduce ATFM delay, however the current method of trajectory prediction is not accurate enough to apply such models in real operation (Dek [29]).

2.7. Arrival Sequencing

In the final phase of the flight, the arrival, aircraft are lined up for the runway on which these aircraft are supposed to land. This sequencing for most airports comes down to a First-Come First-Served (FCFS) policy. In FCFS the main parameter to space the flight is the weight class in which an aircraft falls (light, medium, heavy, super heavy). This could be planned more efficiently, with the main goal to maximize the runway throughput. One of the problems that arise when altering the arrival sequence, is that some flights could be delayed, which has to be minimized as well. In Brentnall and Cheng [23] a comparison between several sequencing algorithms is made and several combinations of the sequencing algorithms and delay-share strategies were used and tested. While some performed better than others, it remains very dependent on the type of traffic that arrives, especially weight classes, but on the airport geometry and air traffic controllers as well.

A data-driven approach combined with a learning algorithm is proposed by Jung et al. [40] and Hu and Chen [35] present a learning algorithm combined with an optimization algorithm to improve arrival sequencing throughout the day. Both studies showed that a learning algorithm can improve the arrival sequencing or even mimic the process of an air traffic controller, although it has to be noted that it is very difficult to incorporate all human aspects into an algorithm. Jung et al. [40] does include probabilistic preferences between aircraft pairs, how likely an air traffic controller will put one type of aircraft after another. Probability theory is often used for sequencing in the form of queuing models.

Even in the final part of the flight, the arrivals, there is still quite some uncertainty. This is why studies that apply the stochastic behaviour of the traffic provide interesting insights. In queuing theory, agents arrive in a queue according to a certain probabilistic distribution and are handled by means of another, or the same, probabilistic distribution. In Itoh and Mitici [36] a data-driven approach in combination with a *G/G/c* queuing model is proposed and compared to actual operations for Tokyo Airport. Many other queuing models are available, such as *M/G/c/K* queuing models (Itoh and Mitici [37]) or *M/G/1* queuing models (Bäuerle et al. [19]). These different queuing models all represent different distributions by which traffic arrives and is handled, or it can be a different or more accurate way of approaching arrival sequencing. The queuing models presented in the studies mentioned, but also other studies, have shown to provide a solution for minimizing arrival delay during the arrival sequencing process. The weight classes of the aircraft remain one of the most important factors in sequencing, but there are many other challenges. To apply a model that represents the actual operation, thorough data analysis is necessary to find the underlying distributions. It is unclear whether such models can be implemented in real operations, as most air traffic controllers work by the FCFS method. Lastly, as is mentioned in the arrival queuing study by Teoh [58] and becomes apparent from the different approaches to minimize the delay in air transportation, is that the air transportation system is very complex, with many different operators and choices to be made.

2.8. Complex Systems

Complexity science, or Complex Network Theory (CNT), is mainly applied to network systems to find connections and interactions in such a system. Transportation systems are often studied using complex network theory. It can be used to study the effectiveness of a system, but also underlying aspects such as sociology and welfare. Lin and Ban [44] provide a detailed overview of the application of complexity science to transportation systems. Before continuing, it is important to note that transportation systems in complex network theory are often modeled using graph theory. Graph theory is a representation of a (mathematical) model using nodes and links to show inter-dependencies in a system.

2.8.1. Complex Network Theory

In the representation of complex network theory, two types of graphs can be used, planar and non-planar. In simple terms, planar graphs are systems where links never intersect without for example a bridge as in road transport, and non-planar graphs are systems where links do intersect, such as in aviation.

There are a few interesting parameters in CNT for aviation networks. The first of which is Degree, which is a measure of the number of links connected to a node. In air transportation hub-airports will have a higher degree than regional airports. The strength of a node can be found by adding the weights of the links, which could for example be the number of flights between a city pair. Betweenness shows the importance of a node in the network, which can be defined by the number of shortest paths in a network that pass through a node. And thirdly the Clustering coefficient, which is the number neighbours of a node that are directly connected as well, forming triangles (Cook et al. [26]).

The air transportation network is often characterized as a *small-world* network, a network with a high clustering coefficient and short average path length. The air transportation network can be visualized fairly simply because of the non-planar properties, but it is quite different from other transportation networks. For example, there are airports with a high degree, so the number of destinations, but that are not very important in the overall network.

The evolution of air transportation systems remains interesting in CNT, with the growth of air transportation around the world, at least before the COVID-19 pandemic, CNT can show potential to optimize the overall system.

2.8.2. Resilience

CNT is often used to study the resilience of a network, or in other words, how does the network respond to sudden disruptions? As defined by Beaumont and Casti [20], resilience is the measure of a system to persist, to absorb a disruption without drastically decreasing the nominal operation of the system. There are many kinds of disruptions imaginable in the air transportation network. As explained in Cook et al. [26], there can be interactions between disruptions. Some questions can be raised such as, what disruptions have the biggest influence on ATFM delay? And once ATFM delay is issued, is the system able to recover and how quickly? What are the conditions for the air transportation system to best absorb the disruption? Sanaei et al. [54] apply several machine learning algorithms to estimate ATFM delay and improve the restorative performance of the system and Lillo et al. [43] apply Network Theory to ATM, both showing that CNT can provide more insights into the system as a whole. Resilience can be applied in a very broad context and can be difficult to quantify, but it can also identify critical elements of a system.

2.8.3. Modeling

The ATM system can be modeled in many ways and CNT can be applied to different models as well. What makes complex networks difficult, is that often the focus on one variable or parameter cannot provide many insights, but that it is the combination and interaction of different variables that change the system. Some commonly used techniques are Agent-Based Modeling ([24, 51, 55]) and Bayesian Networks ([25, 52, 53, 61]).

Agent-Based Modeling

Agent-Based Modeling (ABM) is a method where agents, for example aircraft, are modeled in a system with each agent having its own set of parameters. Agents can interact with one another and the environment, make decisions and represent real-life behaviour. When multiple agents are operating in such an environment, emergent behaviour can be observed. Emergent behaviour can be observed by looking at the system as a whole and observing the interaction between agents in the system. ABM holds the potential to model real-life situations without the need for historical data, but rather by providing behavioural rules. From the emergent behaviour parameters can be set to measure the performance of a model (Klügl and Bazzan [41]).

Campanelli et al. [24] use ABM to compare the differences in delay propagation between the US air transportation network and the European air transportation network. The European model actually works with ATFM slots, that get reassigned if one is missed. Cruciol et al. [27] and Hall et al. [34] present an ABM for decision making in ATFM. By incorporating Reinforcement Learning (RL), the human factors in planning are incorporated. The reward function in Cruciol et al. [27] is based on safety and fairness which can be compared to historical data. Runway capacities are analyzed through ABM in Peng et al. [51] and in Shah et al. [55] an arrival model is compared to actual data, showing the model was able to mimic the system to a large extend. It should however be noted that ABM always includes simplifications and that the human aspects remain difficult to model.

Bayesian Networks

As was mentioned in Cook et al. [26], the emergent behaviour and the interaction between variables usually provides the best insight into the system as a whole, as one variable often does not alter the performance of a complex system by a large extend. Bayesian Networks (BN) can be represented by graph theory as well and are probabilistic models that can show the interactions and conditional probabilities between variables. The foundation for BN was laid in Pearl [49] and Pearl [50]. In air transportation, many variables influence one another, for example departure delay and arrival delay. BN shows which variables influence other variables, which is always in one direction, a so-called Directed Acyclic Graph (DAG). In a DAG, there are only directed edges and no node is visited more than once (Barber [18]). Every variable is dependent on its parent variables, hence creating conditional probabilities. To create a BN, it is important to know which variable influences other variables and to find out which probability distribution each variable has. In figure 2.1 a simple representation of a BN can be seen. The joint probability distribution can be found by using equation (2.1). For the example in figure 2.1, the joint probability can be found in equation (2.2). BN take the stochastic behaviour of a transportation system into account. The structure of the BN can be created based on knowledge or by applying a data-driven method. By means of backward propagation, it can be found which conditions in a system lead to a certain outcome.

$$P(x_1, x_2, ..., x_n) = P(x_n|x_{n-1}, ..., x_1) \cdots P(x_3|x_2, x_1)P(x_2|x_1)P(x_1) \quad [49] \tag{2.1}$$

$$P(x_1, x_2, x_3, x_4, x_5) = P(x_5|x_4, x_3)P(x_4|x_2)P(x_3|x_2, x_1)P(x_2)P(x_1) \tag{2.2}$$

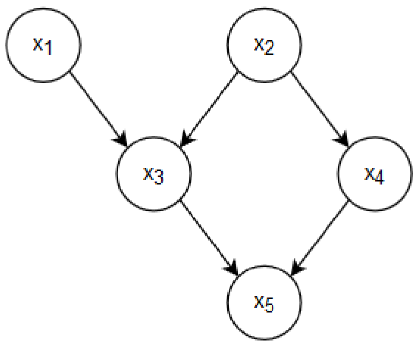


Figure 2.1: Example Bayesian Network

Some studies applied BN to airline networks (Wu and Law [61], Wu and Wu [62]). Airline networks are by itself also complicated operations, where aircraft, crew, passengers and luggage need to be moved as seamlessly as possible. These studies showed that it remains difficult to model such complex systems, but that a BN provides more insights. In Wu and Wu [62], it was even found that flight time distributions are non-IID, indicating that it does depend on historical data, which in this case led to an under-estimation of the schedule buffers necessary in airline operations, which can be related to the EUROCONTROL study [59]. Wu and Law [61] used the BN to identify the bottlenecks in the airline's operation.

Rodríguez-Sanz et al. [52] present a model using a BN to get more insights in the departure delay, by modeling the process from arrival to departure at Madrid airport. 51 variables have been used in this BN of which most airside parameters. The BN was created using operational data. Using forward propagation, the departure delay could be predicted with high accuracy. Using backward propagation, the main contributors to the delay could be identified. Cao and Fang [25] presented a BN structure learning model, using a genetic algorithm, also for departure delay analysis. For a departure process at a hub airport, the study found that higher accuracy is achieved by first creating the BN based on operational data, after which the learning algorithm can optimize the structure of the BN with a fast convergence rate, resulting in a more accurate departure delay prediction.

A later study by Rodríguez-Sanz et al. [53] again created a BN to model delay for Madrid airport. The main difference with Rodríguez-Sanz et al. [52] is that in this case the study is only focused on the arrival process. As stated in this study, applying a BN to a single node of a complex network instead of the entire system allows one to better understand the dynamics within that node. This study focuses on two aspects, the arrival delay and the airport congestion, which is the percentage of the capacity used. Again a data-driven BN is created, trained to find the right distributions and validated. This time, 22 variables are used to eventually predict the two outputs. The BN shows to perform well when compared to the real data, but still showing around 10% errors for the output variables. As a second part of Rodríguez-Sanz et al. [53] Markov chains are used to assess the reliability of the system. This remains a one airport study and it would be interesting to see whether other airports perform in a similar or different way. While a BN has shown the possibility to represent real operations, it remains a probabilistic model just like queuing models, therefore there will always be differences when compared to real operations. Additionally, as nodes are only conditionally dependent on the parent nodes, the inter-dependencies must be modeled accurately.

2.9. Conclusion Literature Review

In this chapter, many approaches have been presented that hold the potential to decrease the ATFM delay for Amsterdam Airport Schiphol. However, these different approaches are somewhat subject to traffic scenarios and geometry at the airport. For AAS, it is not yet clear where the ATFM delay originates from, or what causes it. So before a method is chosen that will be applied to reduce ATFM delay for AAS, further analysis has to be performed. Chapter 3 will analyze the operational conditions at AAS to see whether this can support the decision to pick one of the methods presented in this chapter.

3

Case Study Amsterdam Airport Schiphol

As was explained in the chapter 1, in 2019 Amsterdam Airport Schiphol (AAS) was more subject to Airport Capacity delay than any other airport in Europe. What are the differences between AAS and other airports in Europe? Are there any correlations between operational variables that influence delay at AAS? This chapter takes a deep-dive into operational data to get to the bottom of the ATFM airport capacity delay at Schiphol Airport.

3.1. Airport Comparison

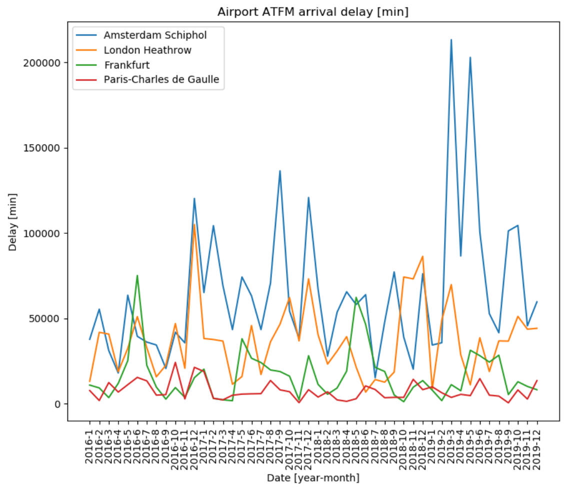
To start this analysis, a comparison between airports in Europe is made based on Air Navigation Service Performance data from EUROCONTROL. Initially, the traffic is compared at 4 major hubs of the European network and the three most common delay reasons are compared, weather, ATC capacity and Aerodrome capacity. A similar analysis was made for airports with a high aerodrome capacity delay.

3.1.1. Hub comparison

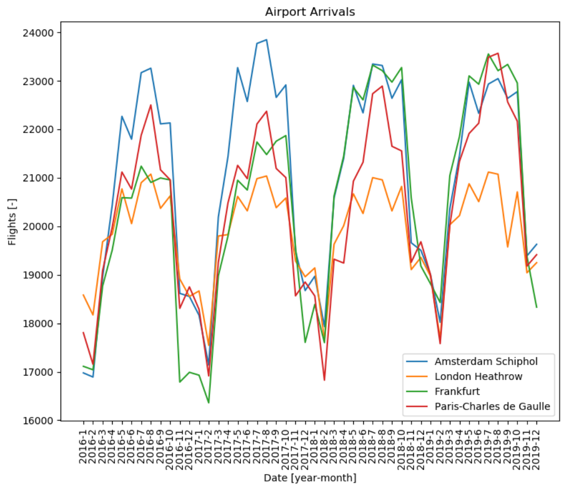
When comparing London Heathrow, Frankfurt Airport, Paris-Charles de Gaulle and Amsterdam Airport Schiphol, it is important to start from a traffic point of view. In figure 3.1b, one can see the number of arrivals for these hub airports. What can be seen is that in the last two years, Frankfurt and Paris have increased in the number of arrivals and that London Heathrow structurally has less traffic in the summer season, which is most likely due to the number of runways at London Heathrow (2), which is lower than at Frankfurt (4), Paris-Charles de Gaulle (4) and Amsterdam (6). Nonetheless, this figure shows that these airports are almost similar in terms of traffic and all have a hub-function in the European airport network.

When comparing the total ATFM delay at these airports (figure 3.1a), it can be seen that AAS has had the highest ATFM delay in total over the past years and it has been increasing throughout the years. When this is normalized to the number of arrivals (figure 3.1f), it can be seen that the average delay per arrival at AAS is around 3 minutes, while this is 1 minute lower at London Heathrow, even 1 minute lower at Frankfurt airport and Paris-Charles de Gaulle has the lowest average delay per arrival of these 4 hubs, at only 0.37 minutes delay per arrival.

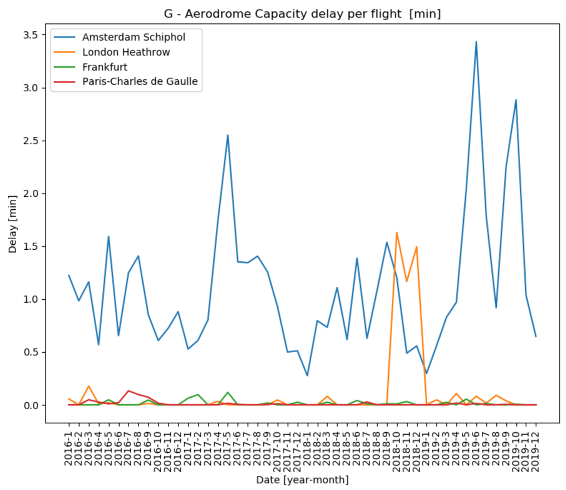
When breaking the ATFM delay down into the three major causes, it can be seen that London Heathrow and AAS perform similarly in terms of weather delay (figure 3.1e), given that both are in close vicinity to the North Sea providing somewhat similar weather, where Amsterdam has a higher overall rainfall and slightly higher wind speeds [15]. In terms of ATC capacity in figure 3.1d, only London Heathrow seems to have a high number of ATC Capacity delay per flight, especially in 2019. Finally, when comparing the aerodrome capacity delay (figure 3.1c), it can be seen that this is where AAS deviates a lot from the other hub airports in Europe, which is interesting as one might expect that airports with similar traffic numbers and function within the network would have similar aerodrome capacity delay. The aerodrome capacity delay is the type of ATFM delay that differentiates AAS from these other hub airports.



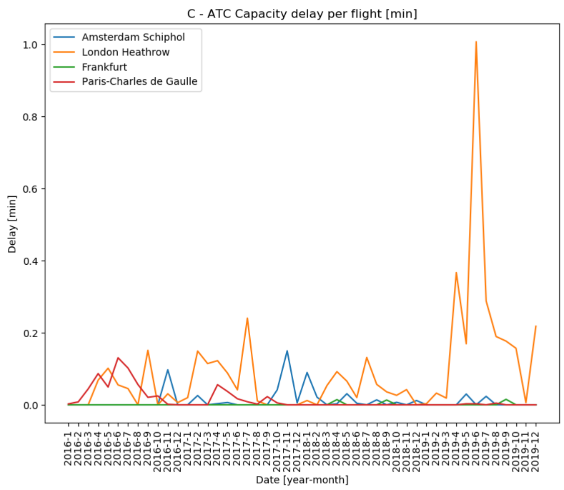
(a) ATFM delay per month



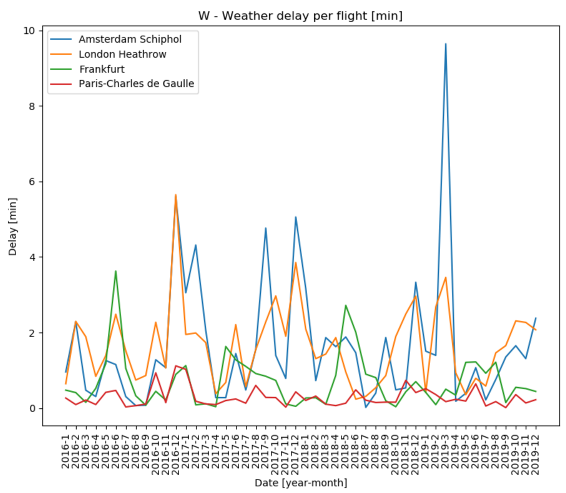
(b) Arrivals per month



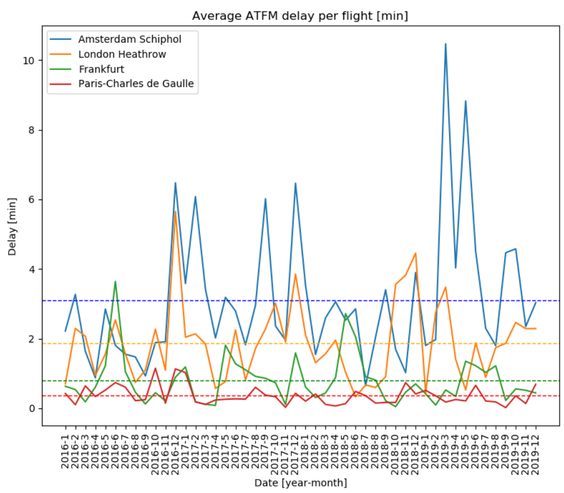
(c) Aerodrome capacity delay per month



(d) ATC capacity delay per month



(e) Weather delay per month

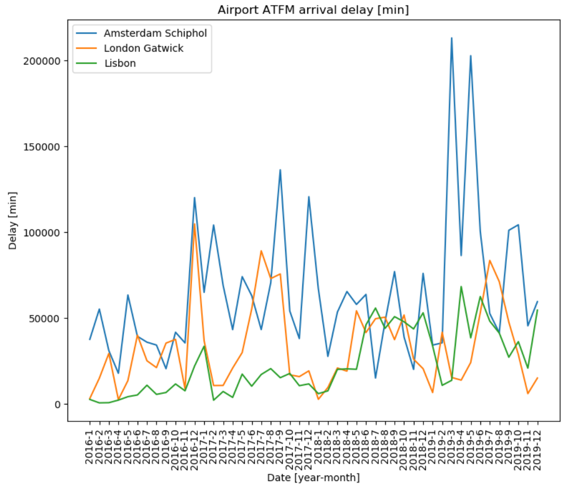


(f) Average ATFM delay per month

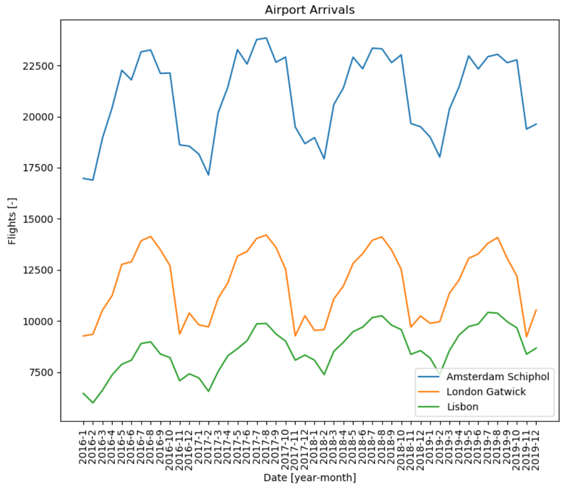
Figure 3.1: Comparison of hub-airports in Europe

3.1.2. Comparison Aerodrome Capacity Delay

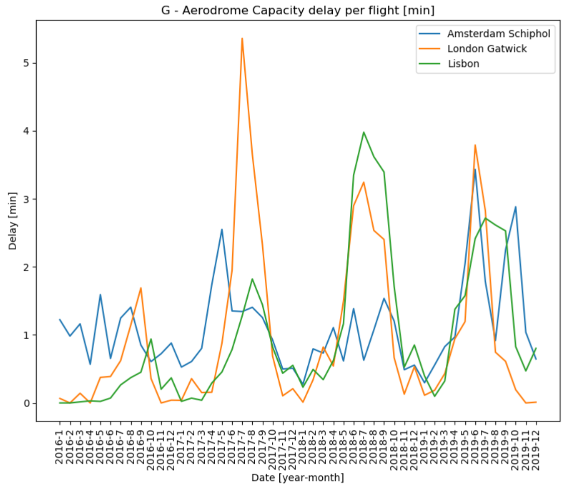
When looking at figure 1.1, there were 2 other airports in 2019 with a relatively high airport capacity delay, which are London Gatwick and Lisbon. So for these airports, a similar analysis was performed as for the hub-airports. From figure 3.2b it can be seen that the traffic numbers of these three airports differ a lot, which is to be expected given the different functions these airports have in the network, as well as difference in infrastructure. London Gatwick has 2 runways, as well as Lisbon [10, 12]. The total average ATFM delay per arrival is roughly similar, as well as the ATFM delay due to weather and ATC capacity. When looking at figure 3.2c, it can be seen that the aerodrome capacity delay for these airports is almost the same per arrival. This raises the question, do these three airports have something in common? Besides the aerodrome capacity delay, there seem to be very little similarities in terms of infrastructure and traffic numbers. To continue, it is important to understand what aerodrome capacity delay is.



