Modelling the airport departure process under the influence of uncertainty

A Vienna Airport case study

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by

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TU Delft

Preface

This thesis is written in collaboration with EUROCONTROL. The data used in this research is made available via the SafeClouds project, of which Autro Control (Air Navigation Service Provider at Vienna Airport) is one of the participants. Delft University of Technology and EUROCONTROL are also participants in this European research project.

The thesis consists of two parts. Readers who are interested in a concise version of the research are referred to the paper in part I. A more thorough explanation of the work done and the results is given in part II, which contains the full report.

I would like to thank my two supervisors, Mihaela Mitici from Delft University of Technology and Bruno Desart from EUROCONTROL, for their vision, supervision and support during this thesis. I am grateful that EUROCONTROL gave me the opportunity to write the thesis in collaboration with them. A special thank-you note goes out to Floris Herrema, who helped me with obtaining and understanding the data provided by Austro Control. Finally, I would like to thank all my friends and family for their support.

Article

Estimating the flight departure duration at a single airport

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One of the main bottlenecks in air transport operations is the runway capacity at airports. As such, managing aircraft arrivals and departures is of great importance to ensure smooth and efficient airport operations. The research objective of this article is to model the airport departure process at Vienna Airport under the influence of uncertainty. In order to simulate the departure process, the process is divided into smaller pieces. The process consists of push-back, unimpeded taxi-out time, additional taxi-out time, waiting time and runway occupancy time. The waiting time is found by using queue theory and analysing runway availability. The queue is modelled as a G/G/1 queue, where the service time is modelled as a gamma distribution. The other phases are modelled as stochastic variables, given by an appropriate distribution. The model is capable of estimating the flight departure duration on a runway with departing flights only with a mean error of 0.54 minutes. For mixed-mode operations, the model estimates the flight departure duration with a mean error of 0.7 minutes.

Nomenclature

AABT	Actual On Block Time	$P(A\|C)$	Probability of available runway
ATOT	Actual Take-Off Time	R	Historic runway waiting time
ATA	Actual Time of Arrival	S	Service time
AOBT	Actual Off Block Time	T	Time between aircraft arriving at queue
D_{aTXOT}	Additional taxi-out time	TOT	Take-Off Time
D_{DROT}	Departure runway occupancy time	W	Waiting time
D_{PB}	Duration of push-back	W_Q	Queue waiting time
D_{uTXOT}	Unimpeded taxi-out time	W_R	Runway waiting time

1. Introduction

One of the main bottlenecks in air transport operations is the runway capacity at airports. Therefore, managing aircraft arrivals and departures is of great importance to ensure smooth and efficient airport operations. Current research mainly focuses on solving this problem by proposing deterministic optimisation models that either minimise delays or maximise throughput.[1,2] However, during the actual operations, aircraft arrivals and departures are characterised by a high level of uncertainty. The duration of the taxi-out process can be influenced by the lay-out of the runways, the separation requirements, visibility, wind, type of aircraft and other random factors.[3] Also the decisions made by pilots, air traffic control or airport staff can influence the departure process. These uncertainties are not captured in deterministic models, but are captured in a stochastic model.

The research objective of this article is to model the airport departure process under the influence of uncertainty, where the duration of push-back, taxi-out and runway occupancy are modelled as stochastic variables. This model is then used to predict the take-off time.

This article is structured as follows: A study on relevant literature on modelling of the departure process is given in section 2. The case study data of Vienna Airport is given in section 3. Section 4 explains the analysis of departure flight profiles. The model formulation is given in section 5. The model parameters are estimated from the data, described in section 6. Section 7 presents and analyses the results. Finally, conclusions and recommendations are provided in section 8.

2. Related work

This section describes existing literature on modelling the airport departure process. The literature is divided into two groups: models based on queue theory and models based on statistical analysis. Both groups are explained below.

Models based on queue theory

Queuing theory is a way to determine the extra taxi-out time due to waiting time at the runway entrance. It is proven[4] that the take-off queue size is identified to be the main causal factor that effects the taxi-out time.

To model the departure process using queuing theory, it is necessary to divide the process into smaller pieces. The simplest division that can be made, is by splitting the process into a travel time and a queue time. The travel time can be determined by looking at the average taxi-out time in quiet periods of the day.[5] It is also possible to model the travel time by a normal distribution made of data when the number of aircraft in the system is low.[6,7] These models assume that the travel time remains unchanged and the queue waiting time is the only factor that increases when the number of departing aircraft increases.

However, the estimation of the travel time can be improved by making a distinction between the unimpeded taxi-out time and additional taxi-out time.[8–10] In this case, the unimpeded taxi-out time equals the time an aircraft needs to taxi without any interruptions and is represented by a distribution for each runway-airline combination,[10] or found by analysing the relation between the taxi-out time and the runway queue length.[8,9] International organisations EUROCONTROL[11] and the FAA[12] also developed a method to determine the unimpeded taxi-out time. The additional taxi-out time is used to model the extra taxi-out time due to interactions between aircraft in the taxi system, as there is a relation between the number of aircraft in the system and the taxi-out time.[8]

Once the travel time is determined, it can be added to the actual off-block time to determine the queue entry time, which results in a deterministic queue input.[6–8,10] It is also possible to model the queue input as a non-homogeneous Poisson process.[5,9] In this case, the travel time is added to the calculated queue time to determine the total duration of the departure process. The queuing delay is determined by the input rate and the service rate of the queue. The service time is found by analysing the time between two take-offs during busy periods of the day. The service time is often modelled by a (time-dependent) Erlang distribution.[5,9,10] Another method to model the output flow of the queue is using a server absence model,[5,6] where a probability states if the runway is available. Finally, it is possible to model the number of take-off opportunities in a time period as a Poisson process.[7]

Models based on statistical analysis

The duration of the departure process can also be determined by statistical analysis. In these types of models it is important to find out which factors influence the taxi-out time. The taxi-out time is then predicted by multiple linear regression or by advanced machine learning methods.