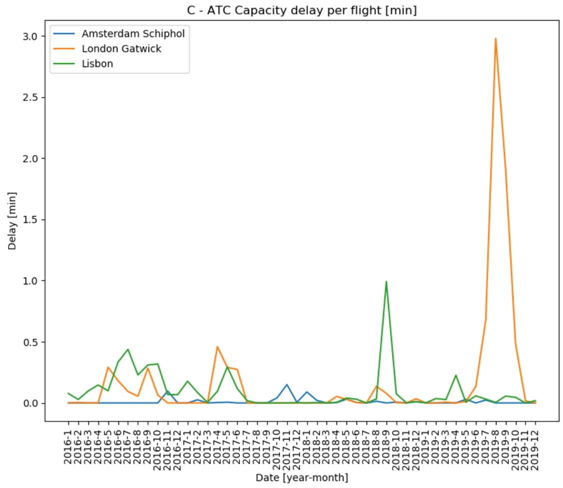
(a) ATFM delay per month



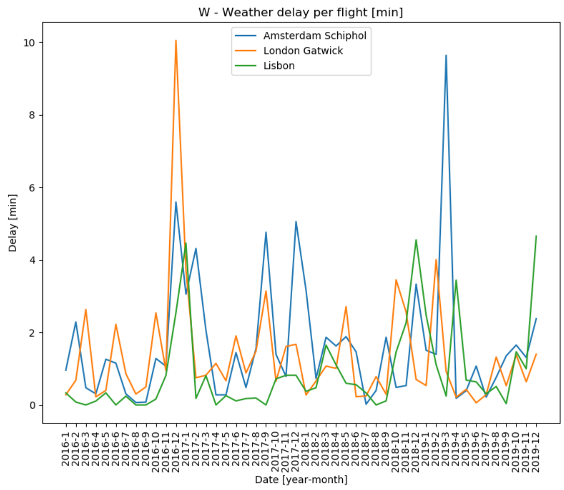
(b) Arrivals per month



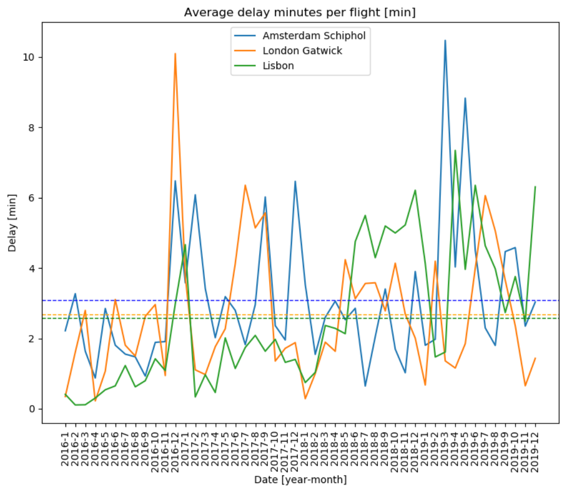
(c) Aerodrome capacity delay per month



(d) ATC capacity delay per month



(e) Weather delay per month



(f) Average ATFM delay per month

Figure 3.2: Comparison of high aerodrome capacity delay airports in Europe

3.2. Aerodrome Capacity Delay

The aerodrome capacity delay is the type of ATFM delay that distinguishes AAS from other airports in Europe. The definition of aerodrome capacity delay is as follows:

> *"Reduction in declared or expected capacity due to the degradation or non-availability of infrastructure at an airport. e.g. Work in Progress, shortage of aircraft stands, etc. Or when demand exceeds expected aerodrome capacity" [30]*

This definition as provided by EUROCONTROL, is a rather broad one. It could range anywhere from runway maintenance, to the availability of gates or simply traffic demand. In short, many kinds of delays can be attributed to aerodrome capacity delay. Therefore, operational data from AAS, LVNL and EUROCONTROL is analyzed to see if some parameters can be identified that contribute the most to aerodrome capacity delay.

In this section and later sections, some correlation tests are performed. The correlation test performed is usually Spearman correlation test, as the data is not normally distributed. If the data were to be normally distributed, one can use the Pearson correlation test. These tests return a value between -1 and +1, where -1 indicates a strong negative relationship and +1 indicates a strong positive relationship. 0 indicates no relationship [7, 8]. How to interpret a correlation coefficient can be found in table 3.1. Whether the data is normally distributed or not, is determined by using the Shapiro Wilk normality test [14]. It has to be noted that a correlation does not necessarily indicate a causal relationship.

Table 3.1: Correlation coefficient interpretation [47]

Correlation coefficient (±)	Interpretation
.90 – 1.00	Very high correlation
.70 - .90	High correlation
.50 - .70	Moderate correlation
.30 - .50	Low correlation
.00 - .30	Negligible

3.2.1. Regulations

EUROCONTROL releases data regarding the applied regulations in the Network Manager Interactive Reporting Dashboard (NMIR). The regulations data provides more detail regarding the regulation applied, why this was applied and it even allows the air traffic controller to enter a detailed description regarding the regulations.

In 2018 and 2019, 37.4% of the ATFM delay minutes are due to aerodrome capacity delay and 60.4% of the regulations issued were due to aerodrome capacity in 2018 and 2019. Of this 60.4% of aerodrome capacity delay regulations, 20.6% has a detailed description. Unfortunately, most of these descriptions are *Regulation Extended*, but are difficult to trace back to the root of the delay. So filtering these out, this leaves four reasons for aerodrome capacity delay, which can be seen in figure 3.3.

It can be seen that 6% of all aerodrome capacity delay, has as reason high demand, while there are also some moments when the weather was filed as a reason for aerodrome capacity delay. This is odd since there is an ATFM delay code for weather available. Nonetheless, this can happen. When for example regulations are in place regarding aerodrome capacity delay, but suddenly bad weather comes up, there is simply a combination of both and an air traffic controller can only file one reason. This system is therefore prone to errors like these, because of the operational complexity at times.

This, unfortunately, did not give a precise reason for the aerodrome capacity delay, as these percentages are so small that no conclusions can be made. According to professionals from air traffic control, aerodrome capacity delay is most of the time issued in case of high demand.

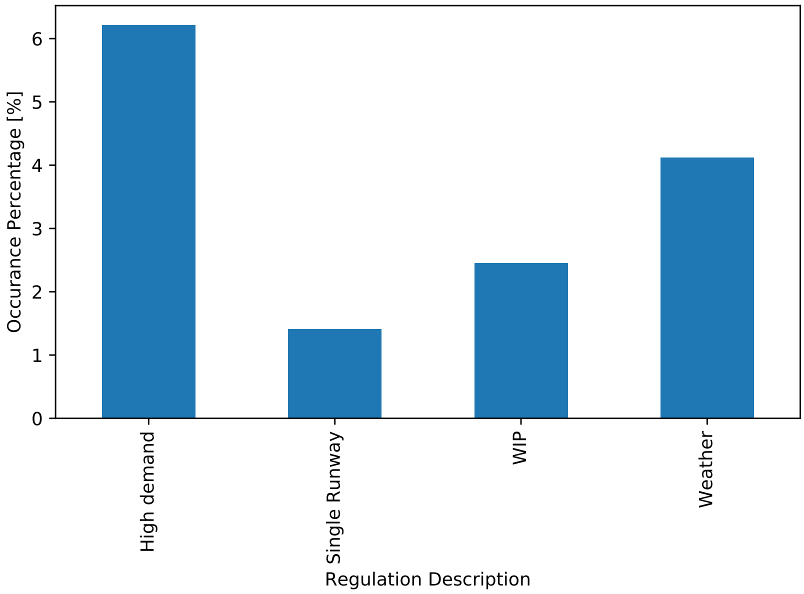


Figure 3.3: Detailed description of aerodrome capacity delay

3.2.2. Arrivals

The NMIR dashboard publishes many types of data regarding post-operations. This allows for several analyses to be made, such as daily or monthly information regarding ATFM delay. Looking at figure 3.4, the aerodrome capacity delay in minutes can be seen versus the number of arrivals per day or month. It can be seen that, for some moments in time, the aerodrome capacity delay increases drastically above a certain number of arrivals, however this is not always the case. When applying a Spearman relationship test to these two data sets, the daily data showed a correlation coefficient of 0.446 and the monthly data showed a correlation of 0.624, a low and moderate correlation, respectively.

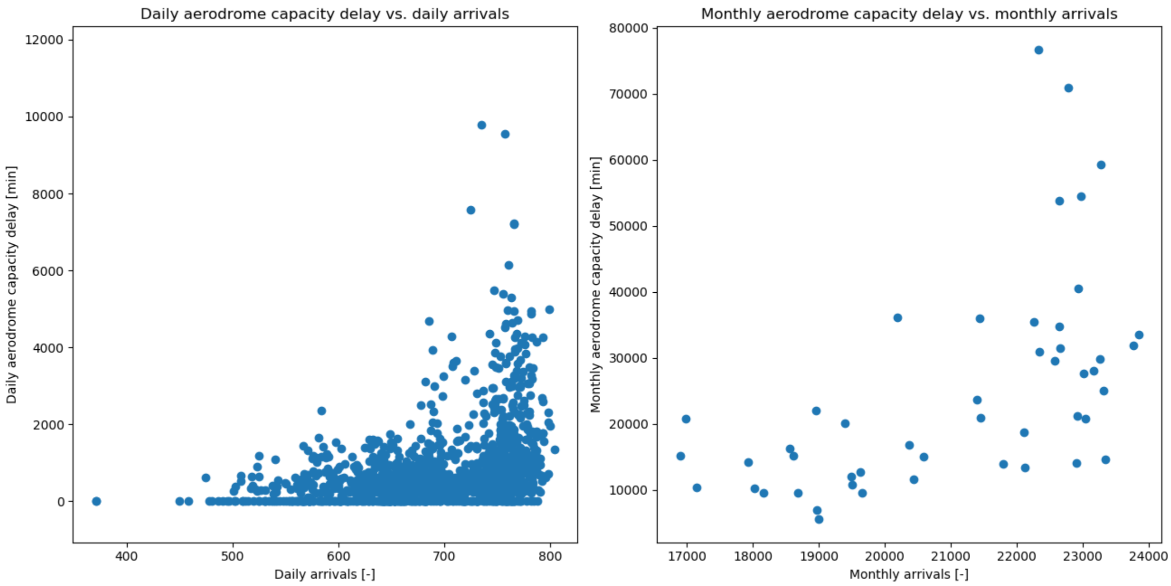


Figure 3.4: Aerodrome capacity delay and the number of arrivals

3.2.3. Runway Configurations

A more detailed analysis regarding the arrivals was performed, for the runway configurations. AAS has 6 runways, of which 5 are used for international aviation and 1 is used for general aviation, but if necessary it can be used for international aviation as well [4]. The layout of Schiphol can be seen in figure 3.5. Depending on the weather, there are many possible runway configurations for AAS, over 2018 and 2019 there have been a total of 122 unique runway configurations.

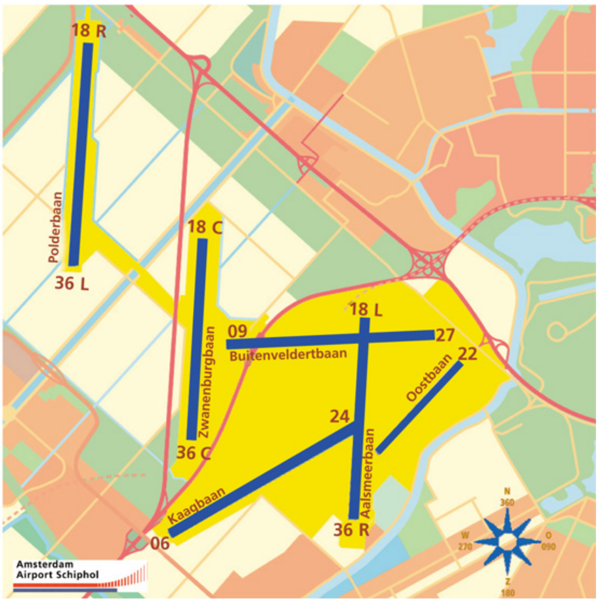


Figure 3.5: Runway configurations Amsterdam Airport Schiphol [6]

The runway configurations come from LVNL data, which was combined with EUROCONTROL data. When looking at all the runway configurations over 2018 and 2019 that handled at least 3% of the total traffic, 13 runway configurations can be found which can be seen in figure 3.6. What can be seen from figure 3.6, is that there is one dominant departure configuration L:18R - TO:24-18L, or to put that in words, landings take place on runway 18R and departures take place on runway 24 or 18L. This is a departure configuration since there is 1 arrival runway and 2 departure runways in use. Usually, AAS makes use of a 2+1 or 1+2 configuration, however, when demand is high for example when switching between an inbound and an outbound peak, a 4 runway configuration can be used. This is not preferred as the residents living near Schiphol will experience more nuisance.

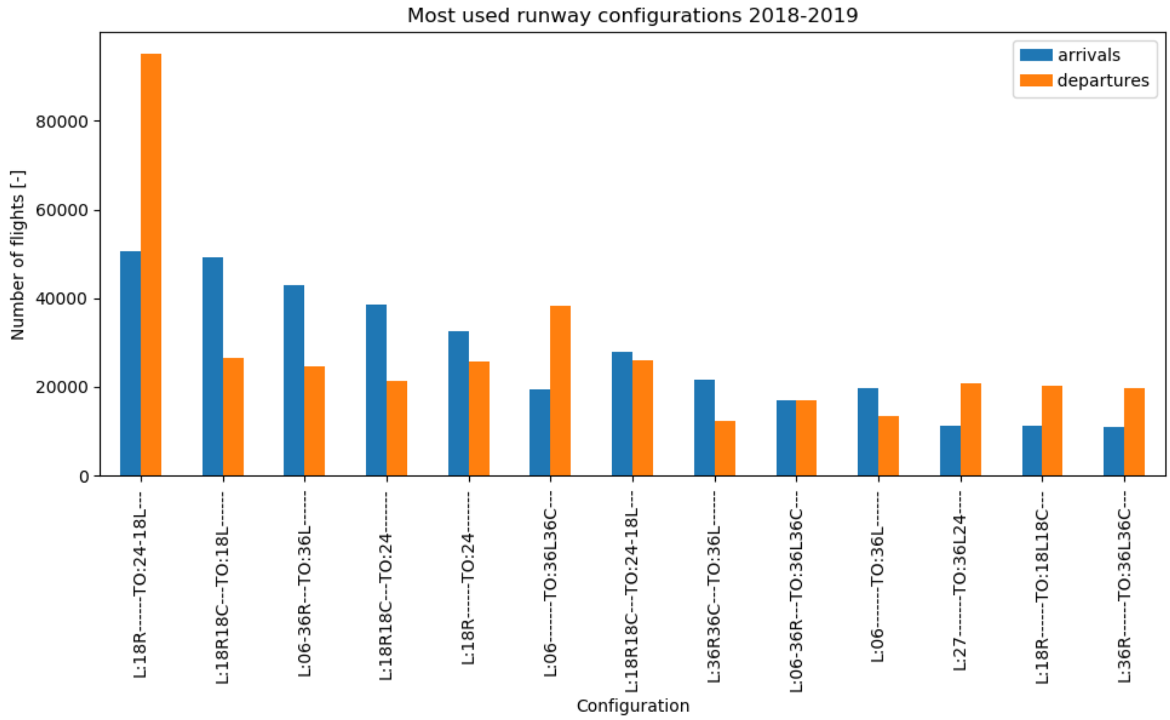


Figure 3.6: Most used runway configurations in 2018 and 2019

However, these are the runway configurations that handled all the traffic, so arrivals and departures. When only looking at arrivals, the top 10 configurations can be seen in figure 3.7. Interestingly enough, the configuration that handled most arrivals was a departure configuration, but this is closely followed by arrival configurations. From figure 3.6 it could be seen that there is one dominant departure configuration, whereas there are multiple arrival configurations with similar amounts of traffic. There are two 4-runway configurations present in figure 3.6, indicating that these configurations are used relatively often.

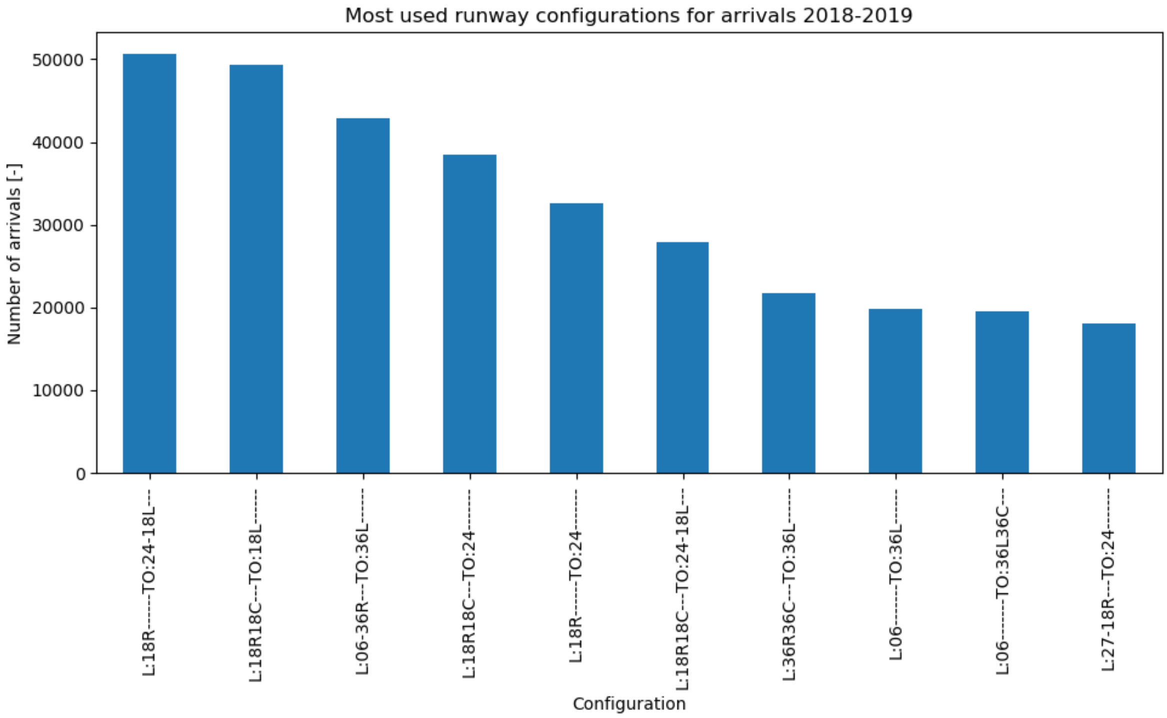


Figure 3.7: Top 10 arrival configurations in 2018 and 2019

Lastly, the top 10 runway configurations that have the most aerodrome capacity delay are shown in figure 3.8. There is a bit of a difference between the arrival configurations that handled the most arrivals and the aerodrome capacity delay. The top 4 are all arrival configurations, which makes sense as aerodrome capacity delay is issued for arriving aircraft. A detailed comparison can be seen in table 3.2. It can be seen that the highest aerodrome capacity delay per arrival is for departure configurations, as there is only one arrival runway available. From table 3.2, there is not one configuration that performs significantly worse than another. These 10 configurations cover 66% of the total aerodrome capacity delay over 2018 and 2019 and 53% of the total arrivals.

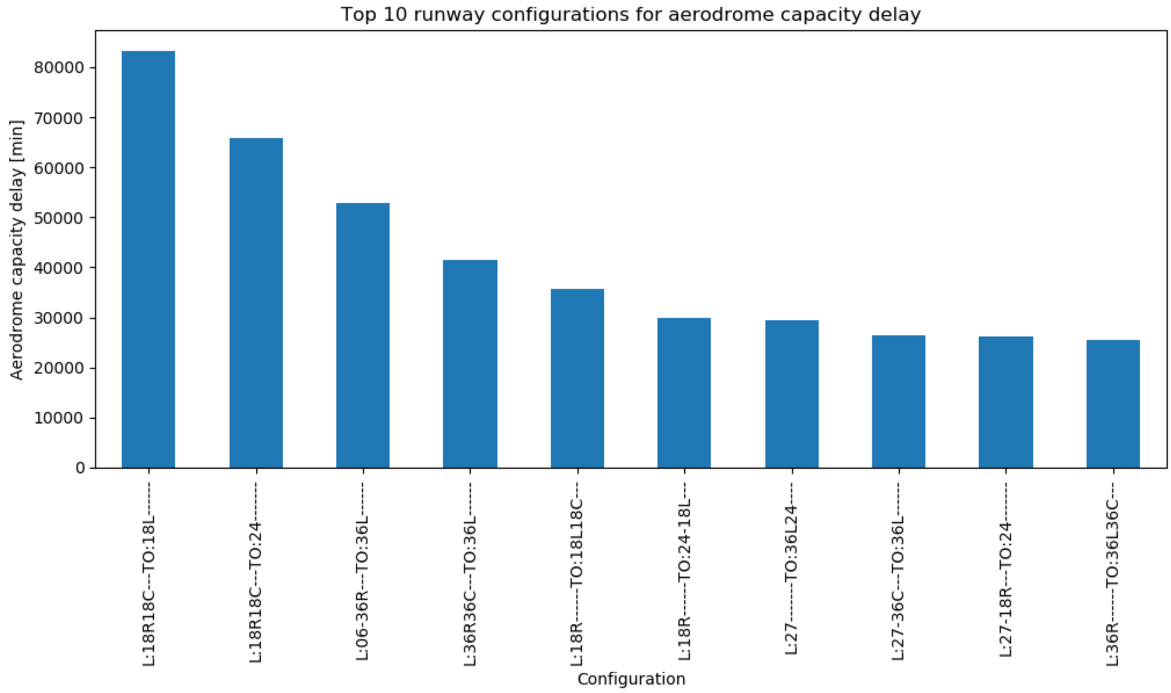


Figure 3.8: Top 10 arrival configurations with the most aerodrome capacity delay minutes over 2018 and 2019

Table 3.2: Runway configurations for aerodrome capacity delay and number of arrivals 2018-2019

Configuration	**Aerodrome capacity delay [min]**	**Percentage of aerodrome capacity delay [%]**	**Number of arrivals [-]**	**Percentage of arrivals [%]**	**Average aerodrome capacity delay per arrival [min]**
L:18R18C—TO:18L—	83171.39	13.17%	49310	9.90%	1.69
L:18R18C—TO:24—-	65731.78	10.41%	38507	7.73%	1.71
L:06-36R—TO:36L—	52959.62	8.39%	42875	8.61%	1.24
L:36R36C—TO:36L—	41500.06	6.57%	21695	4.36%	1.91
L:18R——TO:18L18C	35742.64	5.66%	11105	2.23%	3.22
L:18R——TO:24-18L	29994.36	4.75%	50717	10.19%	0.59
L:27——-TO:36L24-	29318.48	4.64%	11140	2.24%	2.63
L:27-36C—TO:36L—	26437.59	4.19%	11703	2.35%	2.26
L:27-18R—TO:24—-	26120.37	4.14%	18038	3.62%	1.45
L:36R——TO:36L36C	25586.30	4.05%	11039	2.22%	2.32

3.3. Early Arrivals

As was mentioned in [59], the difference in departure delays and arrival delays has been increasing over the past years. This is mainly due to airlines applying schedule buffers to the flights, in order to anticipate expected ATFM delay. As a result, more flights are arriving ahead of schedule, especially when no ATFM delay is issued. Since there has been very little ATFM delay in 2020, more flights are arriving early which can be seen in figure 3.9. In figure 3.9, the data for 2020 up to September is included. It is uncertain if these early arrivals influence the ATFM delay when these arrive at unexpected times. This is especially the case for intercontinental flights, as these are not subject to ATFM delay so arrive unexpectedly when early. This section takes a detailed look into early arrivals, the effect on ATFM delay, total delay and on time performance. In this section arrival delay is the total arrival delay, defined as the difference between the Scheduled In-Block Time (SIBT) and the Actual In-Block Time (AIBT).

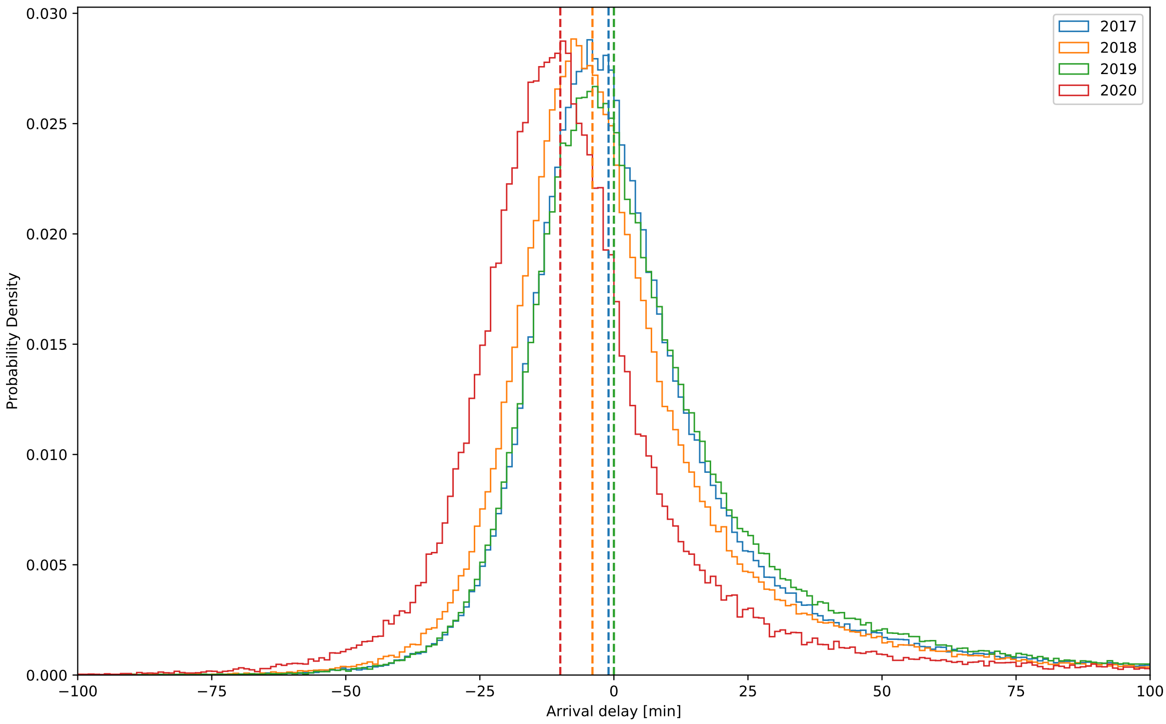


Figure 3.9: Histogram arrival delay

3.3.1. Early Arrivals and Aerodrome Capacity Delay

Looking at figure 3.9, it can be seen that 2020, a year with little ATFM delay, has many early arrivals. This could have to do with airlines not altering the flight schedules even though the schedule buffers could be decreased. Looking at Arrival Sequencing and Metering (ASMA) additional time figure 3.10, the delay issued in a circular area with a radius of 40NM around an airport, AAS has less ASMA delay than London Heathrow. The reason for this comes down to the airport operations, the main difference between AAS and London Heathrow is that for Heathrow almost all arrivals have to wait in holding stacks, in turn London Heathrow has less ATFM delay, which was also presented in [31].

Hence, it seems like the early arrivals most of the time do not have to wait in a holding stack and are simply allowed to land at AAS. These early arrivals, more than 15 minutes early, do disrupt the operations in some way, but it is unclear how and what the impact is.

First, when taking a look at the percentage of early arrivals throughout the years, it can be seen that this has stayed more or less equal between 2017 and 2019 (figure 3.11), fluctuating between 10% and 20% of the daily arrivals. When looking at the early arrivals in comparison to the aerodrome capacity delay in figure 3.12, not a clear relationship can be seen. When applying a Spearman correlation on these datasets, since both are not normally distributed, a correlation coefficient of -0.135 was found, a negligible correlation. By looking at figure 3.12, in combination with the Spearman correlation coefficient, it can be fair to say that there is no correlation between early arrivals and aerodrome capacity delay.

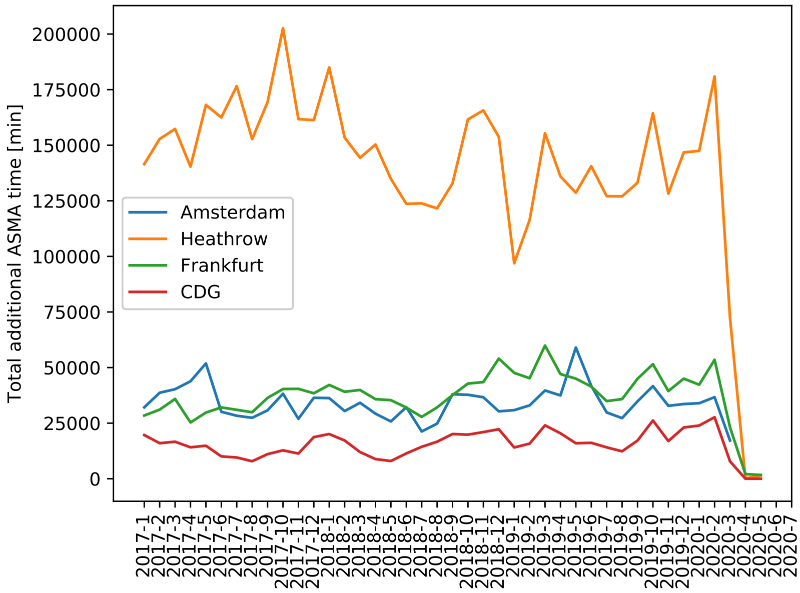


Figure 3.10: ASMA delay

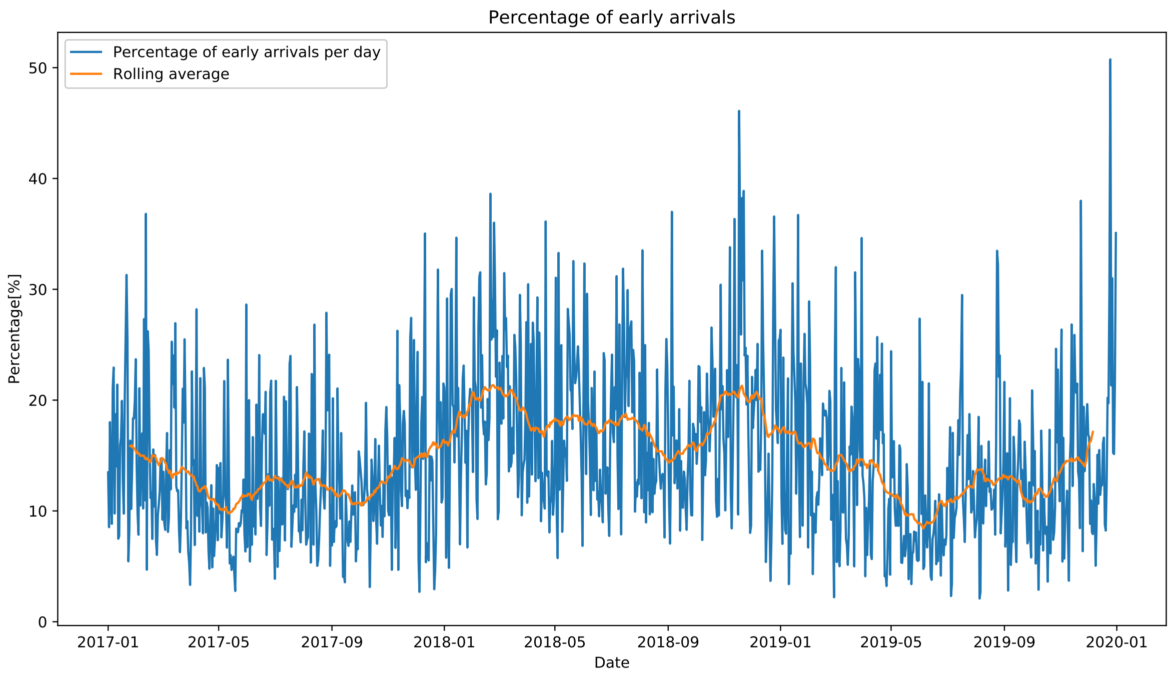


Figure 3.11: Percentage of early arrivals

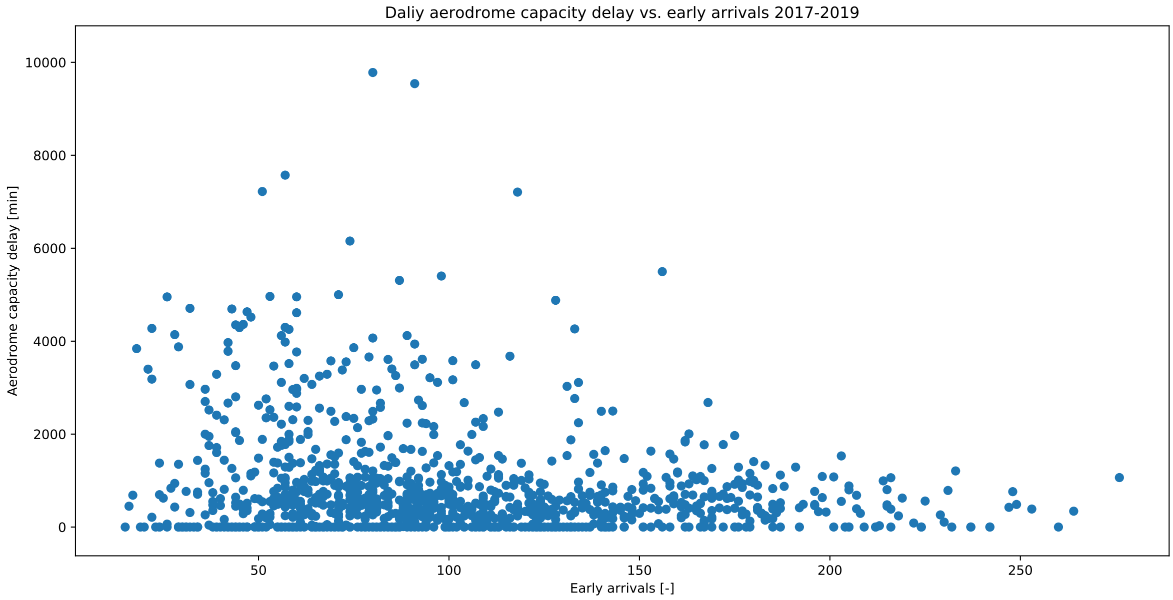


Figure 3.12: Aerodrome capacity delay and early arrivals

3.3.2. Early arrivals daily distribution

It was found that there is no correlation between early arrivals and the aerodrome capacity delay, nonetheless, it would be interesting to see if the early arrivals have some other impact on the operation at AAS.

When looking at the early arrivals throughout the day in figure 3.13 and figure 3.14, it can be seen that between 2017 and 2019, most early arrivals take place in the morning, especially for intercontinental traffic. At the same time, the on time performance (OTP) of the departures is high in the morning but decreases drastically around 9:00h in the morning. Given the fact that most early arrivals take place in the morning, and that the OTP of the departures decreases throughout the day, one could say that the early arrivals influence the process in such a way that departures can no longer depart on time since these early flights have to be handled too. When applying a Spearman correlation test to this data presented in figure 3.13, a correlation of 0.503 was found. This is a moderate correlation.

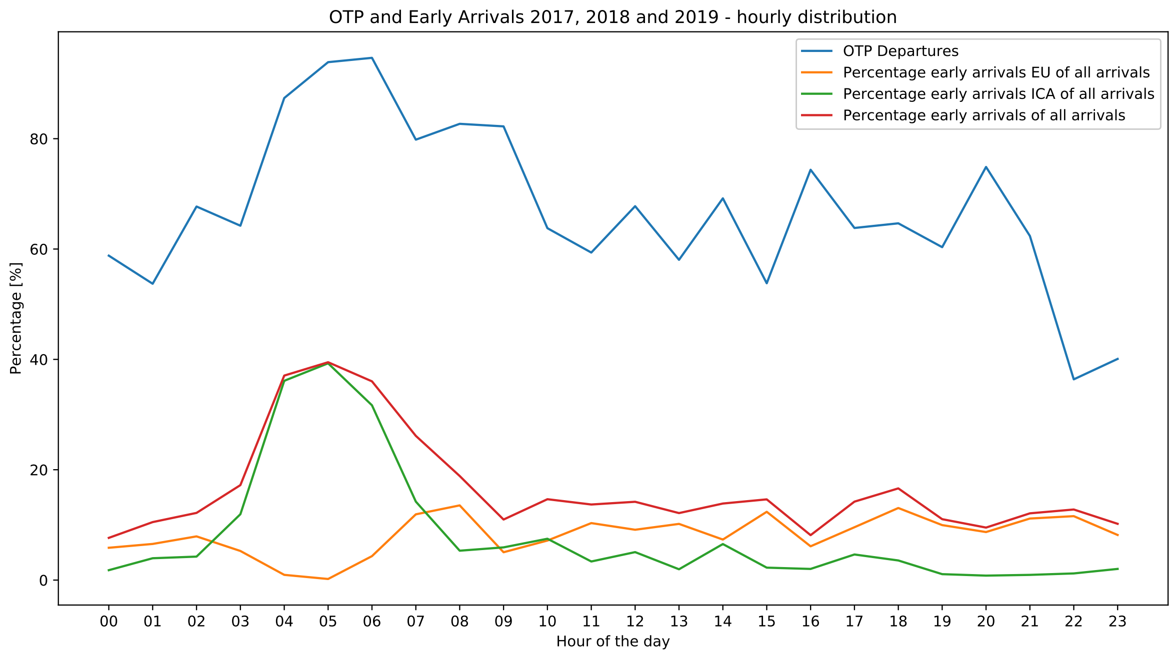


Figure 3.13: On time performance and the percentage of early arrivals per hour

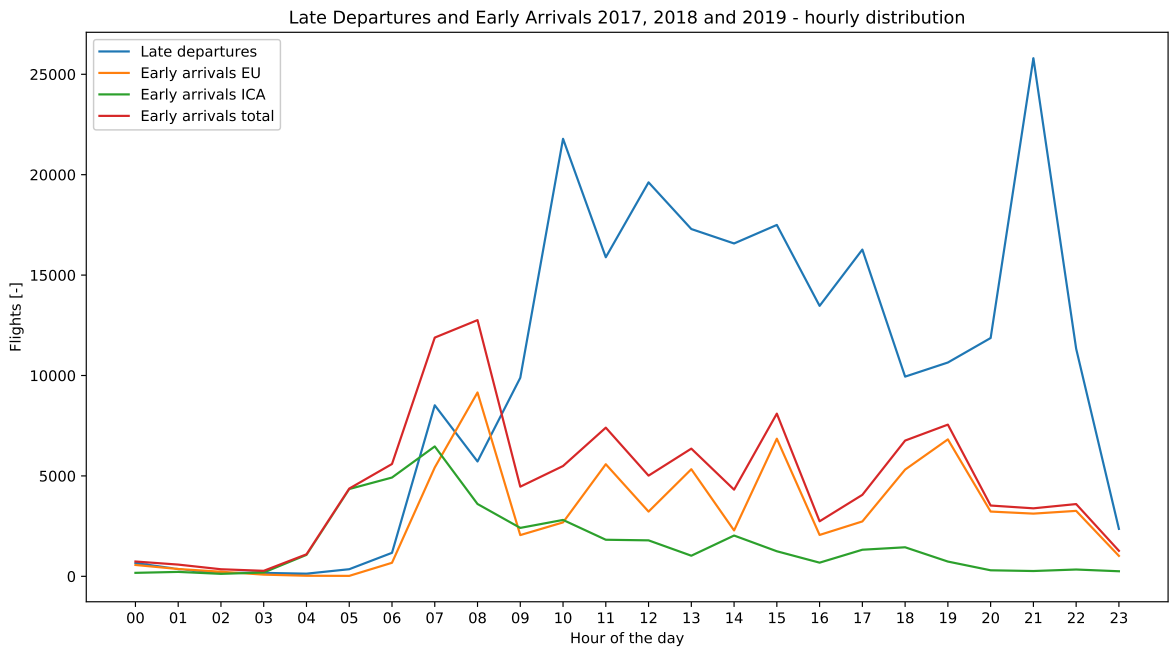


Figure 3.14: Total late departures and total early arrivals per hour

However, in aviation and at airports, many processes are happening at the same time. This makes it difficult to analyze one or two parameters at a time. For these two parameters, it is important to understand the dynamics of the individual parameters as well. When looking at the OTP of the departures, one has to realize that this is not just influenced by early arrivals. In the morning, aircraft can usually depart on time because these are already at AAS. Throughout the day, aircraft arrive which have to depart later that same day. If one of these aircraft arrives late, there is a big chance that these will depart late as well. This is the so-called *Reactionary Delay*, which is delay caused by the delay of the arriving flight. In reactionary delay there are many reasons for the next flight to depart late, besides the actual aircraft, this can also be crew, luggage and passengers [13]. Given the arrival delay present at AAS, it is very likely that a flight can arrive late and therefore delays the next flight. At the same time, most flights arrive early in the morning because throughout the day the airspace gets more congested which can result in arrival delay as well. Also, many intercontinental flights arrive in the morning as these are usually overnight flights from North-America and Asia to Europe. Taking these operational aspects into account, the high OTP of the departures in the morning and the high percentage of early arrivals in the morning could also be coincidental, since there is simply less traffic, less reactionary delay and less congestion in the morning.

While this analysis on early arrivals remains interesting, it also remains unclear what the impact of early arrivals is on the operational delay at AAS. When looking at a daily level in figure 3.12, there seems to be no correlation between aerodrome capacity delay, from ATFM, and early arrivals. Therefore it was concluded that early arrivals do not influence the aerodrome capacity delay and will not be the main focus.

3.4. On Time Performance

On time performance is a measure of the punctuality of the operation. OTP can be determined for both outbound and inbound traffic. OTP is expressed as the percentage of traffic that departed or arrived within a certain delay window. Usually, OTP is defined as the percentage of traffic that arrived or departed with less than 15 minutes of delay according to the schedule [16]. Again, the delay in this section is the difference between scheduled in-block or off-block times, and actual in-block or off-block times.

Applying this definition of OTP to the operational data from AAS, the result for 2017 to 2019 can be seen in figure 3.15. It can be seen that the OTP is high, especially for the arrivals. It starts high in the morning and decreases throughout the day, mainly due to reactionary delay. Now, this seems like a good performance, but this also included flights that depart or arrive very early. So when taking another look at OTP, an analysis was performed for all traffic with a delay between -5 and +15 minutes, creating a 20 minute window around the scheduled arrival time at the gate in figure 3.16. The departure performance is more or less the same, however the arrival performance has dropped significantly. The traffic that arrives close to the scheduled arrival time, is only 40% at best, with lower percentages as well. This indicates that a large percentage of the traffic falls outside this window.

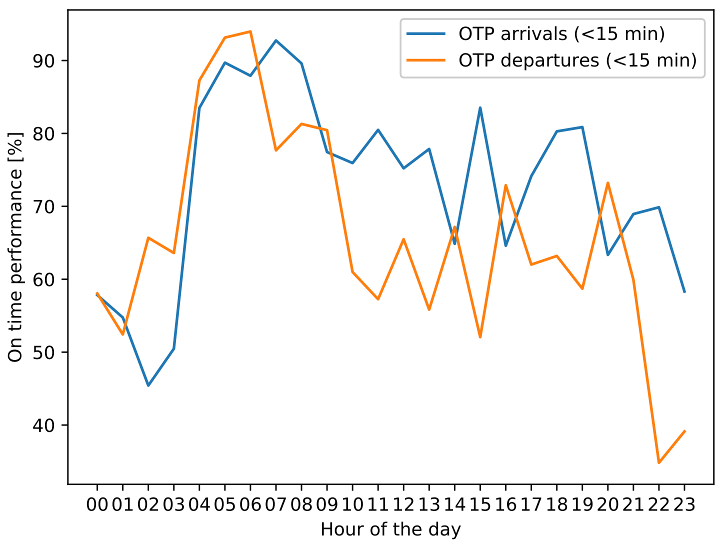


Figure 3.15: On time performance 2017-2019 with less than 15 minutes delay

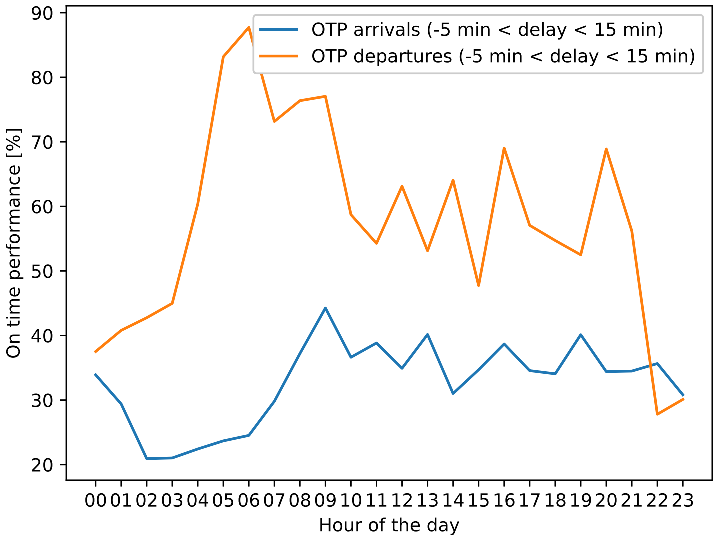


Figure 3.16: On time performance 2017-2019 with delay between -5 and +15 minutes

An analysis was performed to analyze the arrival delay in blocks of 5 minutes for 2017 to 2019 in table 3.3. This is the arrival delay measured as the difference between the scheduled on-block time and the actual on-block time. The blocks between -30 minutes of delay and +30 minutes of delay, cover 85% of all the arrivals in the time. Interestingly enough, 50% of the arrivals is too early whereas only 35% of the arrivals is too late. This is in line with what can be seen in figure 3.16.