Factors that influence the taxi-out time are the runway configuration, both capacity and lay-out, the distance from gate to the runway, weather and the departure demand.[4] Other research adds the number of arrivals as an influencing factor, especially in mixed-mode operations.[13] The departure demand and resulting queue size are stated as the most significant factors.[4] A research performed at a European airport[14] discovered that the distance from gate to runway, in combination with the amount of turns and other traffic in the system, explains the largest part of the variability in taxi times.

Finally, much research has been done to machine learning methods that can be used to determine the taxi-out time. It is found that fuzzy rule-based models, where human knowledge is combined with mathematical models by if-then statements, is a method that is suited for taxi time prediction.[15] Furthermore, the technique of reinforcement learning can be used.[16] This method is compared to other machine learning techniques and it is found that the regression tree method outperforms the reinforcement learning method.[17]

3. Case study data

Vienna airport has 2 runways: runway 11/29 and runway 16/34 (see Figure 1). The airport makes use of several runway configurations. However, during peak hours, the configuration D29M34, i.e., departing flights from runway 29 and mixed-mode operations on runway 34, is used most frequently. As such, in this paper, we consider the configuration D29M34.

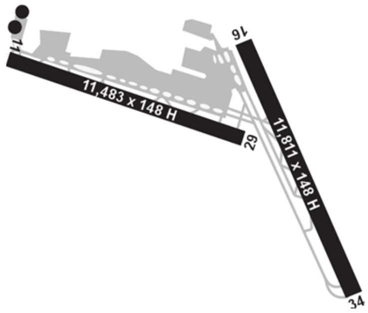


Figure 1: Layout of runway system at Vienna International Airport.

The case study reported in this paper is based on flight data at Vienna Airport for the period 1st July until 31st December 2015. We consider all flights departing and arriving at runways 29 and 34. In total, there are 80,000 arrivals and departures, of which 53,000 flights are executed while the airport is in configuration D29M34. Table 1 shows the distribution of flights per runway, under configuration D29M34. It can be seen that 77% of the flights depart from runway 29, while the other 23% depart from runway 34, where a mixed-mode configuration is used. Almost all arrivals are, as required by configuration D29M34, landing on runway 34.

Table 1: Number of arrivals and departures per runway, under configuration D29M34, Vienna Airport, July-December 2015.

	Departures		Arrivals	
	Number	Percentage	Number	Percentage
Runway 29	21138	77%	84	0.3%
Runway 34	6315	23%	25739	99.7%
Total	27453	100%	25823	100%

The flight data we consider is obtained from Advanced Surface Movement Guidance and Control Systems (A-SMGCS), which specifies the Actual Off Block Time (AOBT), the Actual Take Off Time (ATOT), the Actual Time of Arrival (ATA) and the Actual On Block Time (AABT), as well as the flight tracks recorded by the radar, which specify the aircraft latitude, longitude, ground speed and flight level at every second. The flight profile is measured from gate location until 30NM around the airport. Table 2 shows an example of flight data considered.

Table 2: Example of flight data considered.

Date	Call sign	Movement type	Runway	Aircraft type	Weight category	AOBT	Gate	ATOT	ATA	AABT
1-Jul-15	RSD008	Departure	34	IL96	H	07:50:09	B52	08:06:20	-	-
1-Jul-15	AUA935K	Departure	29	DH8D	M	07:56:51	E47	08:01:39	-	-
1-Jul-15	AUA607	Depature	29	F70	M	08:00:13	E44	08:04:09	-	-
1-Jul-15	AEE9PK	Arrival	34	A320	M	-	-	-	08:00:18	08:04:56

4. Departure flight profile

We consider a departure flight profile consisting of 4 phases: i) the push back, ii) the taxi-out process, iii) waiting time in front of the runway, and iv) the take-off procedure. The start and end of a departure are marked by the AOBT and ATOT, respectively. Figure 2 shows how a departing flight is divided into several phases. The unimpeded and additional taxi-out time form the taxi-out process.

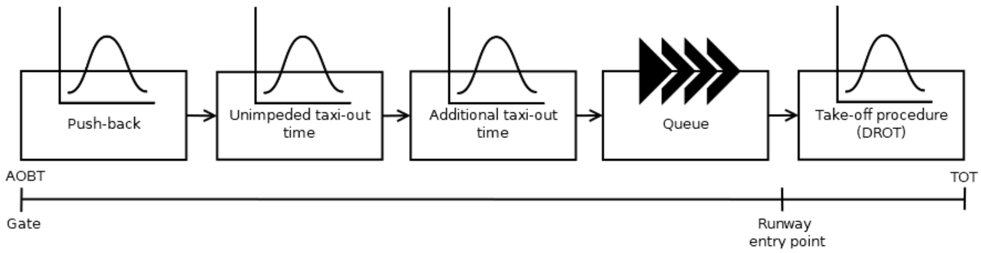
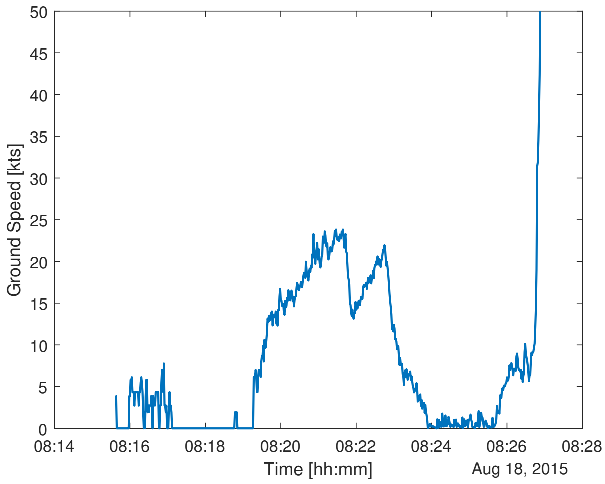


Figure 2: The phases of a departure.