Table 3.3: Arrival delay in 5 minute blocks

Arrival delay					
Minutes early	Arrivals	Percentage of arrivals	Minutes late	Arrivals	Percentage of arrivals
0-5	99788	13.4%	0-5	81583	10.9%
5-10	98755	13.2%	5-10	61373	8.2%
10-15	79347	10.6%	10-15	45079	6.0%
15-20	51305	6.9%	15-20	32963	4.4%
20-25	28468	3.8%	20-25	23969	3.2%
25-30	14521	1.9%	25-30	18356	2.5%

This can even be broken down per runway configuration. When looking at the 4 most used runway configurations for 2018 and 2019, an overview can be seen in table 3.4. What is interesting to see, is that the highest inbound OTP corresponds with the lowest delay per arrival. This happens when landings take place at runway 06 or 36R. Looking back at figure 3.6, it has to be noted that the terminal building at AAS is right in the center of the Kaagbaan, Aalsmeerbaan, Buitenveldertbaan and Zwanenburgbaan. Hence, landings at runway 06 or 36R have hardly any taxi distance to cover, when compared to landings at runway 18R. As a pilot does not always know beforehand on which runway the aircraft will land, additional time could be planned for taxiing, which could be the reason for many flights arriving early when landing on runway 06 or runway 36R.

Table 3.4: Runway configurations OTP

Configuration	Arrivals	Departures	% of total traffic	OTP inbound	OTP outbound	Median delay per arrival [min]	Median delay per departure [min]
L:18R—TO:24-18L	50717	95225	14.7%	75.9%	72.6%	0	7
L:18R18C—TO:18L	49310	26445	7.6%	83.9%	67.5%	-2	8
L:06-36R—TO:36L	42875	24496	6.8%	85.9%	69.4%	-6	7
L:18R18C—TO:24	38507	21356	6.0%	84.3%	69.2%	-2	7

This section looks at the OTP at AAS, by looking at the delay which is in this case not ATFM delay, but the total delay. The total delay, AIBT minus the SIBT, includes many aspects. Besides ATFM delay, this also includes taxi delay or other operational delays that fall outside the spectrum of ATFM. It is interesting to see that while many aircraft arrive too early, even if it is only a few minutes, that at the same time AAS has the highest ATFM delay and aerodrome capacity delay. While this does not look into ATFM delay, it does give an insight into the departures and arrivals at AAS. From figure 3.16 and table 3.3, it can be seen that only a small percentage of arrivals are at the gate close to the scheduled time. The arrival punctuality seems low, and chances are that ATFM delay does play a role in this, similarly how it plays a role in the schedule buffers, which decreases the predictability of arrivals as well.

3.5. Applied Rates and inbound traffic

Thus far, this chapter has looked into other airports, aerodrome capacity delay, early arrivals and on time performance. It was found that the aerodrome capacity delay is the biggest issue in terms of ATFM delay and it is still uncertain where it originates from. This section takes a more detailed look into the daily operations, with a focus on the applied rates and the inbound traffic.

3.5.1. ATFM regulations

When ATFM regulations take place, an applied rate is issued by the ANSP and in the case of AAS, this is LVNL. The applied rate is the amount of aircraft, either departures or arrivals, that can be handled per hour. The nominal capacity during an outbound peak is 36 arrivals per hour and 74 departures per hour. The nominal capacity during an inbound peak is 68 arrivals per hour and 38 departures per hour [9]. Now, when regulations are issued, these rates are often decreased.

When bad weather occurs, the rates are usually decreased drastically, which has a large effect on the ATFM delay. As was analyzed in section 3.2, 56.6% of the time regulations were applied for aerodrome capacity delay. Aerodrome capacity regulations are issued more often than weather regulations but have a lower impact in terms of delay minutes. This can be seen from the applied rate during these regulations. What can be seen from table 3.5, is that during aerodrome capacity regulations 45% of the time the inbound rate is decreased from 68 to 65 aircraft per hour, which is in the inbound peak. 16% of the time during aerodrome capacity regulations the rate is decreased from 36 to 35 arrivals per hour. It can be seen that very often, the inbound rate is only decreased by 1 to 3 aircraft per hour from the nominal rate. This is also why the ATFM delay minutes per aerodrome capacity regulation are not as large as during bad weather, since the rate is only decreased by a small amount and the operation is still close to the nominal operation.

Table 3.5: Applied rates aerodrome capacity delay

Applied rates during Aerodrome Capacity Regulations 2018-2019	
Rate 32 as percentage of total aerodrome capacity delay	6.07%
Rate 35 as percentage of total aerodrome capacity delay	15.79%
Rate 65 as percentage of total aerodrome capacity delay	45.10%
Rate 68 as percentage of total aerodrome capacity delay	18.55%

From an operational perspective, these rates can be decreased by a small amount to make the inbound traffic a little bit more manageable. Often, this inbound traffic exceeds the nominal rate, so therefore regulations are put in place to make sure that if it exceeds the nominal rate, it does not do so by a large amount.

3.5.2. Inbound traffic

It would be interesting to compare the actual inbound traffic to the applied rates and inbound peaks, to get an idea of the actual traffic arriving at AAS. To do this, the applied rate for every 10 minutes is used, which is nominal when no regulations are in place and is decreased when regulations are applied. This is compared to the actual inbound traffic in 10 minutes windows, which is then extrapolated to aircraft per hour by multiplying with 6. This way, everything is compared in aircraft per hour. Everything is converted to UTC time, and the applied rate is shifted by 20 minutes as the applied rates are issued when traffic is at the FIR boundary, from which it takes about 20 minutes to arrive at AAS.

An example can be seen in figure 3.17. This was 8 July 2019 and two things can be seen from this day. First, it can be observed that the incoming traffic is not evenly distributed throughout the inbound peaks. Sometimes the demand is much lower than the capacity, while at other times it is exceeded by a large number. Secondly, it can be seen that sometimes the inbound traffic demand starts increasing before the inbound peak starts, this could be early arrivals. However, this 10 minute distribution of traffic can give a bad representation, as it is somewhat subject to coincidence. If one aircraft arrives just before the next 10 minute window, this window seems like there is a very high traffic demand as it is again multiplied by 6. Hence, another method is introduced as well.

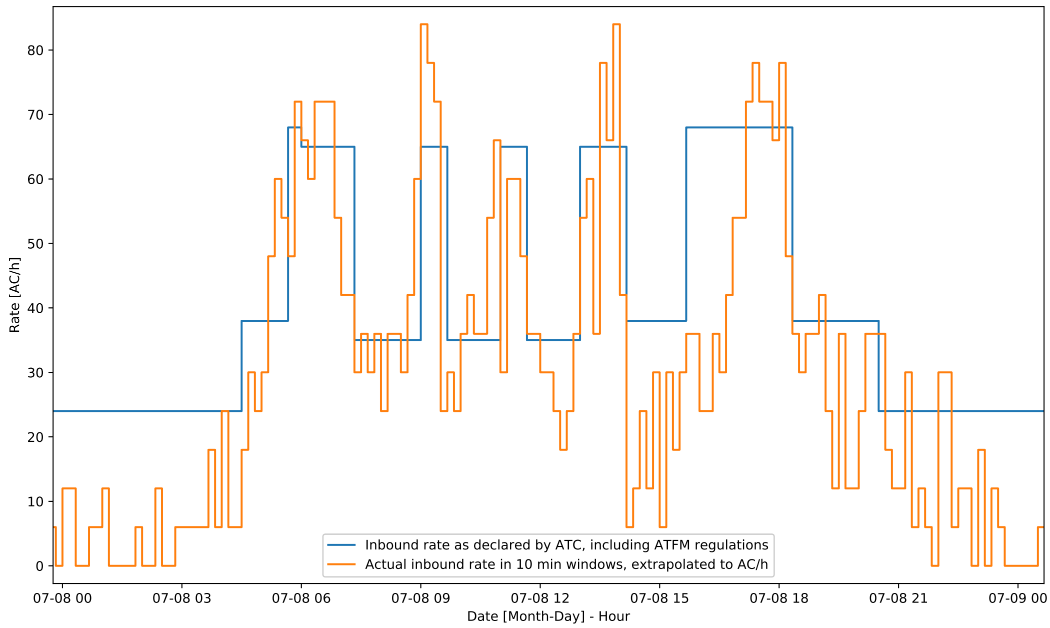


Figure 3.17: Applied rate and inbound traffic per 10 minutes for 8-7-2019

This method makes use of a rolling average and can be seen in figure 3.18. For every hour, for example from 8:00 to 9:00, the average inbound traffic rate is calculated and plotted at 8:30. This is again done for 8:10 to 9:10, which is plotted at 8:40, etc. The result for 8 July 2019 can be seen in figure 3.18. There are no longer peaks that exceed the capacity by a high amount, however it can still be seen that capacity is exceeded for a few moments in time and it can also be observed that the demand still increases before the inbound peak starts. In figure 3.19, the rolling average of the departures is shown as well, as the departure operations also influence the arrival operations, and vice versa. In the middle of the day, at 11:00 UTC time, it can be seen that a departure peak and arrival peak almost coincide. This complicates the operations at AAS and puts more stress on the air traffic controllers and ground operations. It is likely that this adds delay to both departures and arrivals.

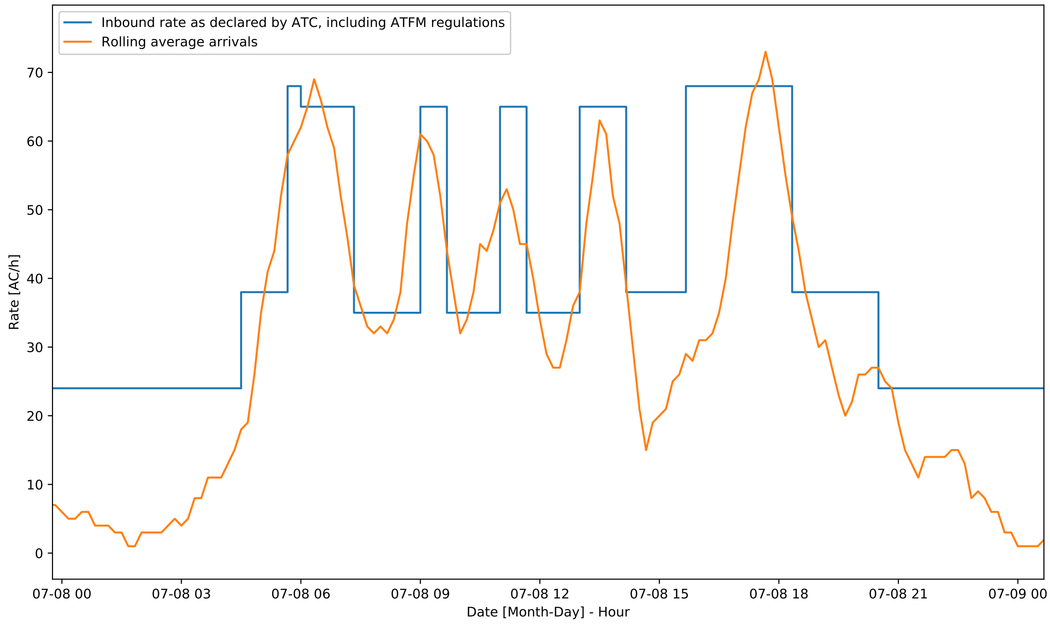


Figure 3.18: Applied rate and inbound traffic rolling average for 8-7-2019

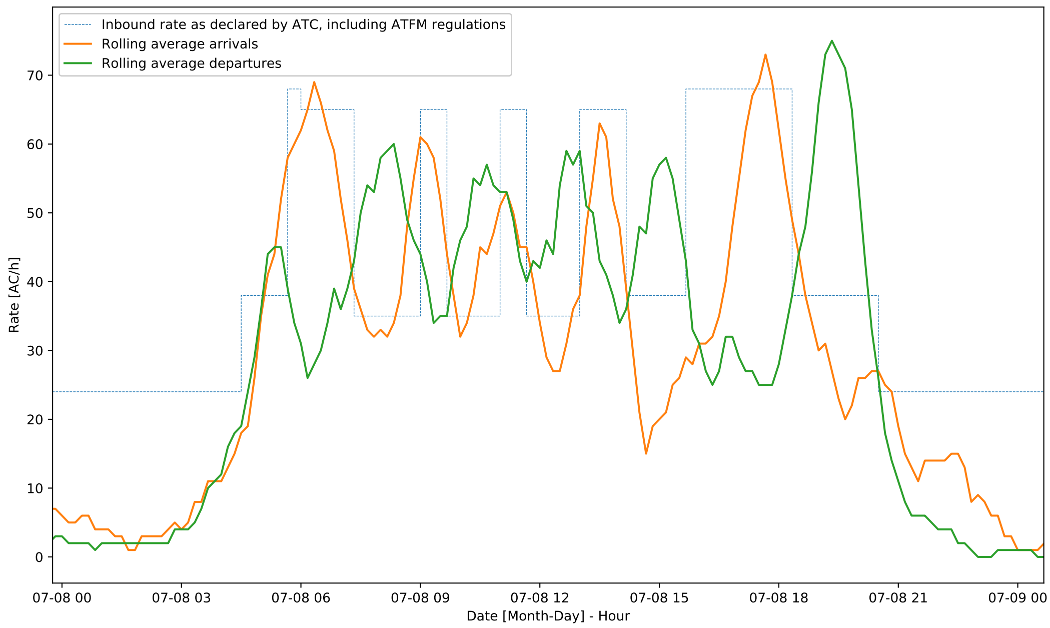


Figure 3.19: Applied rate, inbound traffic rolling average and outbound rolling average for 8-7-2019

Looking at the inbound traffic for 8 July 2019, it can be seen that it is not evenly distributed. The question arises, how much does this distribution add to the aerodrome capacity delay? On 8 July 2019 there was a total of 1286 minutes of aerodrome capacity delay. This is a day with not a very high aerodrome capacity delay, therefore a comparison is made with a day with a higher aerodrome capacity delay, 4 October 2019. On 4 October 2019 there was an aerodrome capacity delay of 7207 minutes.

When looking at figure 3.20, the biggest difference between October 4th and July 8th is that there is some regulation at the end of the day. Besides this, both days have unevenly distributed traffic in the inbound peak and traffic that arrives before the inbound peak starts. The same can be seen in figure 3.21 and figure 3.22. By comparing the inbound traffic in these two days, no large differences can be seen.

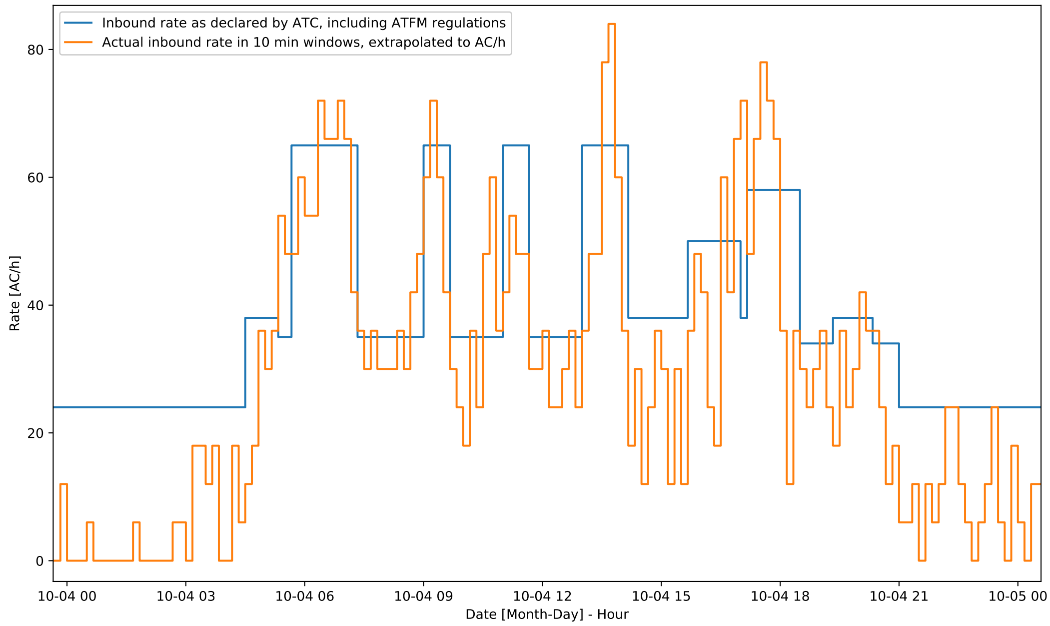


Figure 3.20: Applied rate and inbound traffic per 10 minutes for 4-10-2019

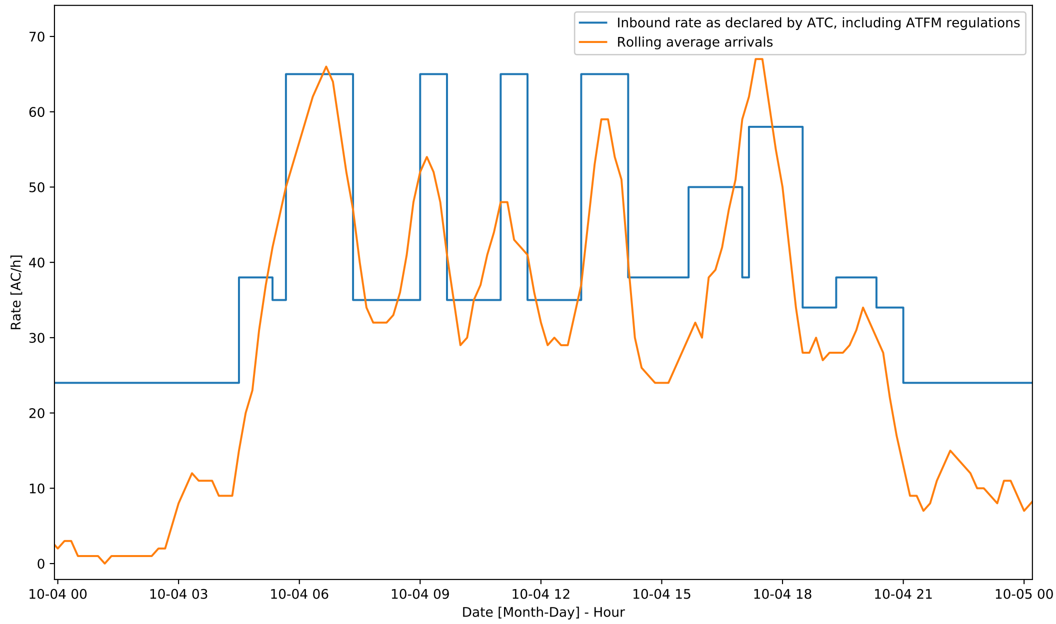


Figure 3.21: Applied rate and inbound traffic rolling average for 4-10-2019

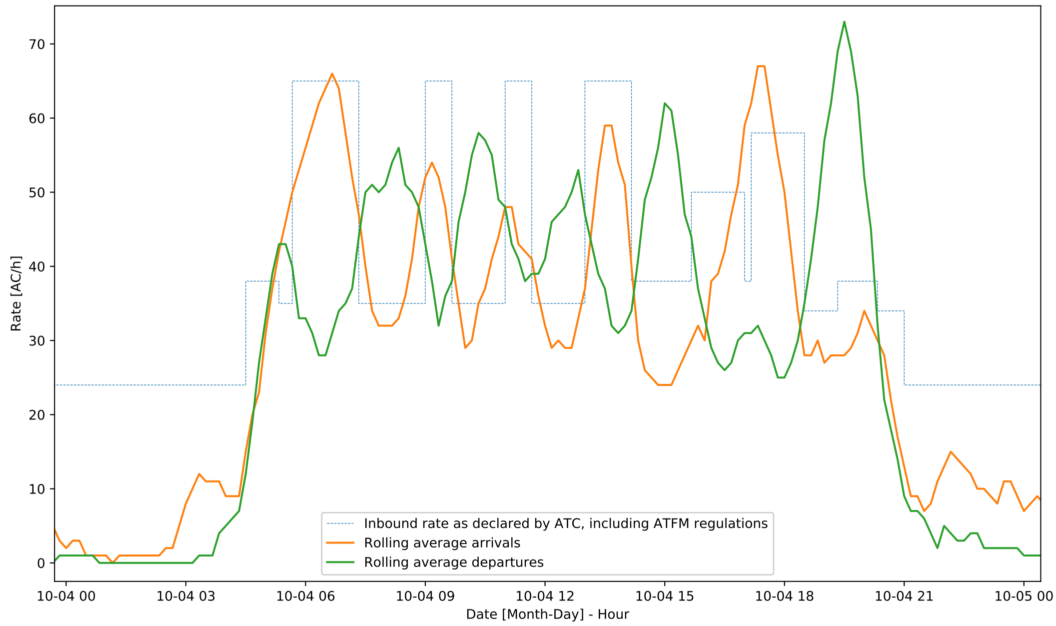


Figure 3.22: Applied rate, inbound traffic rolling average and outbound rolling average for 4-10-2019

3.5.3. Airline schedules and demand

In section 3.5.2 the inbound traffic was presented, both per 10 minutes as well as an hourly average. Some mismatch could be observed between the declared capacity and the actual inbound traffic. One might wonder, if the actual inbound traffic cannot fully meet the declared capacity, what does the airline schedule and the demand look like?

In figure 3.23 and figure 3.24 three graphs can be seen, the upper graph represents the inbound rate according to the airline schedule, the arrival time according to the passenger tickets, which is the latest planning before operation takes place. In the middle graph, the demand for that day can be found.