To define the 4 phases of a departure, we use the departure flight profile, the recorded aircraft ground speed and known timestamps. Figure 3 shows an example of a flight profile and the ground speed for a flight departing from runway 29 at Vienna Airport. The profile, given in figure 3a, shows exactly what route the aircraft took to get to the runway. Figure 3b shows changes in the ground speed that illustrate the 4 phases of the departure. It can be seen that the ground speed first increases to roughly 5kts, after which the aircraft comes to a stop again. This duration is defined as the push-back process. When the ground speed increases again, from 08:19-08:24, the aircraft is taxiing unimpeded to the runway. At the runway entry, the aircraft has to wait in queue, since the ground speed is zero. At 08:26 the aircraft enters the runway to start its take-off procedure. This flight does not encounter additional taxi-out time.

(a) Departure flight profile.



(b) Ground speed.

Figure 3: Departure flight profile and ground speed of flight NLY170F departing from runway 29 - Vienna airport, 18$^{\text{th}}$ August 2015.

Push-back

The push-back duration is determined by time difference between AOBT and the moment that the aircraft starts taxiing to the runway, which we define as the moment the ground speed of the aircraft exceeds the threshold of 7kts for more than 10 consecutive seconds. The threshold of 7kts is chosen such that it is higher than a typical aircraft ground speed during push-back and lower than a typical aircraft taxi speed.

There are two types of parking places for aircraft at Vienna Airport. The first one is located next to a gate and has a passenger loading bridge connected to the gate. Here, a push-back is always necessary before the aircraft can start its taxi-out process. The second one is a parking place on the apron, which is not connected to a gate. In this case, the aircraft may start the taxi-out process without push-back. Using the ICAO map of the airport and satellite images, it is determined which parking spots require a push-back.

Taxi-out time

The taxi phase consists of an unimpeded taxi-out time (uTXOT) and an additional taxi-out time (aTXOT). The uTXOT is defined as the time an aircraft needs to travel to the runway entry without any interruptions. We determine uTXOT as the time the aircraft is taxiing between push-back and runway entry, where the ground speed is higher than the threshold of 7kts.

The aTXOT is determined as the time when, during the taxi process, the aircraft is interrupted, i.e., when the ground speed drops below 7kts. Such interruptions may be caused by other traffic in the taxi system or bad weather.[4]

Waiting time in front of the runway

There are two types of waiting time in front of the runway. The first type is queue waiting time, which is caused by a large demand of departing aircraft. We consider an aircraft to be waiting in the queue when i) the ground speed is below 7kts, ii) the aircraft is within 300m away from the the runway entry and iii) the previous aircraft is departing on the runway or also waiting in the queue. The requirement of 300m is chosen after a geographical analysis of the airport, mainly focused on the entry to runway 29.

The second type of waiting time occurs at a runway in mixed-mode operations, which is waiting time due to an arriving aircraft using the runway. Aircraft waiting due to an unavailable runway are waiting at the runway entry, ready to enter the runway as soon as the arrival took place. We consider an aircraft to be waiting due to runway availability when i) the ground speed is below 7kts, ii) the aircraft is within 300m away from the the runway entry and iii) the previous aircraft is not departing on the runway and not waiting in the queue.

Take-off procedure

The take-off procedure includes line-up and take-off roll. The duration of the take-off procedure is defined as the departure runway occupancy time (DROT). The DROT is determined as the difference between the runway entry time and the actual take-off time.

5. Model Formulation

In this section, we propose a model to estimate the duration of a flight departure process at Vienna Airport. Figure 4 shows a representation of the departure process at Vienna Airport. We consider a system of 2 runways, where one runway is used for departures only (segregated operations), while the other is used for both arrivals and departures (mixed-mode operations).

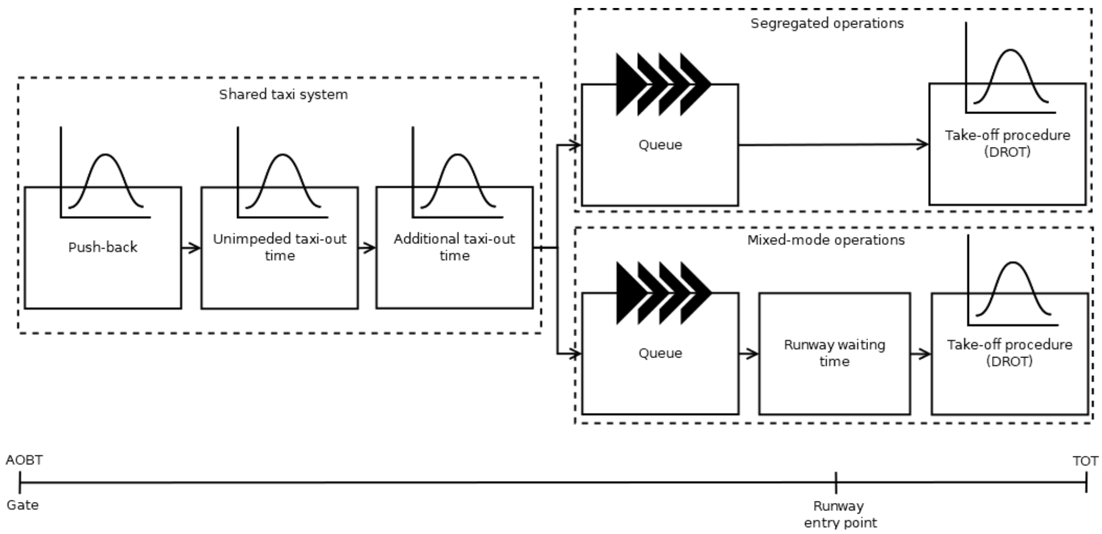


Figure 4: Representation of the departure process with multiple runways

The first part of the model is the shared taxi system. The phases of push-back, the unimpeded taxi-out time and the additional taxi-out time take place in the shared taxi system. A way to model the interactions between all flights in the system is to analyse the additional taxi-out time, since this part of the taxi-out time represents any extra taxi-out time due to interactions with other aircraft. The additional taxi-out time is modelled as a function of the number of aircraft in the system.

When aircraft leave the shared taxi system, the model splits into two directions. The first flow of aircraft takes off at runway 29 (segregated operations), while the second flow of aircraft departs from runway 34 (mixed-mode operations). This means that there are two separate queues, one for each runway. For mixed-mode operations there may be additional waiting time caused by an unavailable runway. This runway waiting time occurs when an arriving aircraft is using the runway.

The duration of each phase is added to obtain the estimated total duration of the flight departure process. The take-off time is determined by:

$$TOT_n = \text{AOBT} + D_{\text{PB},n} + D_{\text{uTXOT},n} + D_{\text{aTXOT},n} + W_n + D_{\text{DROT},n} \tag{1}$$

where $D_{\text{PB},n}$, $D_{\text{uTXOT},n}$, $D_{\text{aTXOT},n}$, W_n and $D_{\text{DROT},n}$ are the duration of the push-back process, the unimpeded taxi-out time, the additional taxi-out time, the waiting time and the departure runway occupancy time, respectively.

The push-back duration, unimpeded taxi-out time, additional taxi-out time and departure runway occupancy time are modelled as random variables with a distribution found by analysing historical data, as explained in section 4. The waiting time is determined by:

$$W_n = W_{Q,n} + W_{R,n} \tag{2}$$

where $W_{Q,n}$ is the queue waiting time and $W_{R,n}$ is the runway waiting time due to arrivals. The models to determine queue waiting time and the runway waiting time due to arrivals are explained in section 5.1 and 5.2, respectively.

5.1. Queue waiting time

We define the queue waiting time, W_Q, as the time that an aircraft has to wait in the runway queue, because previous aircraft are still occupying the runway. We consider a $G/G/1$ queue where the arrival and the service times follow a general distribution.

The service time is modelled as a distribution based on historical data and is determined by the duration between two consecutive take-offs is analysed. This method can only be used when it is certain that the two consecutive aircraft take-off immediately after each other. Otherwise, the time between take-offs is much larger than the service time, because there was simply not enough demand at the runway. Therefore, the service time is defined as difference in ATOT between consecutive aircraft, given that the following aircraft has been waiting in queue.

The time for the $(n)^{th}$ aircraft to enter the queue, $T_{\text{queue entry},n}$, is denoted by:

$$T_{\text{queue entry},n} = \text{AOBT} + D_{\text{PB},n} + D_{\text{uTXOT},n} + D_{\text{aTXOT},n}, \tag{3}$$

where $D_{\text{PB},n}$, $D_{\text{uTXOT},n}$ and $D_{\text{aTXOT},n}$ are the duration of the push-back process, the unimpeded taxi-out time and the additional taxi-out time, respectively.

The queue waiting time of the $(n+1)^{th}$ aircraft, $W_{Q,n+1}$, is recursively calculated using the equation of Lindley[18] :

$$W_{Q,n+1} = \max\left(0, W_n + U_n\right), \tag{4}$$

with $W_1 = 0$ for a runway in segregated operations and $W_1 = W_{R,1}$ for a runway in mixed-mode operations. W_n is the total waiting time of aircraft n. Furthermore, U_n is defined as

$$U_n = S_n - T_n, \tag{5}$$

where T_n is the time between the n^{th} and the $(n+1)^{th}$ aircraft arriving in the queue and S_n is the service time between the n^{th} and the $(n+1)^{th}$ aircraft. The model assumes independent service times in the simulation of the queue.

5.2. Runway waiting time due to arrivals

In mixed-mode operations, the runway does not only serve departures, it also serves arrivals. This means that the runway is not always available for aircraft that are in front of the departure queue. This server absence can be modelled in two different ways. Firstly, it is possible to use the information on arriving flights to determine when the runway is available. The second option is to obtain a probability when the runway is available by analysing historic data. Both options are discussed below.

5.2.1. Model 1: Modelling runway availability using information on arriving flights

This section explains how to estimate the runway waiting time in mixed-mode operations using the arrivals schedule. The method states that a departure is allowed to enter the runway until the moment that the arriving aircraft is at the required separation. The separation is measured from the runway threshold, the beginning of the runway, to the aircraft. For simplicity, the required time separation is set to 2 minutes. The value of 2 minutes is often used by EUROCONTROL in capacity studies at various European airports.

The queue waiting time determined in section 5.2.1 is used to determine the moment when the departing aircraft leaves the queue and is ready to enter the runway, as seen in equation 6.

$$T_{\text{queue exit},n} = T_{\text{queue entry},n} + W_{Q,n} \tag{6}$$

Next, the queue exit time, $T_{\text{queue exit},n}$, is compared with the arrival schedule to find the arriving flight after which there could be a possibility to enter the runway. This is the flight that is less than 2 minutes from the runway threshold at the time of queue exit. The next arrival is more than two minutes from the runway threshold at the queue exit time. This can be defined mathematically by equation 7, where $T_{a_m}^{2\text{min}}$ and $T_{a_{m+1}}^{2\text{min}}$ equal the times that arrivals m and $(m+1)$ are exactly 2 minutes from the runway threshold.

$$T_{a_m}^{2\text{min}} \leq T_{\text{queue exit},n} < T_{a_{m+1}}^{2\text{min}} \tag{7}$$