The demand is defined as the actual arrival time, minus the aerodrome capacity delay, so the time the flight would have arrived if it was not delayed. Lastly, the actual inbound traffic is again presented in the lower graph for comparison. These graphs use a rolling average of 40 minutes, the reason why this is lower than in the previous rolling average graphs is because the larger the time window is, the less expressive it becomes. However, a smaller window is very subject to large changes, hence it was decided to use a 40 minute average to still have some expressiveness in terms of deviations but large enough to not be too affected by large changes.

For July 8th only small differences can be found between the airline schedule, the demand and the actual inbound traffic. The largest difference can be seen in the first arrival peak in the morning, where demand is higher than the capacity, but this peak is decreased by applying ATFM delay. For July 8th the morning shows some early arrivals, and the third inbound peak is much wider than the inbound peak according to schedule, this can both be observed in the schedule, demand and actual inbound traffic.

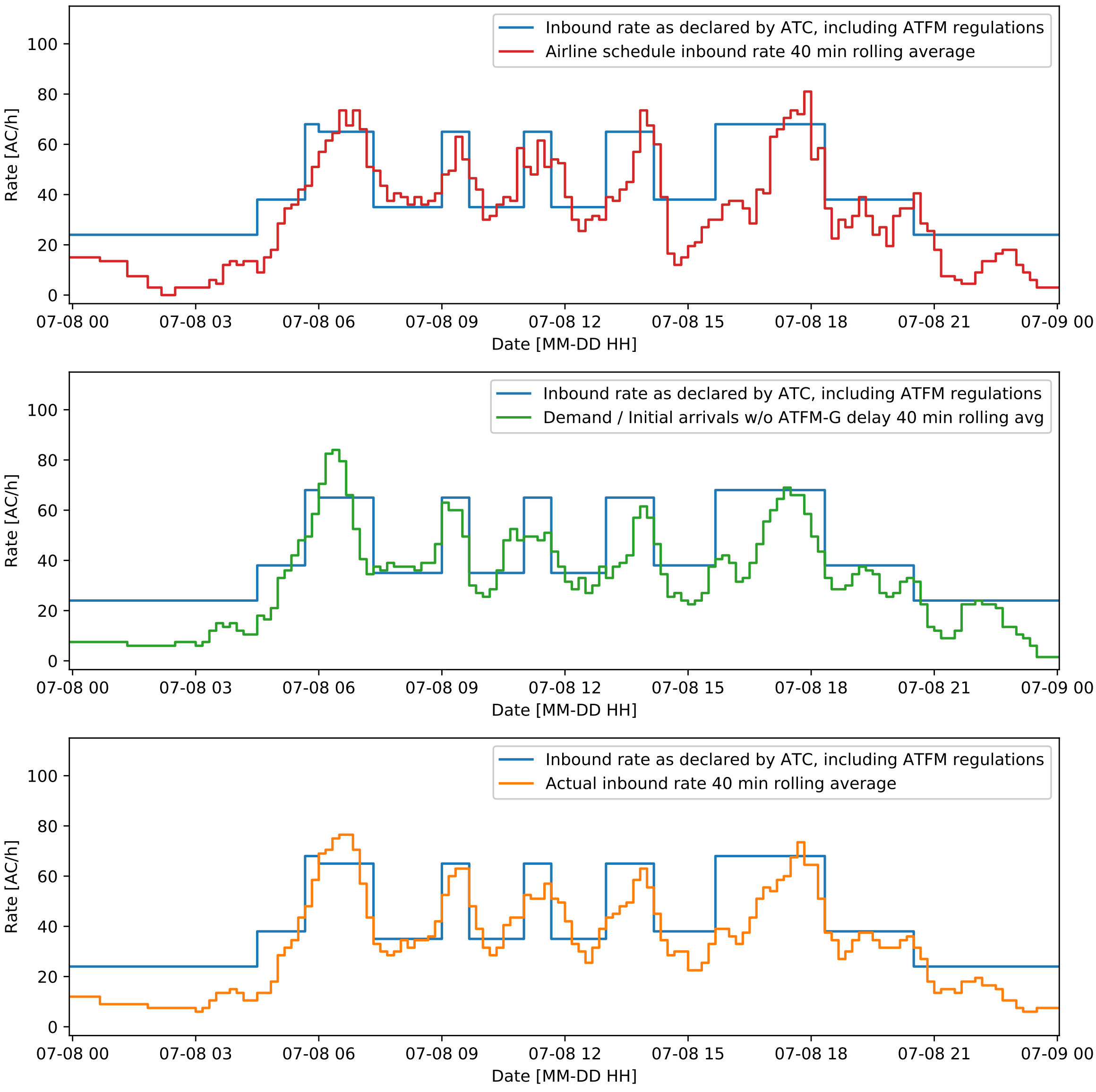


Figure 3.23: Airline schedule, daily demand and actual arrival throughput per 10 minute on 8-7-2019 - rolling average

For October 4th, larger differences can be seen between the airline schedule, demand and actual inbound traffic. The traffic distribution in the airline schedules seems well distributed, despite the last inbound peak which had a drop in declared capacity, but this was most likely not known during the scheduling phase. When looking at the demand for October 4th, the first and fourth inbound capacity are exceeded, and the fifth inbound demand peak is even higher. After ATFM delay was issued, it can be observed that for the actual inbound traffic it fits reasonably within the inbound peaks, showing the effectiveness of ATFM delay on this day. What can be observed for both days, is the difference between the airline schedules and the declared capacity. One would expect that these should perfectly fit, however, it can also be observed that the demand on the day of operation already differs from the schedule. So there are some differences on these days in terms of airline schedule, demand and how the demand is fitted to the inbound peaks. To get a better understanding of the differences between these two days, some additional comparisons are made.

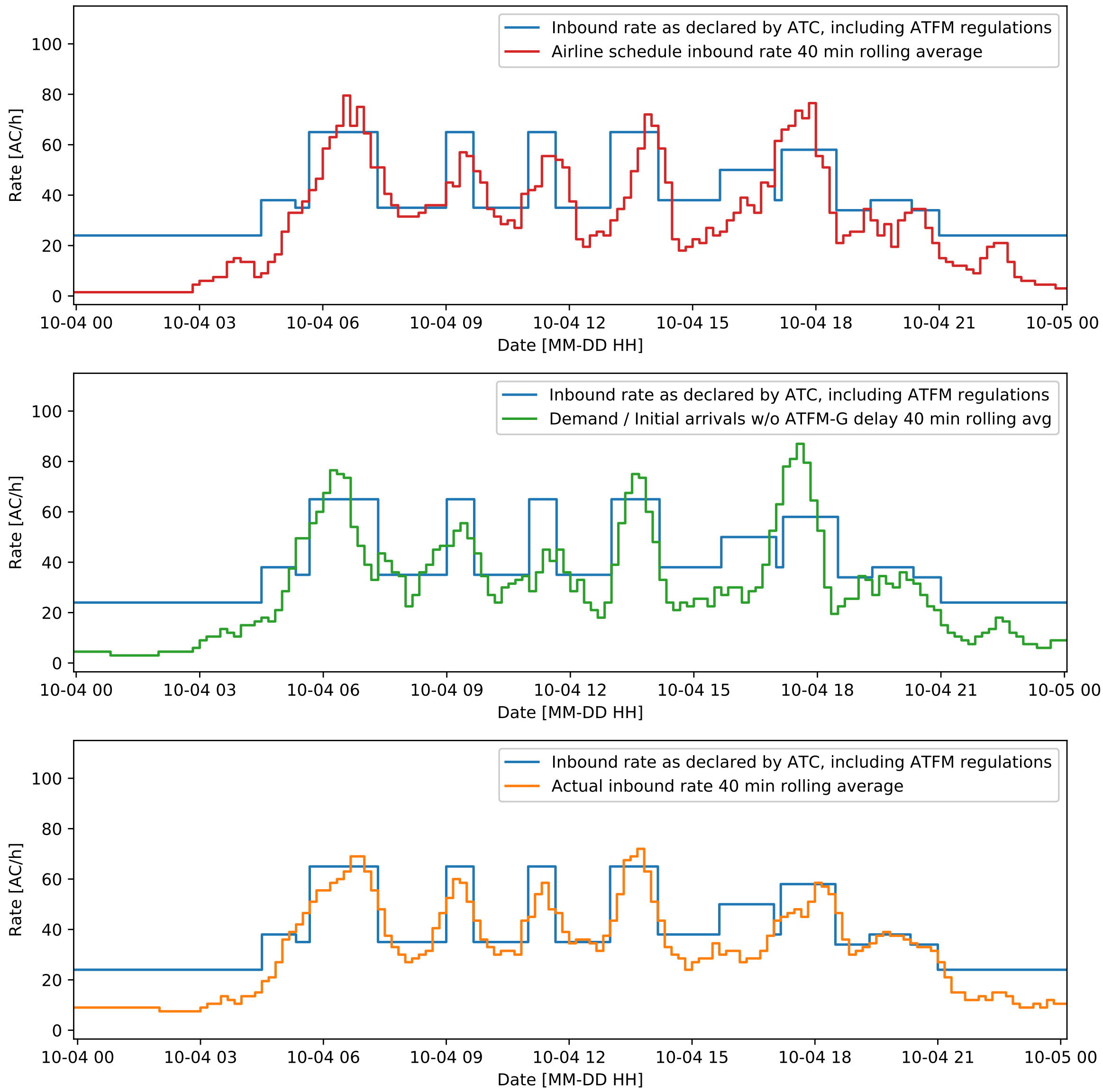


Figure 3.24: Airline schedule, daily demand and actual arrival throughput per 10 minute on 4-10-2019 - rolling average

3.5.4. Comparison

By combining data from EUROCONTROL, LVNL, AAS and the KNMI, a lot of information can be put together. In table 3.6, the main parameters available are compared between the two days. From looking at the values in table 3.6, a few parameters differ, which are:

- Cloud base (both arrivals and departures)
- Wind direction
- Rainfall
- ATA-ETA
- Early arrivals
- Late departures
- Total arrival delay
- Total departure delay

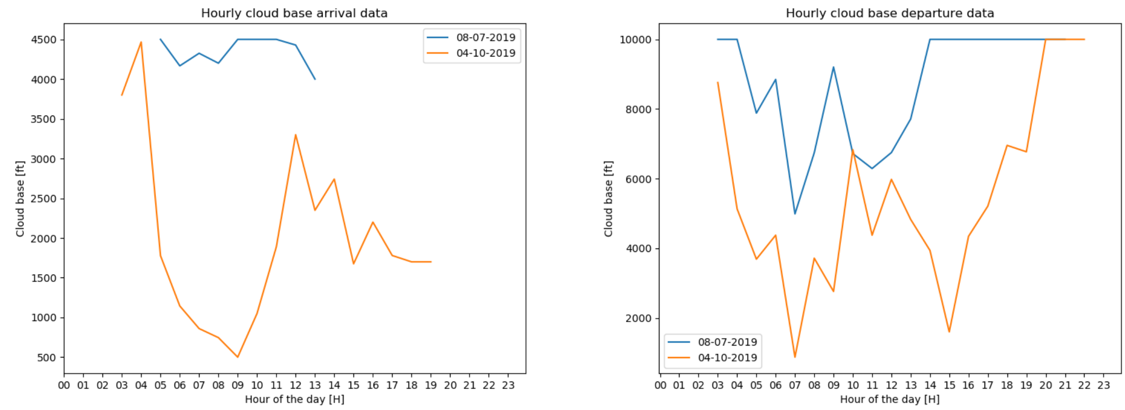
These variables are compared with more detail to see whether a clear reason can be found for the significantly higher aerodrome capacity delay on 4 October 2019.

In table 3.6 the value for *Aircraft too many* indicates the sum of aircraft that caused the inbound flow to exceed the capacity available. *Aircraft before inbound peak* indicates the sum of aircraft that caused the inbound flow to exceed the capacity available, only in the 30 minutes before an inbound peak starts.

Table 3.6: Comparison of 8 July 2019 and 4 October 2019

Date	08/07/2019	04/10/2019
Day of the week	Monday	Friday
Cloud base arrivals median (many data gaps) [ft]	4500	1700
Cloud base departures median [ft]	10000	3000
FIR delay total [min]	584.45	613.4667
FIR delay median [min]	0.25	0.4
ATA-ETA median [min]	0.533	1.083
ATA-planned median [min]	0.35	0.617
ATOT-TTOT median [min]	0.20	0.60
AOBT-TOBT median [min]	5.91	7.03
Landing interval median [s]	104	103
Start interval median [s]	95.5	100
Visibility median [ft]	10000	10000
Wind speed median [m/s]	5.0	4.0
Wind direction median [°]	320	140
Hourly average rainfall [mm]	0.017	0.47
Early arrivals total [-]	56	118
Late arrivals total [-]	186	99
Arrivals total [-]	739	709
Departures total [-]	742	695
Late departures total [-]	272	174
European arrivals [-]	598	567
Total arrival delay [min]	6874	950
Median arrival delay [min]	3	-4
Total departure delay [min]	13336	9247
Median departure delay [min]	9	6
Aircraft too many [-]	51	45
Aircraft before inbound peak [-]	22	21
ATFM Aerodrome capacity delay [min]	1286	7207
Total ATFM delay [min]	1286	7207
Arrival congestion index [%]	78.9	85.7

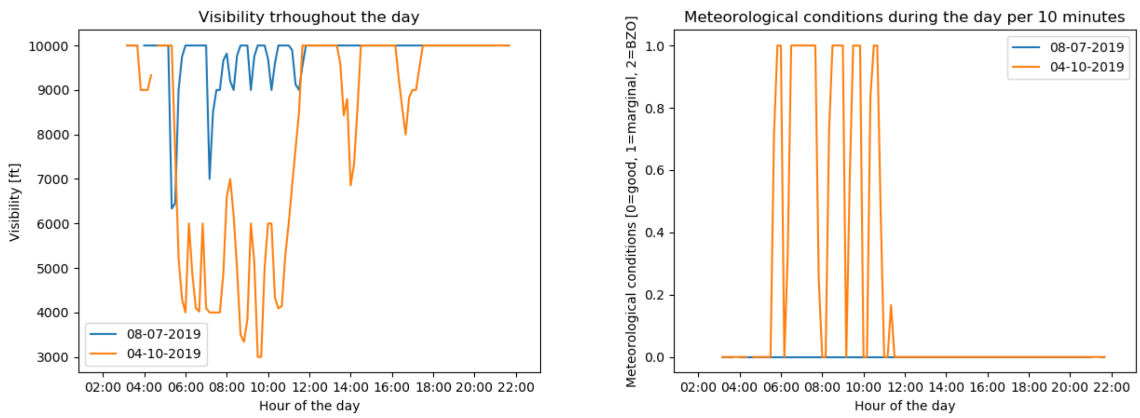
First, a comparison is made regarding the weather conditions that day. From figure 3.25a it can be seen that the cloud base information from arrival data for 8 July 2019 is scarce, but the data that is available, shows a higher cloud base compared to 4 October 2019. The departure data showed more information, in figure 3.25b it can be seen that the cloud base on 8 July 2019 was higher than on 4 October 2019. The cloud base is the lowest point of visible clouds. Regarding the visibility, from figure 3.26a it can be seen that the visibility is worse on 4 October 2019, especially in the morning between 05:00 and 11:00. This can also be seen in figure 3.26b, during the same hours, the value for the meteorological conditions often equals 1, which indicates marginal conditions. 0 indicates good meteorological conditions and 2 indicates very poor conditions.



(a) Cloud base arrival data

(b) Cloud base departure data

Figure 3.25: Cloud base data

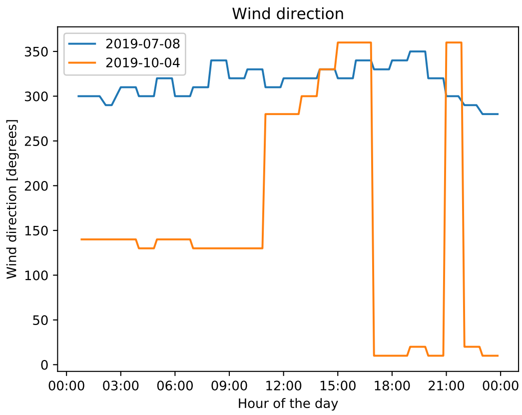


(a) Visibility

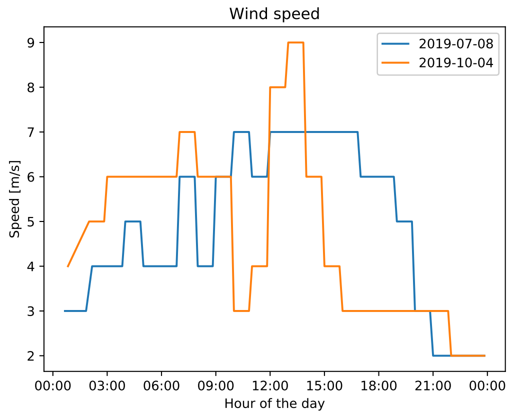
(b) Meteorological conditions

Figure 3.26: Visual conditions

In addition to the weather data available from LVNL, data from the KNMI is analysed as well. When looking at the wind conditions in figure 3.27, it can be seen in figure 3.27a that on 4 October 2019 there was a large change in wind direction around 11:00, which goes together with at strong increase in wind speed which can be seen in figure 3.27b. Such a change in wind conditions can lead to a sudden change in runway configurations which could lower the operational capacity. Please note that in figure 3.27a a large change can be seen at 17:00 on October 4th, however, this is a change in wind direction from 350°to 0°, which is only a 10°change of wind direction. Additionally, the morning of 4 October also had quite some rain, which can be seen in figure 3.28.

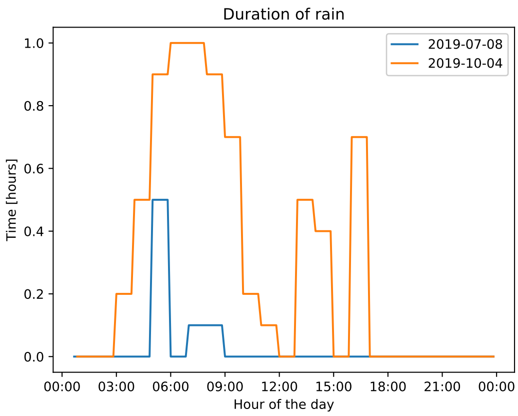


(a) Wind direction

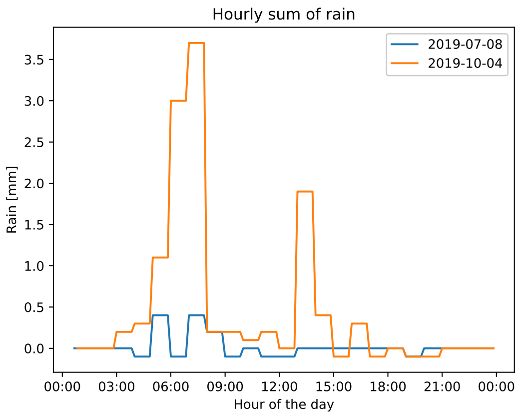


(b) Wind speed

Figure 3.27: Wind conditions



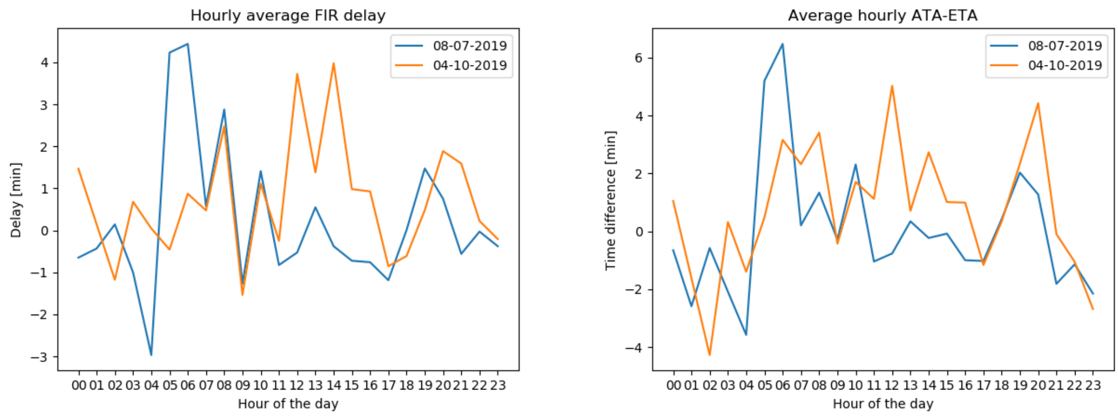
(a) Rain duration



(b) Total rain

Figure 3.28: Rain conditions

Now that it is known that the clouds were lower on 4 October 2019, that the morning had marginal visual conditions which was paired with rain, and there were some deviations in wind direction and speed after the rain in the morning, some other comparisons are made. First, the difference between the ATA and ETA is analyzed, as this is twice as high on average for 4 October 2019. In figure 3.29a the FIR delay can be seen and in figure 3.29b the ATA minus the ETA. In the early morning, 8 July 2019 had a short moment of high delay on the arrivals in the final sector. The FIR delay is the planned landing slot minus the ETA. The ETA is determined at the first moment LVNL can see the aircraft on the radar. Later throughout these days, the delay decreases on 8 July 2019 but increases on 4 October 2019. This is a bit odd as one might expect that the delay is highest in the morning, when visual conditions are worse for October 4th. When looking at all the incoming traffic instead of the hourly average, no large differences can be seen in figure 3.30.