The mathematical definition of $T_{a_m}^{2\text{min}}$ and $T_{a_{m+1}}^{2\text{min}}$ is given in equation 8 and 9. Here, S_n is the arrival schedule that is known from live information.

$$T_{a_m}^{2\text{min}} = \max_{m \in S_a} \left\{ T_a^{2\text{min}}(m) | T_a^{2\text{min}}(m) \leq T_{\text{queue exit},n} \right\} \tag{8}$$

$$T_{a_{m+1}}^{2\text{min}} = \min_{m \in S_a} \left\{ T_a^{2\text{min}}(m) | T_a^{2\text{min}}(m) > T_{\text{queue exit},n} \right\} \tag{9}$$

The next step is to analyse whether it is possible for the departing aircraft n to enter the runway between arriving aircraft m and $(m+1)$. This is done by comparing the time that aircraft m has landed, the ATA, with the time that aircraft $(m+1)$ is exactly 2 minutes from the runway threshold.

When the ATA of arriving aircraft m is smaller than the time that aircraft $(m+1)$ is 2 minutes from the runway threshold, the departing aircraft is allowed to enter the runway. In that case, the runway entry time for departing aircraft n is given by equation 10. The waiting time due to an unavailable runway is given by equation 11.

$$T_{\text{runway entry},n} = \max\left(T_{\text{ATA},m}, T_{\text{queue exit},n}\right) \tag{10}$$

$$W_{R_n} = T_{\text{runway entry},n} - T_{\text{queue exit},n} \tag{11}$$

When aircraft $(m+1)$ is closer than 2 minutes from the runway threshold at the time that aircraft m leaves the runway, there is no possibility for a departure. In that case, the next possibility to depart is after aircraft $(m+1)$. This process continues until aircraft n can depart.

5.2.2. *Model 2: Modelling runway availability by analysing historical data*

It is also possible to model the runway availability by analysing historic data. For every aircraft that arrives at the runway entry, there is a chance that the runway is not available, i.e. a server absence. This conditional probability is determined from historical data. The probability is defined as:

$$P\left(A|C\right) = P\left(\text{Runway is not available}|\text{Departing aircraft arrives at runway entry point}\right) \tag{12}$$

The waiting time, $W_{R,n}$ is then defined by:

$$W_{R,n} = P\left(A|C\right) \cdot R_n \tag{13}$$

where R_n equals the distribution for runway waiting time R, which is found by analysing historical data. The runway waiting time is defined as explained in section 4.

6. Parameter Estimation

After analysing each flight profile separately and calculating the duration of each state, as explained in section 4, it is possible to create a distribution for each phase of the departure process. Each empirical distribution is fitted with a parametric or non-parametric distribution. The goodness of fit is tested using a one-sample Kolmogorov-Smirnov test with a 5% significance level.

The push-back process cannot be modelled by a parametric distribution, since the Kolmogorov-Smirnov test with 5% significance level rejects these distributions. Therefore, the kernel estimation is chosen to represent the empirical data. The cumulative distribution function for the push-back process is shown in figure 5.

The unimpeded taxi-out time depends on the distance between the gate and the runway.[4] To maintain enough data points in the distribution, data of gates that are close to each other and prove to have similar unimpeded taxi-out times are combined. This results in fourteen gate groups, that each require a distribution. The empirical distribution for each group is fitted with a normal distribution. Figure 6 is made for gate group C1, which consists of seven adjacent gates. The distributions for all other gate groups show a similar shape. The Kolmogorov-Smirnov test with a 5% significance level states the majority of the distributions belong to the normal distribution.

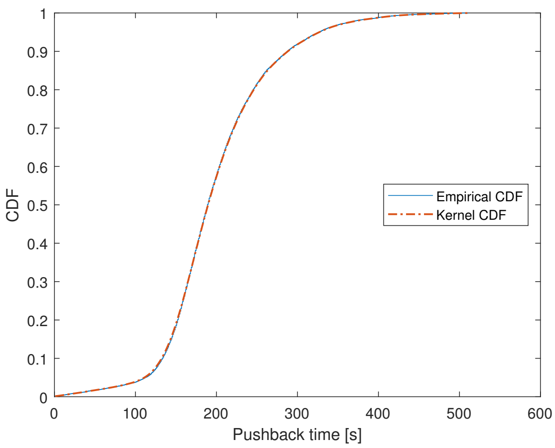


Figure 5: CDF of push-back duration with kernel estimation

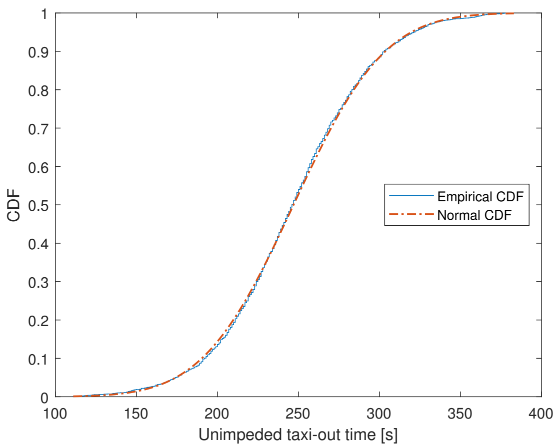


Figure 6: CDF of uTXOT with normal fit - Group C1

The distribution for additional taxi-out time depends on the number of aircraft in the system. Figure 7 shows the empirical CDF of the aTXOT for flights departing from runway 34. It can be seen that the CDF shifts to the down-right corner, which indicates a higher aTXOT for increasing number of aircraft in the system. For each of the six groups specified in figure 7, a distribution for aTXOT is created. First, the percentage of flights that do not have aTXOT is determined. For the percentage of flights that do encounter aTXOT, a distribution is created. These distributions are fit with an exponential distribution. D_{aTXOT} is defined as:

$$D_{\text{aTXOT}} = \begin{cases} 0 & \text{with} \quad p = p_{\text{No aTXOT}} \\ exp(\lambda) & \text{with} \quad p = 1 - p_{\text{No aTXOT}} \end{cases} \tag{14}$$

The service time is defined as the difference in ATOT between consecutive aircraft, given that the following aircraft has been waiting in queue. The cumulative distribution function of the service time and the gamma fit is depicted in figure 8. Although the Kolmogorov-Smirnov test with a 5% significance level rejects this distribution, it is decided to use the gamma distribution as input to the simulation model. As explained in section 2, it is common to model the service time as a distribution from the gamma family.