(a) FIR delay (b) ATA - ETA

Figure 3.29: Delay during the last phase of the flight

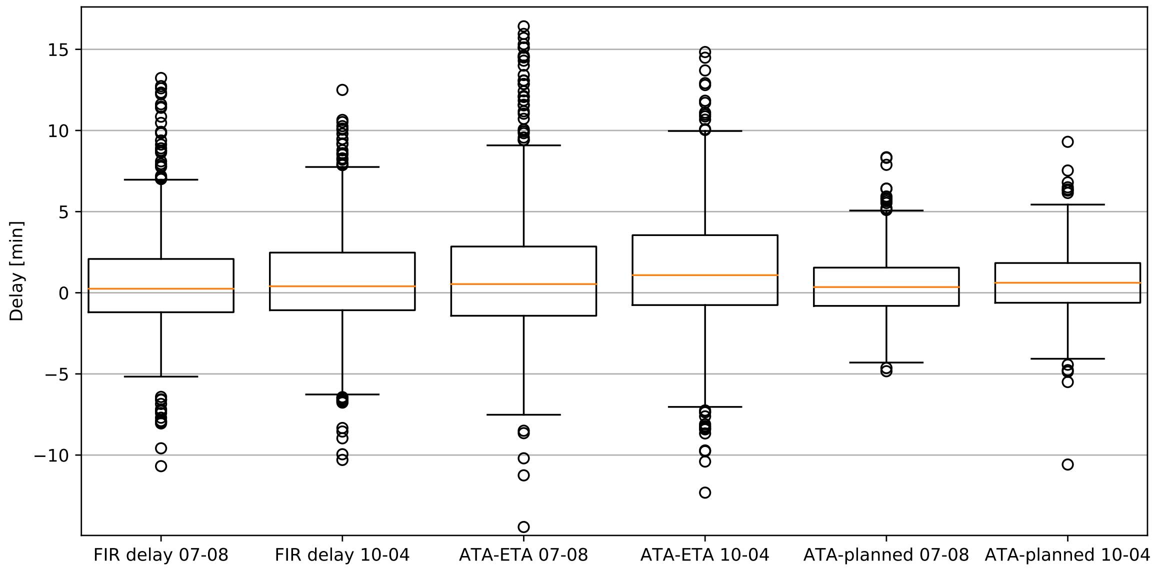
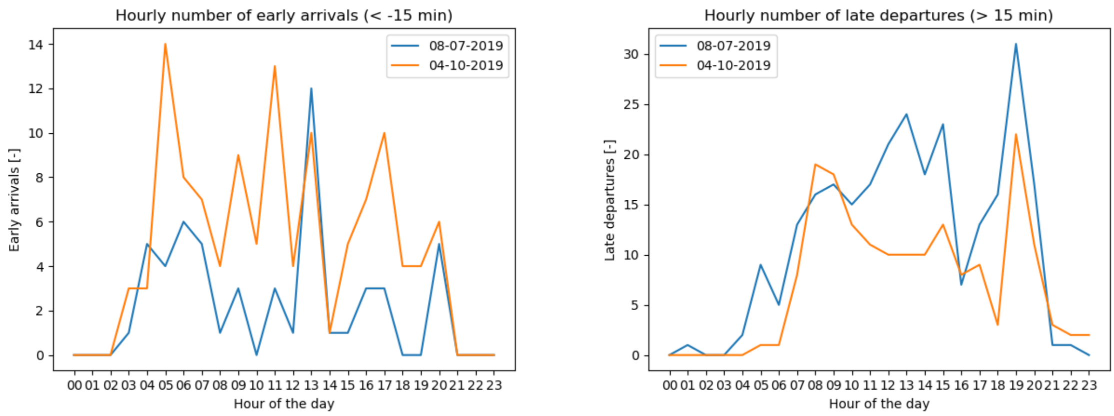


Figure 3.30: FIR delay, ATA-ETA and ATA-planned delay

When looking at table 3.6 and figure 3.31, it can be seen that 4 October 2019 has more early arriving traffic than 8 July 2019. This could explain the low delay during the morning of 4 October, as these flights have negative delays. Throughout the day, the early arrivals remain quite high for October 4 although FIR delay is higher. Regarding the departures in figure 3.31b, the end of the day on July 8th showed a much higher number of delayed departures compared to October 4th. Where October 4th showed twice as many early arrivals, July 8th had almost 100 additional delayed departures. This could be because an early arrival probably departs on time, whereas a late arrival has a higher chance of departing late as well which is in line with what can be seen by the total late arrivals in table 3.6, which was also higher for July 8th.



(a) Early arrivals

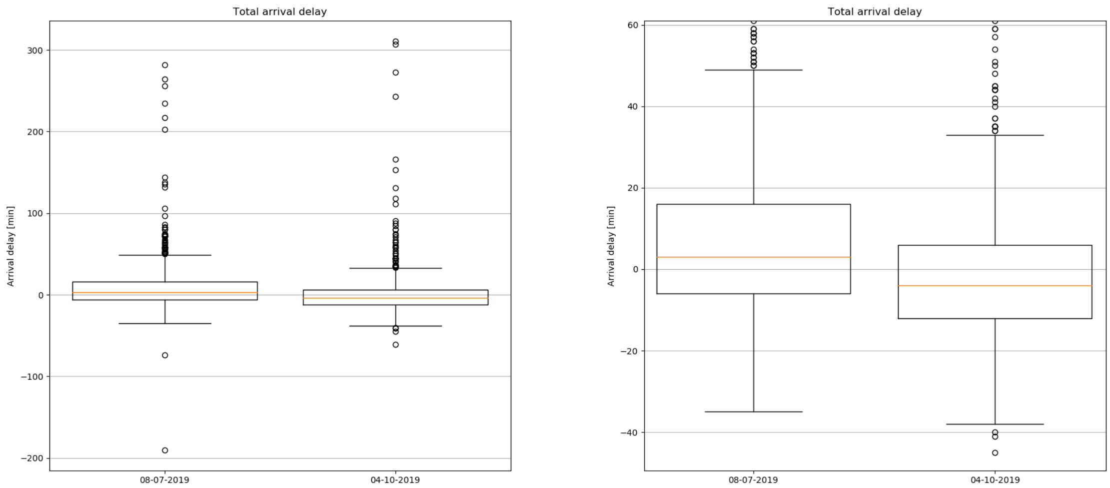
(b) Late departures

Figure 3.31: Early arrivals and late departures

Now, when looking at the total arrival delay and aerodrome capacity delay, something strange can be seen. July 8th has 1286 minutes of aerodrome capacity delay, but a total of 6874 minutes of arrival delay. October 4th has 7207 minutes of aerodrome capacity delay, but only 950 minutes of total arrival delay. This can be explained by looking at figure 3.32, mainly by looking at figure 3.32b it can be seen that on 4 October 2019 a large part of the arrivals has a negative delay, so by summing all the arrival delay minutes, the value of 950 minutes is a result of many negative delays. It can be seen that the median for October 4th is at -4 minutes and for July 8th at 3 minutes. It seems as if a higher aerodrome capacity delay results in less total arrival delay, and the other way around. To test this, the daily aerodrome capacity delay was compared to the daily total arrival delay. The comparison can be seen in figure 3.33. By using a Spearman correlation test, a correlation coefficient of 0.109 was found, which is negligible.

When looking at the aerodrome capacity delay over the days, the afternoon of 4 October is most regulated, which can be seen in figure 3.34, this could also be seen in earlier figures such as figure 3.20. In figure 3.34 two figures can be seen, the upper figure indicates the aerodrome capacity delay on the ATA of the flight, however, the aerodrome capacity delay is issued for the time that the flight would have arrived, because at that time the aerodrome capacity was expected be under high demand. This can be seen in the lower figure, which is similar to the upper figure but with at time shift. Between 17:00 and 18:00 most of the aerodrome capacity delay was issued, which could also be seen by the drop in declared capacity in figure 3.20. It is odd that this drop in declared capacity happens late in the afternoon, while the morning had poor visibility and bad weather, combined with a change in wind direction and speed.

The arrival congestion index is a measure of the percentage of arrival capacity used, as defined by Rodríguez-Sanz et al. [53]. When looking at figure 3.35 and table 3.6, it can be observed that October 4th had a slightly higher congestion index, but this is also the case because of the drop in declared capacity in the final inbound peak. Especially the morning of both days shows a high arrival congestion index.



(a) Arrival delay all

(b) Arrival delay zoomed in

Figure 3.32: Arrival delay minutes

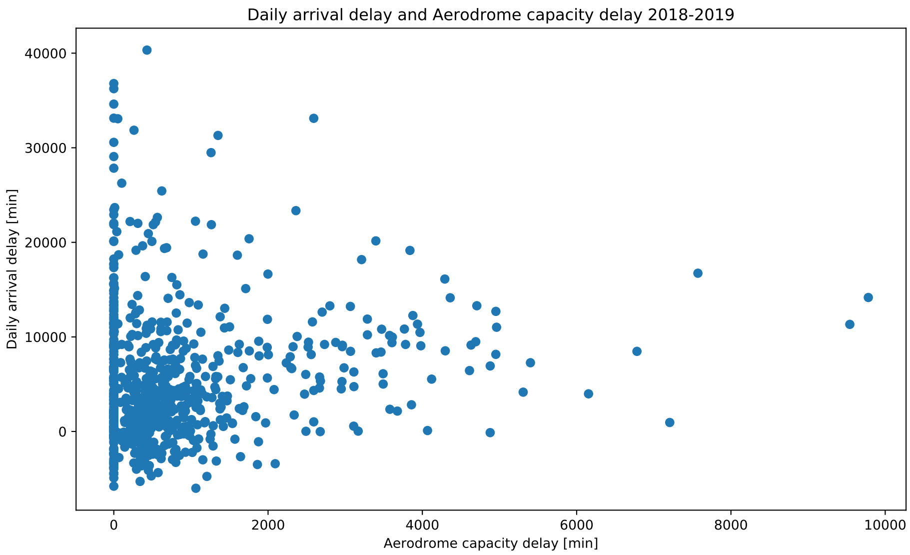


Figure 3.33: Arrival delay and aerodrome capacity delay

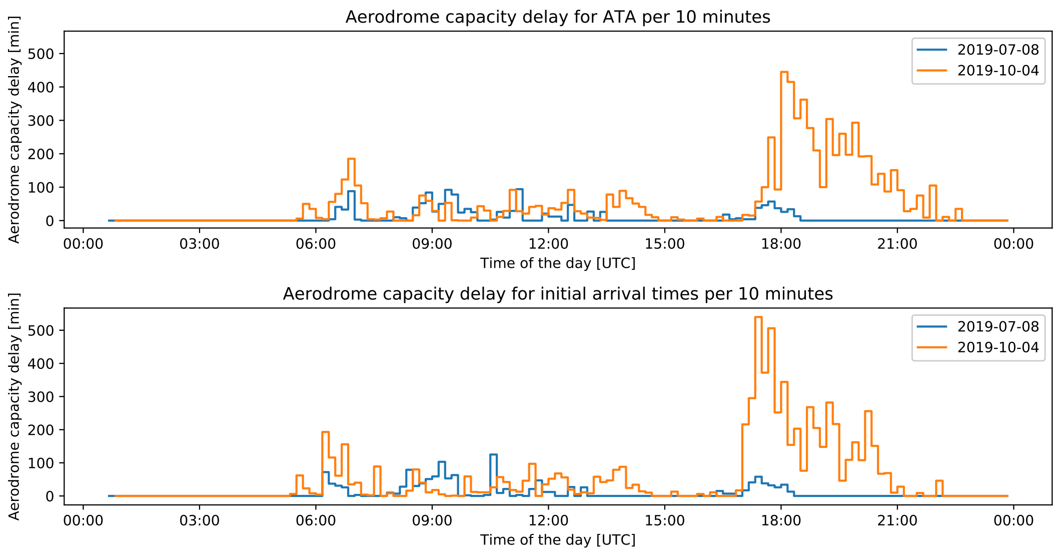


Figure 3.34: ATFM aerodrome capacity delay

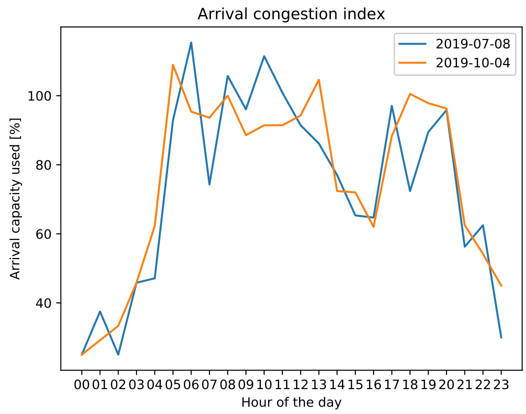


Figure 3.35: Congestion index

As a last comparison, the used runway configurations are compared. Both days used a high number of different runway configurations, however 4 October 2019 shows that the arrivals are distributed over multiple configurations, whereas 8 July 2019 has one configuration that was used the most. 4 October 2019 shows that even opposite landing configurations were used, indicating that the wind direction might have changed throughout the day. This is in line with what was found in figure 3.27, and in figure 3.36 one can see the changes in runway configurations throughout the day around the same time as the change in wind direction and strength from figure 3.27. One thing that can be noticed from looking at 8 July 2019, is that a 4-runway configuration was used for a high percentage of arriving traffic. 4-runway configurations are only used when necessary, meaning that July 8th could have had difficult traffic situations or unexpected congestion, which could explain the higher total arrival delay seen from figure 3.32.

Table 3.7: Runway configurations used

08-07-2019		04-10-2019	
Runway configuration	Percentage of arrivals	Runway configuration	Percentage of arrivals
L:06-36R—TO:36L—	30.7%	L:18R18C—TO:09—	17.9%
L:06-36R—TO:36L36C	17.6%	L:18R——TO:24-09	13.8%
L:27-36C—TO:36L—	13.5%	L:27——-TO:36L24	10.4%
L:27——-TO:36L24-	10.4%	L:06-18R—TO:09—	10.4%
L:06——-TO:36L—	8.5%	L:06——-TO:36L–	9.7%
L:36R——TO:36L36C	6.9%	L:27-18R—TO:24—	9.2%
L:06——-TO:36L36C	4.5%	L:36C——TO:36L09	7.1%
L:27——-TO:24—-	3.1%	L:18R——TO:24—	6.8%
L:36R——TO:36C—	1.6%	L:18R18C—TO:24-09	5.8%
L:06——-TO:36C—	1.5%	L:18R18C—TO:24—	5.2%
		L:36C——TO:09—	2.1%

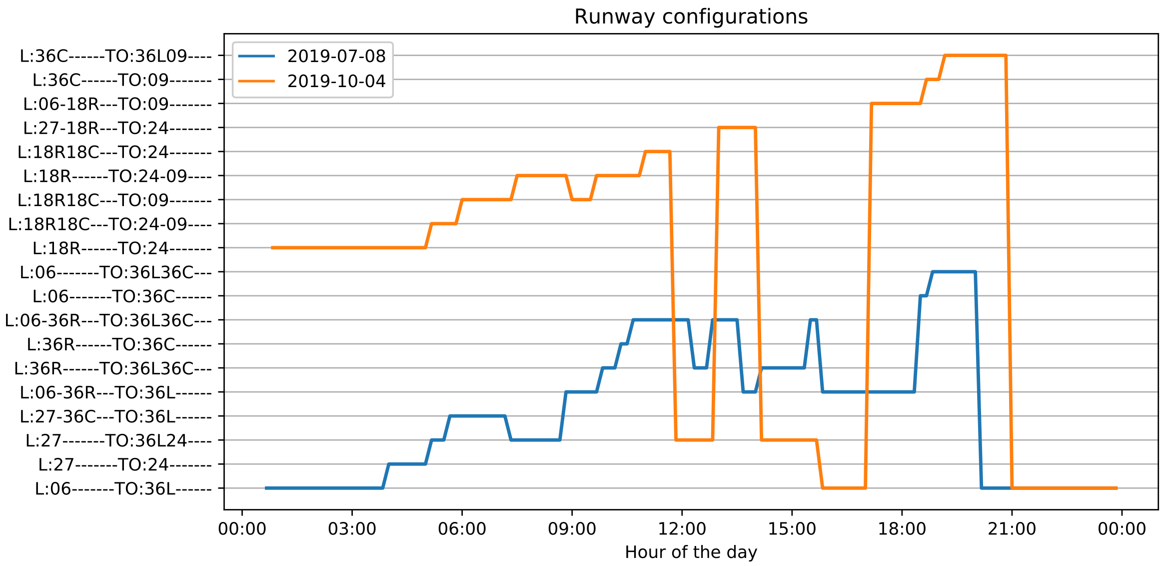


Figure 3.36: Runway configurations

3.6. Correlation matrix

In section 3.5, a comparison was made between two days were one showed an uneven distribution in the inbound traffic, but had only 1286 minutes of aerodrome capacity delay, with a day that had a similar inbound distribution throughout the day, but had 7207 minutes of aerodrome capacity delay. From this comparison, a few difference showed but there was not one clear parameter found that caused the delay.

In this section, a correlation matrix is presented. For every 10 minutes of 2018 and 2019, the mean of a parameter is taken, or in some cases the sum which is then mentioned. The correlation matrix of this data can be seen in table 3.8. The correlation coefficients are calculated by using the Spearman correlation method, as there are hardly any normally distributed variables.

There are a few parameters that one can use to verify the data used, such as relatively high positive correlation coefficients between departures and departure runways and negative correlation coefficients between visibility and meteorological conditions. Most interesting are the rows for the median or total arrival delay, and the ATFM aerodrome capacity delay. Unfortunately, there seem to be only weak relationships between the median and total arrival delay, and other parameters. This is also the case for ATFM aerodrome capacity delay. In appendix A a correlation matrix of all variables can be found, as in table 3.8 only the most interesting parameters are included for sake of readability.

Table 3.8: Correlation matrix for every 10 minutes of 2018 and 2019

	Landing interval	FIR delay	Number of landing runways	Number of take-off runways	Cloud base	Meteo	Visibility LVNL data	Early arrivals	Late arrivals	Arrivals	Demand / Initial arrivals without ATFM delay	Arrivals airline schedule	Departures	Late departures	Median arrival delay	Median departure delay	Total arrival delay	Total departure delay	Declared arrival capacity	High demand	AC too many	AC before inbound peak	ATFM Aerodrome capacity delay	ATFM Aerodrome capacity delay for initial ETA	Arrival congestion index
Landing interval	1.000	-0.315	-0.188	-0.194	-0.298	-0.015	-0.282	-0.114	-0.238	-0.593	-0.540	-0.438	-0.356	-0.285	-0.052	-0.244	-0.063	-0.303	-0.399	-0.258	-0.245	0.022	-0.264	-0.257	-0.556
FIR delay	-0.315	1.000	-0.039	0.110	0.019	0.041	0.094	-0.046	0.151	0.188	0.153	0.110	0.136	0.103	0.120	0.080	0.122	0.108	-0.064	0.169	0.164	0.040	0.110	0.102	0.323
Number of landing runways	-0.188	-0.039	1.000	-0.219	0.208	0.033	0.160	0.272	0.149	0.744	0.693	0.561	0.051	0.117	-0.103	0.163	-0.099	0.118	0.652	0.299	0.305	0.119	0.306	0.303	0.418
Number of take-off runways	-0.194	0.110	-0.219	1.000	0.231	0.002	0.183	0.010	0.079	0.043	0.051	0.046	0.685	0.381	0.040	0.206	0.059	0.411	0.021	0.028	0.025	0.176	-0.069	-0.062	0.164
Cloud base	-0.298	0.019	0.208	0.231	1.000	-0.248	0.540	0.124	0.141	0.353	0.337	0.329	0.400	0.316	-0.018	0.307	0.008	0.344	0.380	0.118	0.117	0.062	0.129	0.129	0.258
Meteorological conditions	-0.015	0.041	0.033	0.002	-0.248	1.000	-0.169	-0.005	0.040	0.037	0.049	0.043	0.038	0.031	0.030	0.043	0.024	0.035	0.004	0.046	0.044	0.010	-0.017	-0.014	0.052
Visibility LVNL data	-0.282	0.094	0.160	0.183	0.540	-0.169	1.000	0.034	0.176	0.321	0.310	0.301	0.374	0.306	0.061	0.299	0.076	0.323	0.293	0.128	0.124	0.056	0.189	0.188	0.262
Early arrivals	-0.114	-0.046	0.272	0.010	0.124	-0.005	0.034	1.000	-0.233	0.298	0.315	0.181	0.097	-0.051	-0.603	-0.073	-0.586	-0.042	0.265	0.128	0.133	0.105	0.019	0.043	0.202
Late arrivals	-0.238	0.151	0.149	0.079	0.141	0.040	0.176	-0.233	1.000	0.271	0.300	0.228	0.173	0.351	0.631	0.362	0.769	0.351	0.160	0.217	0.216	0.024	0.146	0.125	0.267
Arrivals	-0.593	0.188	0.744	0.043	0.353	0.037	0.321	0.298	0.271	1.000	0.902	0.655	0.322	0.290	-0.053	0.280	-0.038	0.303	0.702	0.417	0.415	0.145	0.372	0.374	0.798
Demand / Initial arrivals without ATFM delay	-0.540	0.153	0.693	0.051	0.337	0.049	0.310	0.315	0.300	0.902	1.000	0.650	0.335	0.305	-0.045	0.293	-0.026	0.318	0.666	0.446	0.447	0.164	0.289	0.341	0.701
Arrivals airline schedule	-0.438	0.110	0.561	0.046	0.329	0.043	0.301	0.181	0.228	0.655	0.650	1.000	0.318	0.309	0.023	0.301	0.022	0.321	0.610	0.274	0.271	0.048	0.298	0.297	0.424
Departures	-0.356	0.136	0.051	0.685	0.400	0.038	0.374	0.097	0.173	0.322	0.335	0.318	1.000	0.628	0.030	0.389	0.054	0.666	0.309	0.133	0.129	0.168	0.076	0.083	0.316
Late departures	-0.285	0.103	0.117	0.381	0.316	0.031	0.306	-0.051	0.351	0.290	0.305	0.309	0.628	1.000	0.227	0.776	0.257	0.898	0.278	0.131	0.128	0.074	0.086	0.077	0.249
Median arrival delay	-0.052	0.120	-0.103	0.040	-0.018	0.030	0.061	-0.603	0.631	-0.053	-0.045	0.023	0.030	0.227	1.000	0.254	0.813	0.226	-0.108	0.039	0.035	-0.052	0.063	0.037	0.020
Median departure delay	-0.244	0.080	0.163	0.206	0.307	0.043	0.299	-0.073	0.362	0.280	0.293	0.301	0.389	0.776	0.254	1.000	0.278	0.821	0.254	0.141	0.140	0.052	0.097	0.085	0.234
Total arrival delay	-0.063	0.122	-0.099	0.059	0.008	0.024	0.076	-0.586	0.769	-0.038	-0.026	0.022	0.054	0.257	0.813	0.278	1.000	0.253	-0.082	0.044	0.041	-0.049	0.064	0.035	0.028
Total departure delay	-0.303	0.108	0.118	0.411	0.344	0.035	0.323	-0.042	0.351	0.303	0.318	0.321	0.666	0.898	0.226	0.821	0.253	1.000	0.290	0.139	0.136	0.082	0.084	0.078	0.266
Declared arrival capacity	-0.399	-0.064	0.652	0.021	0.380	0.004	0.293	0.265	0.160	0.702	0.666	0.610	0.309	0.278	-0.108	0.254	-0.082	0.290	1.000	0.066	0.058	-0.061	0.210	0.202	0.207
High demand	-0.258	0.169	0.299	0.028	0.118	0.046	0.128	0.128	0.217	0.417	0.446	0.274	0.133	0.131	0.039	0.141	0.044	0.139	0.066	1.000	0.992	0.430	0.236	0.248	0.546
AC too many	-0.245	0.164	0.305	0.025	0.117	0.044	0.124	0.133	0.216	0.415	0.447	0.271	0.129	0.128	0.035	0.140	0.041	0.136	0.058	0.992	1.000	0.446	0.218	0.229	0.549
AC before inbound peak	0.022	0.040	0.119	0.176	0.062	0.010	0.056	0.105	0.024	0.145	0.164	0.048	0.168	0.074	-0.052	0.052	-0.049	0.082	-0.061	0.430	0.446	1.000	0.051	0.063	0.272
ATFM Aerodrome capacity delay	-0.264	0.110	0.306	-0.069	0.129	-0.017	0.189	0.019	0.146	0.372	0.289	0.298	0.076	0.086	0.063	0.097	0.064	0.084	0.210	0.236	0.218	0.051	1.000	0.865	0.283
ATFM Aerodrome capacity delay for the time the flight would have arrived	-0.257	0.102	0.303	-0.062	0.129	-0.014	0.188	0.043	0.125	0.374	0.341	0.297	0.083	0.077	0.037	0.085	0.035	0.078	0.202	0.248	0.229	0.063	0.865	1.000	0.292
Arrival congestion index	-0.556	0.323	0.418	0.164	0.258	0.052	0.262	0.202	0.267	0.798	0.701	0.424	0.316	0.249	0.020	0.234	0.028	0.266	0.207	0.546	0.549	0.272	0.283	0.292	1.000

3.7. Conclusion case study

A detailed data analysis has been performed to find correlations between variables that could potentially cause arrival delay or aerodrome capacity delay.