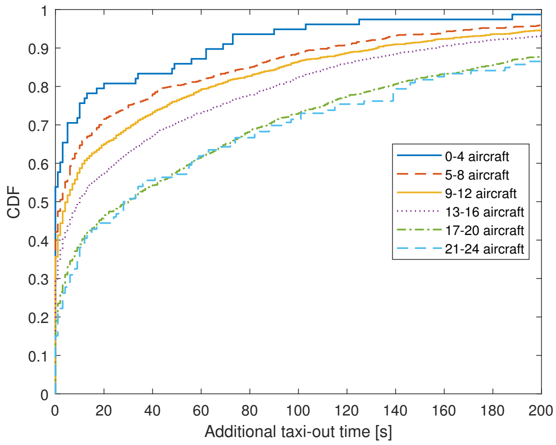


Figure 7: CDF of aTXOT for increasing number of aircraft, flights departing from runway 34.

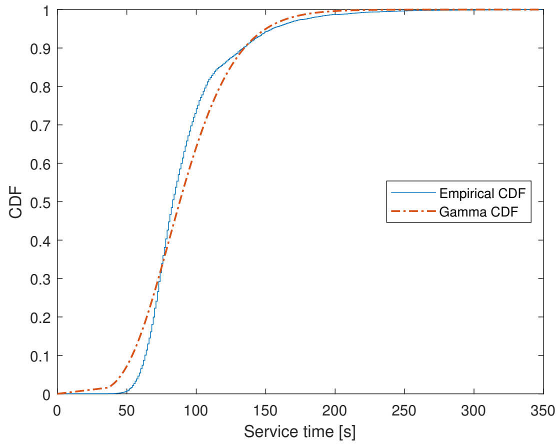


Figure 8: CDF of service time and gamma distribution.

The distribution for departure runway occupancy time is determined for every ICAO weight category. Figure 9 shows cumulative distribution function of the DROT for medium aircraft. The kernel distribution is chosen as fit, because the parametric distributions are rejected by the Kolmogorov-Smirnov test.

The distribution for runway waiting time is needed when the mixed-mode operations are simulated by model 2. The distribution consists of two parts: the probability that an aircraft has to wait at runway entry and, if it has to wait, the runway waiting time. The available data proves that the probability equals 0.2477, which means that roughly 75% of the flights do not encounter runway waiting time. The cumulative distribution function for runway waiting time is given in figure 10. It is chosen to use an exponential fit, since other parametric and non-parametric distributions include negative values in the fit.

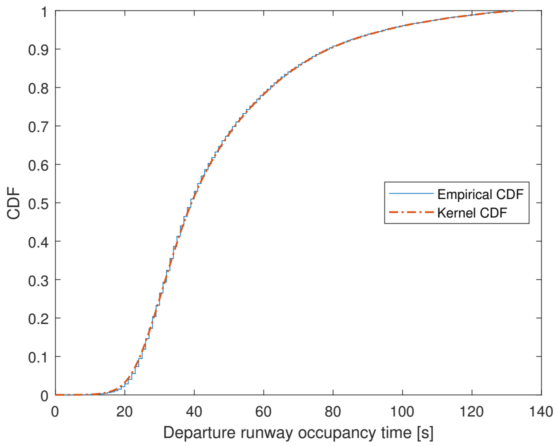


Figure 9: CDF of departure runway occupancy time with kernel estimation

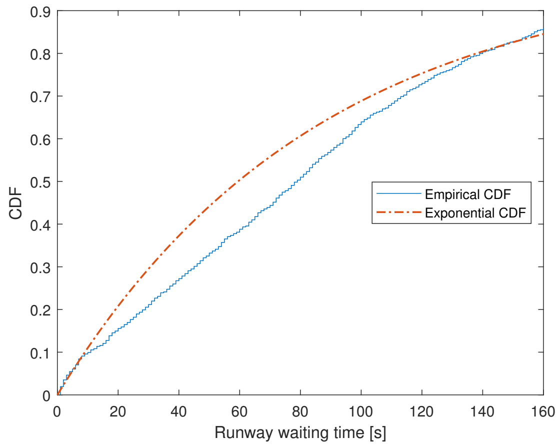


Figure 10: CDF of runway waiting time with exponential fit

7. Results

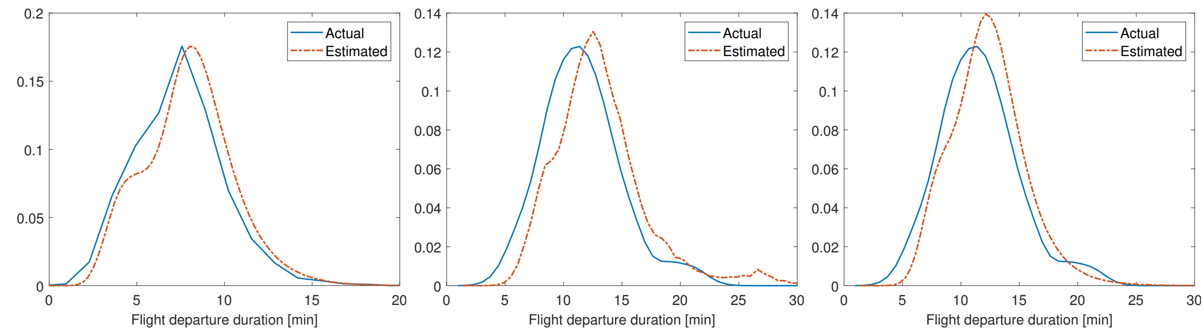
In this section we present the estimates for the flight departure duration, from gate to take-off, for Vienna Airport. We consider a system of 2 runways, where one runway is used only for departures, while the other runway is used for mixed-mode operations. We consider 7 days in the period 1st July until 31st December 2015, which are 18 Aug, 18 Sept, 28 Sept, 4 Nov, 9 Nov, 27 Nov, 10 Dec. These dates are chosen randomly from the data sample. In total, we consider 1614 flights departing from runways 29 and 34. A Monte Carlo simulation with 10,000 simulation runs is used to determine the results presented in this section.