The main area of interest from ATFM delay is the aerodrome capacity delay. This is the type of ATFM delay that is issued often for AAS. This type of delay can have several reasons and it seems that it is more likely to increase above a certain number of daily arrivals. This is in line with what was found regarding the reasons for aerodrome capacity delay, which is often due to high demand. Runway configurations have been compared, but there was not one configuration performing significantly worse than others.

With increasing ATFM delay over the years, airlines are responding to this by applying schedule buffers to try and predict the delay that will be imposed. It can be the case, that these schedule buffers are so large that traffic will arrive early, which is something that 2020 has shown as there was little ATFM delay. The percentage of early arrivals has stayed more or less the same over 2017 to 2019, and no correlation was found between early arrivals and aerodrome capacity delay. It remains unclear what the effect of early arrivals is on the operation of AAS.

When looking more into arrival delay and less into aerodrome capacity delay, it was found that the OTP of arriving traffic is not very high in terms of flights that arrive with a delay between -5 and +15 minutes. Many flights arrive early and only a small percentage actually arrives on time indicating low arrival punctuality. This affects the predictability of traffic.

Looking at the ATFM regulations issued for AAS, a large amount is due to aerodrome capacity. When looking at the applied regulations and the applied rates from LVNL, compared to the actual incoming traffic, a slight mismatch can be seen. Often demand exceeds capacity, aircraft arrive outside of the arrival peak and traffic is not evenly distributed throughout the inbound peaks, which is in line with the findings from a study performed by LVNL earlier in 2020, Obbens and Dijkgraaf [48]. Here it is stated that the ATFM delay for AAS is caused by the uneven distribution of SIBT.

Two days have been compared with the data available from EUROCONTROL, LVNL, KNMI and AAS. A few things were different, such as cloud base, wind and visibility, but in terms of operations, the only differences found were the early arrivals, arrival delay and aerodrome capacity delay.

Lastly, a correlation matrix is presented showing the Spearman correlation coefficients between all variables available for every 10 minutes of 2018 and 2019. No clear relationships emerged from this, at least not for arrival delay and aerodrome capacity delay. Nonetheless, this data analysis showed that what was said in chapter 2 about Complex Networks could very well apply to the arrival delay and aerodrome capacity delay for AAS. A very thorough analysis was performed, yet not one variable showed a strong relationship with either one of the delays, apart from the arrivals. The aerodrome capacity delay and arrival delay for AAS is caused by something. In chapter 4 it will be presented how more insights will be created into the operational aspects of AAS.

4

Research Proposal

In this chapter, the future planning and outline of the thesis are presented. It will recap the literature study and data analysis performed and present research questions. The proposed methodologies and experiments are presented, the expected outcome of this thesis, and the contribution to the scientific community.

4.1. Research performed

From the literature review in chapter 2, many possible topics were presented that could provide more insights into ATFM delay and possible solutions as well. As this is a research study for Amsterdam Airport Schiphol, the focus will be on the airport itself, as the airport is the main contributor to the ATFM delay in the European airspace network. Most of the methodologies presented in chapter 2 show the potential to decrease the arrival delay or ATFM delay at an airport, however many studies are simplified for only one or two runways, some do not take the stochastic behaviour of air transportation into account and others are very sophisticated methods for the whole network such as 4D planning.

One thing that became apparent during the literature review, is that not every method can simply be applied to every airport or air transportation network. CNT showed that there are for example differences between the EU network and the US network and that the importance of an airport, or a node, in the network makes a difference as well. Additionally, airport geometry and operational characteristics seem to play an important role in how delays can be assessed and minimized. It also became apparent that the different methodologies can be applied during different phases of a flight, for example en-route or in the final sequencing before landing.

All in all, ATFM is a complex measure for a complex network. As said in Rodríguez-Sanz et al. [53], the nodes in a complex network can be complex systems as well with their own characteristics. To figure out which method could be applied best to the airport ATFM delay at AAS, it is important to figure out what the actual cause of the delay is. As was mentioned in Cook et al. [26], in a CNT it is usually multiple variables and the interaction between them that causes the delay. This could also be seen in chapter 3, where not one variable was found that had a strong relationship with the aerodrome capacity delay, yet the aerodrome capacity delay remains high. Therefore, it seems that a Bayesian Network can be used to find the interaction between variables and try to estimate the arrival delay. Then, by applying backward propagation, the main variables causing the delay can be found.

In chapter 3 many variables were used to find correlations between arrival delay or aerodrome capacity delay, yet there was not one variable found that had a strong relationship with one or the other. This is in line with what was presented by Cook et al. [26], so a BN could provide more insights into the operation of AAS. In the comparison between the two days, the differences found were mainly weather related, and a few small differences in operational data could be found.

4.2. Research objective

The research objective of this study is the following:

> *In the European airspace, Air Traffic Flow Management is used to optimize the flow of traffic and prevent traffic from airborne holding as a form of delay. Airports are often the bottlenecks of the air transportation network and for Europe, Amsterdam Airport Schiphol is the biggest contributor to airport ATFM delay, also classified as aerodrome capacity delay. The main causes for aerodrome capacity delay and arrival delay for Schiphol are difficult to distinguish, as there are many interactions between the different operators in air transportation. This research aims to get more insights into aerodrome capacity delay and arrival delay for Amsterdam Airport Schiphol by identifying the conditions that lead to aerodrome capacity delay or arrival delay, understanding the interactions between operational parameters and identifying the parameters that influence aerodrome capacity delay and arrival delay the most, through a Bayesian Network.*

There is a fairly clear objective to this research, to get more insights into the causes for aerodrome capacity delay and arrival delay for Amsterdam Airport Schiphol. This is translated to the following research question:

> *What operational conditions have the highest chance of resulting in a high aerodrome capacity delay or arrival delay for Amsterdam Airport Schiphol?*

It was found that there can be many causes for delay, all with their own respective impact on the operational conditions. The air transportation network, and airports by themselves, can be viewed as complex networks. In complex networks, it is often a combination of and the interaction between variables that lead to delay, not one variable by itself.

One of the interesting findings was the resolution at which landing slots are planned during strategic planning. In essence, the predictability of the arrival delay is low. Strategic planning could be improved to increase the predictability of traffic.

A Bayesian Network approach is proposed to find more insights in the operational conditions for AAS. A BN can show the inter-dependencies between variables and possibly highlight new inter-dependencies as well. Recent studies ([52, 53]) have shown that BN were successful in predicting arrival or departure delay at airports.

To answer the research question, some sub-questions are proposed to provide a more detailed overview of the research. These questions are:

1. *What parameters have a direct effect on aerodrome capacity delay and arrival delay?*
2. *What combination of parameters has the highest impact on aerodrome capacity delay and arrival delay?*
    (a) *What parameters have the strongest conditional probabilities?*
    (b) *What parameters are most sensitive in the Bayesian Network?*
3. *Can a more detailed strategic planning result in better predictability of arrival delay?*
    (a) *Will a more detailed strategic planning result in a more even distribution of inbound traffic in the arrival peak?*
    (b) *Will a more detailed strategic planning result in less aerodrome capacity delay?*
4. *What parameters can be changed in the operation of Amsterdam Airport Schiphol to decrease the aerodrome capacity delay and arrival delay?*
5. *What future methods would be best suitable to decrease the aerodrome capacity delay and arrival delay at Amsterdam Airport Schiphol?*

4.3. Experimental setup

This section will explain how the Bayesian Network will be created and trained, and how it will be used in experiments. Therefore, this experimental set-up is two-fold, as first the Bayesian Network has to be created and trained after which it will be combined with an objective function.

4.3.1. Bayesian Network

There are several ways to create a Bayesian Network. It is important to understand which parameters influence which, that can be done either by using knowledge from experience, but there are also data-driven ways to create a BN as explained in Rodríguez-Sanz et al. [52]. Additionally, every parameter has its own probability distribution as well, which needs to be established.

Using knowledge obtained from the literature study a first BN will be constructed. However, it would be interesting to see whether an algorithm could find possible inter-dependencies that are not found by using knowledge from the operations. So additionally, a data-driven BN will be created to see the differences and compare performance.

The BN will be created in Python by using one of the libraries for BN, such as pomegranate, bayespy or BayesFusion. BayesFusion showed the possibility to create a BN by using Bayesian Search on the data provided, a technique that showed potential in identifying correlations and causal relationships. However, there are several other methods to create a BN such as Naive Bayes, which makes assumptions regarding the independence of the data points (Friedman et al. [33]). The performance of a Bayesian network can be found by means of the Bayesian score, which is a measure that shows how well the BN can represent the data it was built upon. Which exact library will be used is yet to be determined.

Before the BN can be created, all data has to be in place. As the main problem is aerodrome capacity delay and arrival delay, it is proposed to focus mainly on these aspects of the operation. The following parameters are proposed to be using in the BN:

- Month
- Day of the week
- Hour of the day
- Cloud base
- Visibility
- Wind direction
- Wind speed
- Meteorological conditions
- Aircraft weight class
- Departure airport
- Airline type
- Departure delay
- Inbound or outbound peak
- Nominal capacity
- Regulated capacity
- Arrival throughput
- Runway configuration
- Arrival runway
- Scheduled on-block time
- Scheduled landing slot
- Strategic planning landing slot
- ETA at FIR entry
- FIR delay

- ATA
- Landing interval
- Arrival delay
- Aerodrome capacity delay
- Congestion index

This is a high number of variables, but most of these are already available and some can be found in chapter 3. Nonetheless, some variables still need to be found but these should be available in time. One interesting parameter is the congestion index, this idea was proposed by Rodríguez-Sanz et al. [53] to measure the congestion as a percentage of the operational capacity used.

This first part of the research will include an extensive data analysis, to construct the BN and to answer sub-question 1. Once that is constructed and optimized, backward propagation will be applied and a thorough sensitivity analysis will be executed, to find the main parameters causing aerodrome capacity delay and arrival delay, and to answer sub-questions 2 and 3.

4.3.2. Data

The BN will be trained on a part of the operational data available, and its performance can be tested on the part of the operational data that is not used for training and building the BN.

Thus far, data was made available by AAS, EUROCONTROL and LVNL. This data contains almost all the information necessary for the proposed BN. Some additional data will be used as well, such as weather data from the KNMI, departure delay data and additional data is necessary regarding the strategic landing slots. All in order to perform experiments that represent reality as detailed as possible. The performance of the BN can be assessed by looking at the Bayesian score.

4.3.3. Experiments

The Bayesian Network will be created and trained based on operational data from 2018 and 2019. As an airport, AAS is able to influence certain operational parameters. Some can be found in the list of parameters from the proposed BN model, such as: *strategic planning landing slot, scheduled landing slot, regulated capacity, landing runway* and *runway configuration*.

The Bayesian Network will be a model that represents the interactions in the airports system, also the days with high delays. In the experiments, the BN will be combined with an objective function. The goal of this function will be to minimize the aerodrome capacity delay and arrival delay. An objective function together with some well defined constraints for parameters such as the inter-arrival times, can represent real-life scenarios without exceeding operational safety minima. The exact form of the objective function is yet to be determined.

When the BN and the objective function are finished, experiments can take place. As the BN will be based on operational data, a real-life traffic scenario can be used from the operational data. By using a certain traffic scenario as input for the BN with the objective function, the BN can find the best way to handle this traffic with the least delay. As output, the BN with objective function will provide a complete traffic scenario with a lower delay when compared to the actual day of operations. Then, by comparing the outcome of the BN with objective function to the actual day of operations, choices that could have led to less aerodrome capacity delay or arrival delay can be observed.

Such experiments will be performed for different traffic scenarios. The main reason for this is that AAS or LVNL cannot influence the wind direction, but the wind direction is the dominant driver for the chosen runway configuration. Hence, several wind conditions will be taken into account. Additionally, the most interesting days to look at are the days which had a high aerodrome capacity delay or arrival delay. The data analysis, creating the BN and the experiments will all be performed using the programming language Python. The second part of the research proposal can answer sub-question 4. The complete model will be able to answer sub-question 5.

4.3.4. Verification and validation

Verification of the proposed BN can be done by inspecting the parameters and to see how the model responds to certain inputs. For example, a large departure delay will most likely result in a significant arrival delay. By applying several sanity checks to the model, one can check whether a certain input results in an expected output.

Validation can be done by checking whether the BN provides results similar to the operational data, which is from real operations. It is always important to validate the data inputs to the model, by for example looking at the number of arrivals over a certain time.

4.4. Limitations

While the literature shows promising results for a BN, there are some limitations. First, it remains a probabilistic model. While probabilistic models can represent reality to some extent, there are always differences compared to real-life examples. It would be interesting to see how the BN would react to a large disturbance in the network for example. In addition to this, no human in the loop is considered. The performance of an air traffic controller or the decisions made, for example to regulate on 65 instead of 68, are not included. This model will not take human reasoning into account.

Another limitation of this study is that the BN that will be created is tailored to AAS. While it would be possible to apply it to another airport, it probably will not work as all operational aspects in the BN are based on AAS data.

A last limitation would be the variables included in the BN. While there are many variables available from the operational data, still not every interaction is included, for example when pilots requests directs to other waypoints or change the flight speed. But, as the focus of this study is on the airport and ATC, it is important that at least all airport related parameters are in place.

4.5. Outcome & Contribution

It is expected that this study will provide more insights into the causes for arrival delay and aerodrome capacity delay for Amsterdam Airport Schiphol. It also holds the potential to show inter-dependencies between variables that were not noticed before. Using this, AAS or LVNL could take appropriate measures to minimize the arrival delay and the need for regulations. The outcome of this research could also support the start of new research, to optimize a certain aspect of the arrival process at Schiphol that was identified by the BN and has an impact on arrival delay.

Bayesian Networks have been applied in multiple studies and showed the potential to predict delays. Yet, there has only been one study performed where the arrival delay is investigated using a BN, as most studies focus on the departure delay or en-route delay. In addition to that, there has been no study found that combined a BN with an objective function in air transportation, or one that applied a BN to an airport with an aerodrome capacity delay comparable to Schiphol. It will be investigated by using the BN and an objective function, how operational decisions could lead to less aerodrome capacity delay and arrival delay.

5 Conclusion

This report presents a literature research for possible solutions to assess airport ATFM delay, a thorough data analysis for AAS and a proposed method with the goal to get more insights into the causes for aerodrome capacity delay and arrival delay for AAS. In the literature review, several methods were presented that showed an interesting approach to minimize ATFM delay. However, it was also found that every airport has a different infrastructure and traffic scenarios, so not every method can be applied to every airport. It is important to understand the dynamics in a complex network such as an airport, as this can provide more insights into the reasons for delay.

The data analysis performed found that it is not easy to find the reasons for the arrival delay. Not one variable was found that caused a lot of delay, yet aerodrome capacity delay and arrival delay are present in high numbers. Therefore it is proposed to create a Bayesian Network based on the operational data available. The Bayesian Network is a probabilistic model that can be trained based on operational data. First, the Bayesian Network will be created and tested on its accuracy, after which it will be used to perform experiments. From these experiments, choices can be observed that could lead to less aerodrome capacity delay and arrival delay for AAS. The focus of these choices will be changes AAS or LVNL are able to make.

It will be an exploratory study to create more insights into the airport ATFM delay and arrival delay for AAS. It will contribute to the usability of Bayesian Networks in air transportation. And it will contribute to knowledge about the factors that cause arrival delay for AAS, such that appropriate measures can be taken to improve the operation.

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A
Correlation matrix

Table A.1: Correlation matrix for every 10 minutes of 2018 and 2019 - part 1/4

	Landing interval	Cloud base arrival data	FIR delay	ATA-ETA	ATA-planned	Number of landing runways	Number of take-off runways	Total runways	AOBT-TOBT	ATOT-TTOT	Cloud base departure data	Meteorological conditions
Landing interval	1.000	0.012	-0.315	-0.454	-0.323	-0.188	-0.194	-0.334	-0.063	-0.065	-0.298	-0.015
Cloud base arrival data	0.012	1.000	0.044	0.049	0.034	-0.004	-0.023	-0.020	-0.012	0.034	-0.624	0.252
FIR delay	-0.315	0.044	1.000	0.746	0.090	-0.039	0.110	0.071	0.026	0.039	0.019	0.041
ATA-ETA	-0.454	0.049	0.746	1.000	0.670	0.128	0.176	0.259	0.044	0.086	0.145	0.078
ATA-planned	-0.323	0.034	0.090	0.670	1.000	0.229	0.134	0.298	0.042	0.087	0.171	0.079
Number of landing runways	-0.188	-0.004	-0.039	0.128	0.229	1.000	-0.219	0.607	0.061	0.099	0.208	0.033
Number of take-off runways	-0.194	-0.023	0.110	0.176	0.134	-0.219	1.000	0.631	-0.009	0.060	0.231	0.002
Total runways	-0.334	-0.020	0.071	0.259	0.298	0.607	0.631	1.000	0.044	0.123	0.360	0.032
AOBT-TOBT	-0.063	-0.012	0.026	0.044	0.042	0.061	-0.009	0.044	1.000	0.082	0.071	0.016
ATOT-TTOT	-0.065	0.034	0.039	0.086	0.087	0.099	0.060	0.123	0.082	1.000	0.077	0.059
Cloud base departure data	-0.298	-0.624	0.019	0.145	0.171	0.208	0.231	0.360	0.071	0.077	1.000	-0.248
Meteorological conditions	-0.015	0.252	0.041	0.078	0.079	0.033	0.002	0.032	0.016	0.059	-0.248	1.000
Start interval	-0.108	0.008	-0.021	0.056	0.095	0.056	0.159	0.163	0.022	0.002	0.407	0.066
Visibility LVNL data	-0.282	-0.092	0.094	0.189	0.170	0.160	0.183	0.289	0.251	0.103	0.540	-0.169
Early arrivals	-0.114	0.007	-0.046	0.007	0.049	0.272	0.010	0.222	-0.032	0.005	0.124	-0.005
Late arrivals	-0.238	-0.006	0.151	0.227	0.169	0.149	0.079	0.190	0.066	0.076	0.141	0.040
LVNL arrivals	-0.593	-0.004	0.188	0.391	0.371	0.744	0.043	0.636	0.086	0.123	0.353	0.037
Demand / Initial arrivals without ATFM delay	-0.540	0.007	0.153	0.349	0.345	0.693	0.051	0.601	0.074	0.119	0.337	0.049
Arrivals airline schedule	-0.438	0.001	0.110	0.298	0.314	0.561	0.046	0.494	0.080	0.116	0.329	0.043
Arrivals AAS	-0.535	0.004	0.145	0.349	0.352	0.705	0.039	0.602	0.077	0.120	0.344	0.047
Departure	-0.356	-0.005	0.136	0.281	0.253	0.051	0.685	0.609	0.036	0.137	0.400	0.038
Late departures	-0.285	-0.025	0.103	0.211	0.188	0.117	0.381	0.409	0.109	0.181	0.316	0.031
Median arrival delay	-0.052	-0.012	0.120	0.129	0.068	-0.103	0.040	-0.044	0.056	0.041	-0.018	0.030
Median departure delay	-0.244	-0.021	0.080	0.179	0.167	0.163	0.206	0.299	0.140	0.180	0.307	0.043
Total arrival delay	-0.063	-0.010	0.122	0.132	0.067	-0.099	0.059	-0.026	0.052	0.045	0.008	0.024
Total departure delay	-0.303	-0.024	0.108	0.225	0.201	0.118	0.411	0.434	0.106	0.182	0.344	0.035
Declared arrival capacity	-0.399	-0.025	-0.064	0.145	0.265	0.652	0.021	0.546	0.048	0.078	0.380	0.004
High demand	-0.258	0.007	0.169	0.244	0.183	0.299	0.028	0.260	0.044	0.061	0.118	0.046
AC too many	-0.245	0.008	0.164	0.239	0.181	0.305	0.025	0.261	0.043	0.063	0.117	0.044
AC before inbound peak	0.022	-0.004	0.040	0.072	0.066	0.119	0.176	0.219	0.015	0.062	0.062	0.010
Aerodrome capacity delay	-0.264	-0.023	0.110	0.199	0.180	0.306	-0.069	0.203	0.085	0.034	0.129	-0.017
ATFM-G Delay for the time the flight would have arrived	-0.257	-0.023	0.102	0.187	0.172	0.303	-0.062	0.207	0.082	0.027	0.129	-0.014
Arrival congestion index	-0.556	0.012	0.323	0.449	0.315	0.418	0.164	0.471	0.070	0.110	0.258	0.052
Wind direction	-0.028	0.103	0.005	0.011	0.002	0.010	0.025	0.030	0.038	0.013	-0.024	-0.006
Wind speed	-0.068	0.151	0.121	0.173	0.121	0.072	0.094	0.136	0.024	0.062	0.004	0.002
Temperature	-0.146	-0.198	0.002	0.023	0.022	0.089	0.156	0.196	0.092	-0.015	0.255	-0.141
Rain duration	0.009	0.233	0.061	0.071	0.046	-0.005	-0.023	-0.020	0.062	0.057	-0.152	0.134
Rain hourly sum	-0.005	0.073	0.030	0.032	0.018	-0.002	-0.015	-0.013	0.044	0.028	-0.051	0.069
Horizontal visibility KNMI	-0.143	-0.317	-0.010	0.019	0.027	0.091	0.146	0.193	0.026	-0.022	0.375	-0.328
Cloud density	0.013	0.360	0.047	0.062	0.053	-0.012	-0.021	-0.024	0.012	0.043	-0.249	0.169
Fog	0.061	0.039	0.028	0.039	0.037	0.004	-0.039	-0.029	-0.001	0.019	-0.092	0.227
Rain	0.018	0.261	0.061	0.074	0.050	-0.004	-0.016	-0.014	0.050	0.054	-0.163	0.115
Snow	0.009	0.045	-0.008	-0.001	0.009	-0.009	0.003	-0.004	-0.009	0.016	-0.041	0.057
Thunderstorms	-0.001	-0.011	0.028	0.049	0.042	0.008	0.010	0.014	0.029	0.025	0.027	-0.017
Ice formation	0.029	0.023	0.002	0.007	0.013	-0.007	-0.013	-0.016	0.003	-0.003	-0.055	0.096
Hour of the day	-0.046	-0.030	-0.062	-0.075	-0.078	-0.131	-0.020	-0.116	0.034	0.059	0.043	-0.046
Month	-0.021	-0.007	0.003	-0.009	-0.011	0.009	-0.002	0.002	0.220	0.003	0.010	-0.034
Day of the week	0.033	0.007	-0.018	-0.026	-0.016	-0.019	-0.006	-0.021	0.001	-0.003	-0.007	0.022