Table 3: Error between estimated and actual flight duration of the departure process and waiting time in the queue, respectively. Results calculated over 7 days.

	Duration departure (min)			Waiting time in queue (min)		
	ME	MAE	RMSE	ME	MAE	RMSE
Runway 29	0.54	1.57	2.08	0.41	0.76	1.19
Runway 34 (Mixed Mode 1)	1.13	2.23	2.91	0.57	1.15	1.70
Runway 34 (Mixed Mode 2)	0.70	2.07	2.68	0.14	0.98	1.28

Table 3 shows the error between the estimated and actual flight departure duration, as well as the error between the estimated and actual time spent by the flights in the queue, prior to using the runway. The results show that for runway 29, the estimated flight departure duration is, on average, 0.54 minutes higher than the actual departure duration. The mean absolute error equals 1.57 minutes. For runway 34, both models provide good estimates for the flight departure duration. The second (stochastic) model outperforms the first (deterministic) model, since the stochastic model has a smaller mean error. The deterministic model assumes a 2-minute separation, which appears to be higher than reality, since the model is overestimating the actual flight departure duration.

Figure 11a shows the actual and estimated pdf for the flight departure duration for flights departing from runway 29. Similarly, figures 11b and 11c show the results for runway 34, using mixed-mode model 1 and 2, respectively. The results show that the distribution for the estimated flight departure duration is in all cases slightly larger than the distribution for the actual departure duration. However, the shape of the estimated distribution is similar to the actual distribution. When comparing mixed mode model 1 and 2, it can be seen that the second model provides better estimates.



(a) Runway 29 (b) Runway 34, mixed-mode model 1 (c) Runway 34, mixed-mode model 2

Figure 11: PDF actual and estimated flight departure duration.

Figures 12 and 13 show the actual and estimated number of departures per 15 minutes on 18th of September 2015 for runway 29 and runway 34. 18th of September is the busiest day in the data sample, since the average hourly throughput (both arrivals and departures) is highest on this day. From 4:00 in the morning until 19:00 in the evening, the D29M34 configuration is used. It can be seen that the model prediction and the observed number of departures per 15 minutes match well.

Figures 14 and 15 show the actual and predicted mean flight departure duration per 15 minutes on the 18th of September. The actual and predicted values are in line with each other, although sometimes differences of a couple of minutes exist. This is explained by the fact that in quiet periods, where only one or

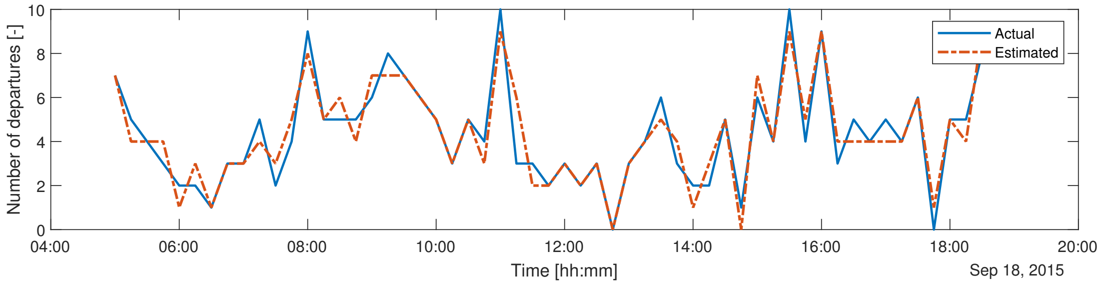


Figure 12: Actual and estimated number of departures per 15 min, 18$^{\text{th}}$ Sept 2015 - runway 29.

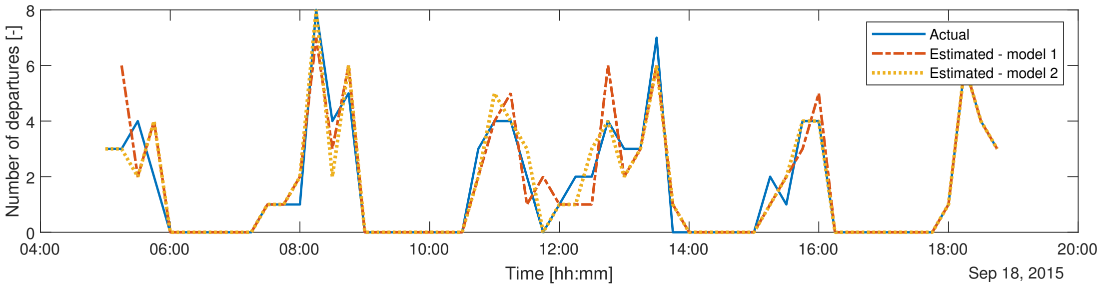


Figure 13: Actual and estimated number of departures per 15 min, 18$^{\text{th}}$ Sept 2015 - runway 34.

two aircraft depart, the average is also only based on one or two flights. This can result in large deviations in the graph. When comparing mixed-mode model 1 and 2, it can be seen that model 2 provides better results. Note that there is an outlier in the actual data, since a flight departure duration of 40 minutes is unrealistic.