Table A.2: Correlation matrix for every 10 minutes of 2018 and 2019 - part 2/4

	Start interval	Visibility LVNL data	Early arrivals	Late arrivals	LVNL arrivals	Demand / Initial arrivals without ATFM delay	Arrivals airline schedule	Arrivals AAS	Departure	Late departures	Median arrival delay	Median departure delay
Landing interval	-0.108	-0.282	-0.114	-0.238	-0.593	-0.540	-0.438	-0.535	-0.356	-0.285	-0.052	-0.244
Cloud base arrival data	0.008	-0.092	0.007	-0.006	-0.004	0.007	0.001	0.004	-0.005	-0.025	-0.012	-0.021
FIR delay	-0.021	0.094	-0.046	0.151	0.188	0.153	0.110	0.145	0.136	0.103	0.120	0.080
ATA-ETA	0.056	0.189	0.007	0.227	0.391	0.349	0.298	0.349	0.281	0.211	0.129	0.179
ATA-planned	0.095	0.170	0.049	0.169	0.371	0.345	0.314	0.352	0.253	0.188	0.068	0.167
Number of landing runways	0.056	0.160	0.272	0.149	0.744	0.693	0.561	0.705	0.051	0.117	-0.103	0.163
Number of take-off runways	0.159	0.183	0.010	0.079	0.043	0.051	0.046	0.039	0.685	0.381	0.040	0.206
Total runways	0.163	0.289	0.222	0.190	0.636	0.601	0.494	0.602	0.609	0.409	-0.044	0.299
AOBT-TOBT	0.022	0.251	-0.032	0.066	0.086	0.074	0.080	0.077	0.036	0.109	0.056	0.140
ATOT-TTOT	0.002	0.103	0.005	0.076	0.123	0.119	0.116	0.120	0.137	0.181	0.041	0.180
Cloud base departure data	0.407	0.540	0.124	0.141	0.353	0.337	0.329	0.344	0.400	0.316	-0.018	0.307
Meteorological conditions	0.066	-0.169	-0.005	0.040	0.037	0.049	0.043	0.047	0.038	0.031	0.030	0.043
Start interval	1.000	0.351	0.059	0.066	0.120	0.127	0.127	0.129	0.054	0.055	-0.020	0.150
Visibility LVNL data	0.351	1.000	0.034	0.176	0.321	0.310	0.301	0.315	0.374	0.306	0.061	0.299
Early arrivals	0.059	0.034	1.000	-0.233	0.298	0.315	0.181	0.324	0.097	-0.051	-0.603	-0.073
Late arrivals	0.066	0.176	-0.233	1.000	0.271	0.300	0.228	0.349	0.173	0.351	0.631	0.362
LVNL arrivals	0.120	0.321	0.298	0.271	1.000	0.902	0.655	0.887	0.322	0.290	-0.053	0.280
Demand / Initial arrivals without ATFM delay	0.127	0.310	0.315	0.300	0.902	1.000	0.650	0.912	0.335	0.305	-0.045	0.293
Arrivals airline schedule	0.127	0.301	0.181	0.228	0.655	0.650	1.000	0.675	0.318	0.309	0.023	0.301
Arrivals AAS	0.129	0.315	0.324	0.349	0.887	0.912	0.675	1.000	0.329	0.311	-0.025	0.303
Departure	0.054	0.374	0.097	0.173	0.322	0.335	0.318	0.329	1.000	0.628	0.030	0.389
Late departures	0.055	0.306	-0.051	0.351	0.290	0.305	0.309	0.311	0.628	1.000	0.227	0.776
Median arrival delay	-0.020	0.061	-0.603	0.631	-0.053	-0.045	0.023	-0.025	0.030	0.227	1.000	0.254
Median departure delay	0.150	0.299	-0.073	0.362	0.280	0.293	0.301	0.303	0.389	0.776	0.254	1.000
Total arrival delay	0.002	0.076	-0.586	0.769	-0.038	-0.026	0.022	-0.002	0.054	0.257	0.813	0.278
Total departure delay	0.081	0.323	-0.042	0.351	0.303	0.318	0.321	0.324	0.666	0.898	0.226	0.821
Declared arrival capacity	0.137	0.293	0.265	0.160	0.702	0.666	0.610	0.688	0.309	0.278	-0.108	0.254
High demand	0.052	0.128	0.128	0.217	0.417	0.446	0.274	0.525	0.133	0.131	0.039	0.141
AC too many	0.054	0.124	0.133	0.216	0.415	0.447	0.271	0.528	0.129	0.128	0.035	0.140
AC before inbound peak	0.011	0.056	0.105	0.024	0.145	0.164	0.048	0.184	0.168	0.074	-0.052	0.052
Aerodrome capacity delay	0.002	0.189	0.019	0.146	0.372	0.289	0.298	0.344	0.076	0.086	0.063	0.097
ATFM-G Delay for the time the flight would have arrived	-0.001	0.188	0.043	0.125	0.374	0.341	0.297	0.349	0.083	0.077	0.037	0.085
Arrival congestion index	0.116	0.262	0.202	0.267	0.798	0.701	0.424	0.661	0.316	0.249	0.020	0.234
Wind direction	0.007	0.101	-0.053	0.067	0.038	0.034	0.032	0.034	0.044	0.071	0.073	0.064
Wind speed	0.039	0.105	-0.037	0.121	0.101	0.116	0.112	0.116	0.144	0.155	0.087	0.138
Temperature	0.040	0.152	-0.028	0.128	0.164	0.123	0.126	0.128	0.155	0.195	0.097	0.170
Rain duration	0.002	-0.057	-0.026	0.024	-0.002	0.003	0.002	0.002	-0.007	0.016	0.029	0.023
Rain hourly sum	-0.001	-0.040	-0.010	0.009	0.007	0.005	0.003	0.006	-0.007	0.005	0.011	0.013
Horizontal visibility KNMI	0.037	0.273	-0.004	0.114	0.154	0.129	0.132	0.134	0.171	0.193	0.063	0.160
Cloud density	0.002	-0.040	-0.022	0.008	-0.009	0.004	0.002	0.001	0.000	-0.011	0.022	-0.012
Fog	0.000	-0.093	-0.022	0.010	-0.040	-0.032	-0.026	-0.033	-0.050	-0.022	0.022	-0.007
Rain	0.004	-0.031	-0.029	0.027	-0.009	0.001	0.001	-0.002	0.001	0.020	0.033	0.021
Snow	0.010	-0.044	-0.001	0.004	-0.013	-0.008	-0.008	-0.010	-0.012	0.008	0.002	0.015
Thunderstorms	0.006	0.010	-0.018	0.032	0.006	0.004	0.008	0.005	0.018	0.046	0.033	0.047
Ice formation	-0.008	-0.058	-0.010	-0.005	-0.025	-0.020	-0.018	-0.019	-0.024	-0.015	0.002	-0.012
Hour of the day	0.008	0.045	-0.204	0.190	-0.082	-0.081	-0.040	-0.080	0.002	0.171	0.268	0.199
Month	-0.013	0.024	-0.001	-0.019	0.023	0.005	0.006	0.007	0.006	-0.010	-0.010	-0.013
Day of the week	0.025	-0.022	-0.006	0.012	-0.038	-0.026	-0.023	-0.027	-0.024	0.007	0.017	0.018

Table A.3: Correlation matrix for every 10 minutes of 2018 and 2019 - part 3/4

	Total arrival delay	Total departure delay	Declared arrival capacity	High demand	AC too many	AC before inbound peak	Aerodrome capacity delay	ATFM-G Delay for the time the flight would have arrived	Arrival congestion index	Wind direction	Wind speed	Temperature
Landing interval	-0.063	-0.303	-0.399	-0.258	-0.245	0.022	-0.264	-0.257	-0.556	-0.028	-0.068	-0.146
Cloud base arrival data	-0.010	-0.024	-0.025	0.007	0.008	-0.004	-0.023	-0.023	0.012	0.103	0.151	-0.198
FIR delay	0.122	0.108	-0.064	0.169	0.164	0.040	0.110	0.102	0.323	0.005	0.121	0.002
ATA-ETA	0.132	0.225	0.145	0.244	0.239	0.072	0.199	0.187	0.449	0.011	0.173	0.023
ATA-planned	0.067	0.201	0.265	0.183	0.181	0.066	0.180	0.172	0.315	0.002	0.121	0.022
Number of landing runways	-0.099	0.118	0.652	0.299	0.305	0.119	0.306	0.303	0.418	0.010	0.072	0.089
Number of take-off runways	0.059	0.411	0.021	0.028	0.025	0.176	-0.069	-0.062	0.164	0.025	0.094	0.156
Total runways	-0.026	0.434	0.546	0.260	0.261	0.219	0.203	0.207	0.471	0.030	0.136	0.196
AOBT-TOBT	0.052	0.106	0.048	0.044	0.043	0.015	0.085	0.082	0.070	0.038	0.024	0.092
ATOT-TTOT	0.045	0.182	0.078	0.061	0.063	0.062	0.034	0.027	0.110	0.013	0.062	-0.015
Cloud base departure data	0.008	0.344	0.380	0.118	0.117	0.062	0.129	0.129	0.258	-0.024	0.004	0.255
Meteorological conditions	0.024	0.035	0.004	0.046	0.044	0.010	-0.017	-0.014	0.052	-0.006	0.002	-0.141
Start interval	0.002	0.081	0.137	0.052	0.054	0.011	0.002	-0.001	0.116	0.007	0.039	0.040
Visibility LVNL data	0.076	0.323	0.293	0.128	0.124	0.056	0.189	0.188	0.262	0.101	0.105	0.152
Early arrivals	-0.586	-0.042	0.265	0.128	0.133	0.105	0.019	0.043	0.202	-0.053	-0.037	-0.028
Late arrivals	0.769	0.351	0.160	0.217	0.216	0.024	0.146	0.125	0.267	0.067	0.121	0.128
LVNL arrivals	-0.038	0.303	0.702	0.417	0.415	0.145	0.372	0.374	0.798	0.038	0.101	0.164
Demand / Initial arrivals without ATFM delay	-0.026	0.318	0.666	0.446	0.447	0.164	0.289	0.341	0.701	0.034	0.116	0.123
Arrivals airline schedule	0.022	0.321	0.610	0.274	0.271	0.048	0.298	0.297	0.424	0.032	0.112	0.126
Arrivals AAS	-0.002	0.324	0.688	0.525	0.528	0.184	0.344	0.349	0.661	0.034	0.116	0.128
Departure	0.054	0.666	0.309	0.133	0.129	0.168	0.076	0.083	0.316	0.044	0.144	0.155
Late departures	0.257	0.898	0.278	0.131	0.128	0.074	0.086	0.077	0.249	0.071	0.155	0.195
Median arrival delay	0.813	0.226	-0.108	0.039	0.035	-0.052	0.063	0.037	0.020	0.073	0.087	0.097
Median departure delay	0.278	0.821	0.254	0.141	0.140	0.052	0.097	0.085	0.234	0.064	0.138	0.170
Total arrival delay	1.000	0.253	-0.082	0.044	0.041	-0.049	0.064	0.035	0.028	0.069	0.096	0.101
Total departure delay	0.253	1.000	0.290	0.139	0.136	0.082	0.084	0.078	0.266	0.069	0.158	0.195
Declared arrival capacity	-0.082	0.290	1.000	0.066	0.058	-0.061	0.210	0.202	0.207	0.032	0.106	0.157
High demand	0.044	0.139	0.066	1.000	0.992	0.430	0.236	0.248	0.546	0.022	0.040	0.040
AC too many	0.041	0.136	0.058	0.992	1.000	0.446	0.218	0.229	0.549	0.023	0.041	0.036
AC before inbound peak	-0.049	0.082	-0.061	0.430	0.446	1.000	0.051	0.063	0.272	-0.002	0.006	0.025
Aerodrome capacity delay	0.064	0.084	0.210	0.236	0.218	0.051	1.000	0.865	0.283	0.019	0.008	0.133
ATFM-G Delay for the time the flight would have arrived	0.035	0.078	0.202	0.248	0.229	0.063	0.865	1.000	0.292	0.016	0.008	0.130
Arrival congestion index	0.028	0.266	0.207	0.546	0.549	0.272	0.283	0.292	1.000	0.037	0.073	0.120
Wind direction	0.069	0.069	0.032	0.022	0.023	-0.002	0.019	0.016	0.037	1.000	0.149	0.094
Wind speed	0.096	0.158	0.106	0.040	0.041	0.006	0.008	0.008	0.073	0.149	1.000	-0.016
Temperature	0.101	0.195	0.157	0.040	0.036	0.025	0.133	0.130	0.120	0.094	-0.016	1.000
Rain duration	0.029	0.014	-0.031	0.015	0.016	-0.006	-0.008	-0.008	0.014	0.090	0.183	-0.103
Rain hourly sum	0.009	0.006	-0.005	0.006	0.006	-0.003	-0.001	-0.001	0.007	0.002	0.048	-0.023
Horizontal visibility KNMI	0.078	0.196	0.212	0.011	0.008	0.009	0.082	0.079	0.075	0.003	0.135	0.447
Cloud density	0.015	-0.013	-0.033	0.009	0.010	-0.001	-0.016	-0.014	0.009	0.100	0.117	-0.143
Fog	0.020	-0.025	-0.076	0.023	0.025	-0.015	-0.039	-0.038	0.004	-0.027	-0.097	-0.115
Rain	0.034	0.016	-0.041	0.017	0.019	-0.004	-0.006	-0.006	0.016	0.148	0.225	-0.117
Snow	0.001	0.007	-0.009	-0.004	-0.004	-0.008	-0.025	-0.026	-0.009	-0.030	0.034	-0.105
Thunderstorms	0.032	0.045	-0.008	0.016	0.017	-0.006	0.000	-0.003	0.016	0.022	0.022	0.053
Ice formation	0.001	-0.019	-0.038	0.003	0.004	-0.007	-0.016	-0.014	-0.007	-0.017	-0.033	-0.079
Hour of the day	0.255	0.173	0.009	-0.083	-0.082	-0.124	-0.091	-0.104	-0.069	0.021	0.046	0.011
Month	-0.017	-0.011	-0.050	0.001	0.002	0.009	0.057	0.058	0.039	-0.020	-0.058	0.184
Day of the week	0.015	0.007	0.000	-0.028	-0.026	-0.016	-0.082	-0.083	-0.042	-0.039	-0.007	-0.006

Table A.4: Correlation matrix for every 10 minutes of 2018 and 2019 - part 4/4

	Rain duration	Rain hourly sum	Horizontal visibility KNMI	Cloud density	Fog	Rain	Snow	Thunderstorms	Ice formation	Hour of the day	Month	Day of the week
Landing interval	0.009	-0.005	-0.143	0.013	0.061	0.018	0.009	-0.001	0.029	-0.046	-0.021	0.033
Cloud base arrival data	0.233	0.073	-0.317	0.360	0.039	0.261	0.045	-0.011	0.023	-0.030	-0.007	0.007
FIR delay	0.061	0.030	-0.010	0.047	0.028	0.061	-0.008	0.028	0.002	-0.062	0.003	-0.018
ATA-ETA	0.071	0.032	0.019	0.062	0.039	0.074	-0.001	0.049	0.007	-0.075	-0.009	-0.026
ATA-planned	0.046	0.018	0.027	0.053	0.037	0.050	0.009	0.042	0.013	-0.078	-0.011	-0.016
Number of landing runways	-0.005	-0.002	0.091	-0.012	0.004	-0.004	-0.009	0.008	-0.007	-0.131	0.009	-0.019
Number of take-off runways	-0.023	-0.015	0.146	-0.021	-0.039	-0.016	0.003	0.010	-0.013	-0.020	-0.002	-0.006
Total runways	-0.020	-0.013	0.193	-0.024	-0.029	-0.014	-0.004	0.014	-0.016	-0.116	0.002	-0.021
AOBT-TOBT	0.062	0.044	0.026	0.012	-0.001	0.050	-0.009	0.029	0.003	0.034	0.220	0.001
ATOT-TTOT	0.057	0.028	-0.022	0.043	0.019	0.054	0.016	0.025	-0.003	0.059	0.003	-0.003
Cloud base departure data	-0.152	-0.051	0.375	-0.249	-0.092	-0.163	-0.041	0.027	-0.055	0.043	0.010	-0.007
Meteorological conditions	0.134	0.069	-0.328	0.169	0.227	0.115	0.057	-0.017	0.096	-0.046	-0.034	0.022
Start interval	0.002	-0.001	0.037	0.002	0.000	0.004	0.010	0.006	-0.008	0.008	-0.013	0.025
Visibility LVNL data	-0.057	-0.040	0.273	-0.040	-0.093	-0.031	-0.044	0.010	-0.058	0.045	0.024	-0.022
Early arrivals	-0.026	-0.010	-0.004	-0.022	-0.022	-0.029	-0.001	-0.018	-0.010	-0.204	-0.001	-0.006
Late arrivals	0.024	0.009	0.114	0.008	0.010	0.027	0.004	0.032	-0.005	0.190	-0.019	0.012
LVNL arrivals	-0.002	0.007	0.154	-0.009	-0.040	-0.009	-0.013	0.006	-0.025	-0.082	0.023	-0.038
Demand / Initial arrivals without ATFM delay	0.003	0.005	0.129	0.004	-0.032	0.001	-0.008	0.004	-0.020	-0.081	0.005	-0.026
Arrivals airline schedule	0.002	0.003	0.132	0.002	-0.026	0.001	-0.008	0.008	-0.018	-0.040	0.006	-0.023
Arrivals AAS	0.002	0.006	0.134	0.001	-0.033	-0.002	-0.010	0.005	-0.019	-0.080	0.007	-0.027
Departure	-0.007	-0.007	0.171	0.000	-0.050	0.001	-0.012	0.018	-0.024	0.002	0.006	-0.024
Late departures	0.016	0.005	0.193	-0.011	-0.022	0.020	0.008	0.046	-0.015	0.171	-0.010	0.007
Median arrival delay	0.029	0.011	0.063	0.022	0.022	0.033	0.002	0.033	0.002	0.268	-0.010	0.017
Median departure delay	0.023	0.013	0.160	-0.012	-0.007	0.021	0.015	0.047	-0.012	0.199	-0.013	0.018
Total arrival delay	0.029	0.009	0.078	0.015	0.020	0.034	0.001	0.032	0.001	0.255	-0.017	0.015
Total departure delay	0.014	0.006	0.196	-0.013	-0.025	0.016	0.007	0.045	-0.019	0.173	-0.011	0.007
Declared arrival capacity	-0.031	-0.005	0.212	-0.033	-0.076	-0.041	-0.009	-0.008	-0.038	0.009	-0.050	0.000
High demand	0.015	0.006	0.011	0.009	0.023	0.017	-0.004	0.016	0.003	-0.083	0.001	-0.028
AC too many	0.016	0.006	0.008	0.010	0.025	0.019	-0.004	0.017	0.004	-0.082	0.002	-0.026
AC before inbound peak	-0.006	-0.003	0.009	-0.001	-0.015	-0.004	-0.008	-0.006	-0.007	-0.124	0.009	-0.016
Aerodrome capacity delay	-0.008	-0.001	0.082	-0.016	-0.039	-0.006	-0.025	0.000	-0.016	-0.091	0.057	-0.082
ATFM-G Delay for the time the flight would have arrived	-0.008	-0.001	0.079	-0.014	-0.038	-0.006	-0.026	-0.003	-0.014	-0.104	0.058	-0.083
Arrival congestion index	0.014	0.007	0.075	0.009	0.004	0.016	-0.009	0.016	-0.007	-0.069	0.039	-0.042
Wind direction	0.090	0.002	0.003	0.100	-0.027	0.148	-0.030	0.022	-0.017	0.021	-0.020	-0.039
Wind speed	0.183	0.048	0.135	0.117	-0.097	0.225	0.034	0.022	-0.033	0.046	-0.058	-0.007
Temperature	-0.103	-0.023	0.447	-0.143	-0.115	-0.117	-0.105	0.053	-0.079	0.011	0.184	-0.006
Rain duration	1.000	0.756	-0.276	0.197	-0.033	0.674	0.079	0.174	-0.013	-0.005	0.041	0.013
Rain hourly sum	0.756	1.000	-0.122	0.036	-0.008	0.037	-0.011	0.096	-0.011	0.001	0.034	0.011
Horizontal visibility KNMI	-0.276	-0.122	1.000	-0.275	-0.176	-0.273	-0.069	-0.025	-0.078	0.120	-0.001	-0.023
Cloud density	0.197	0.036	-0.275	1.000	0.104	0.255	0.033	0.045	0.045	-0.032	0.023	0.006
Fog	-0.033	-0.008	-0.176	0.104	1.000	-0.041	-0.007	-0.010	0.397	-0.066	-0.005	0.022
Rain	0.674	0.037	-0.273	0.255	-0.041	1.000	0.030	0.170	-0.007	-0.008	0.037	0.005
Snow	0.079	-0.011	-0.069	0.033	-0.007	0.030	1.000	0.005	0.001	0.000	-0.084	-0.004
Thunderstorms	0.174	0.096	-0.025	0.045	-0.010	0.170	0.005	1.000	-0.005	0.026	0.015	-0.023
Ice formation	-0.013	-0.011	-0.078	0.045	0.397	-0.007	0.001	-0.005	1.000	-0.044	-0.017	0.011
Hour of the day	-0.005	0.001	0.120	-0.032	-0.066	-0.008	0.000	0.026	-0.044	1.000	-0.002	-0.001
Month	0.041	0.034	-0.001	0.023	-0.005	0.037	-0.084	0.015	-0.017	-0.002	1.000	0.011
Day of the week	0.013	0.011	-0.023	0.006	0.022	0.005	-0.004	-0.023	0.011	-0.001	0.011	1.000