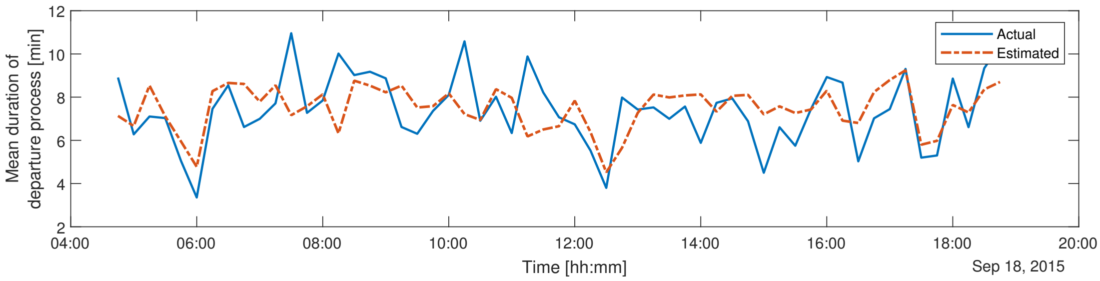


Figure 14: Actual and estimated mean flight departure duration per 15 min, 18$^{\text{th}}$ Sept 2015 - runway 29.

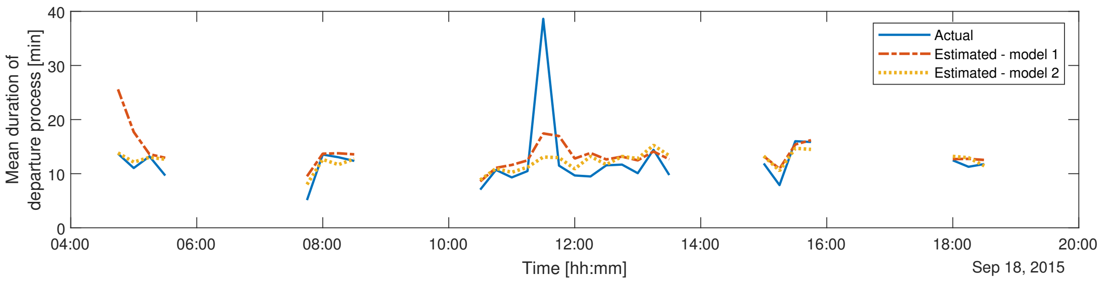


Figure 15: Actual and estimated mean flight departure duration per 15 min, 18$^{\text{th}}$ Sept 2015 - runway 34.

8. Conclusion and Recommendations

It is concluded that the model can predict the flight departure duration for each flight, including confidence interval and standard deviation, using data from 1st July until 31st December 2015. For runway 29 at Vienna Airport, which is used for departures only, the expected take-off time is predicted with a mean absolute error of 1.57 minutes. The duration of the departure process is overestimated with 0.54 minutes compared to the actual data. However, the distribution of the simulation and the actual data prove to have a similar shape.

For mixed-mode operations, there are two types of models developed, a deterministic and a stochastic model. Both types of models are suitable to predict the take-off time, although the second model, the stochastic model, outperforms the first (deterministic) model. For runway 34 at Vienna Airport, the take-off time is predicted with a mean absolute error of 2.23 minutes when using a deterministic model and 2.07 minutes when using a stochastic model. Furthermore, the simulation slightly overestimates the actual distribution, with 1.13 minutes and 0.7 minutes for model 1 and 2, respectively.

Recommendations for further research include a thorough analysis of the service time, since it is expected that a better estimation of the service time will improve the results. This research assumes independent service times, while the service time depends on the type of aircraft (both leader and follower).

Furthermore, the model results may improve by adding the influence of external factors to the model. Weather related effects and seasonal effects should be analysed to determine if it has potential to improve the model estimation.

Finally, to be able to use this model in daily business, it should be extended to all runway configurations.

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II
Report

Contents

Summary

One of the main bottlenecks in air transport operations is the runway capacity at airports. As such, managing aircraft arrivals and departures is of great importance to ensure smooth and efficient airport operations. Current research mainly focuses on solving this problem by proposing deterministic optimisation models that either minimise delays or maximise throughput. However, during the actual operations, aircraft arrivals and departures are characterised by a high level of uncertainty. The research objective of this thesis is to model the airport departure process at Vienna Airport under the influence of uncertainty.

Studying literature revealed that the airport departure process can be modelled by using queue theory and statistical analysis. It is common to separate the process into travel time and queue time. The model in this thesis follows the methods found in literature, however, the process is divided into smaller pieces, since more detailed data is available. Also, there is only little research done to modelling mixed-mode operations, which is necessary in this research.

This model is applied at Vienna Airport, consisting of two runways. The configuration that is modelled in this research is D29M34, where runway 29 is used in segregated operations with only departing flights, while runway 34 is used in mixed-mode operations. In order to simulate the departure process, the process is divided into push-back, unimpeded taxi-out time, additional taxi-out time, waiting time and runway occupancy time.

The first part of the model is the taxi system, where departing and arriving flights from both runways share the taxiways. The push-back process, the unimpeded taxi-out time and additional taxi-out time take place in the taxi system. These phases are modelled as stochastic variables with a distribution obtained from historical data. After the shared taxi system, the model splits in two directions, with separate queues for each of the runways.

For segregated operations, the waiting time is found by modelling the departure queue based on the first-in-first-out principle. The queue is modelled as a G/G/1 queue, where the service time is modelled as a gamma distribution. The service time is obtained from historical data by taking the difference in take-off time of two consecutive aircraft, given that the following aircraft was waiting in queue. The moment of arrival in the queue is determined by adding the push-back, unimpeded taxi-out time and additional taxi-out time to the actual off-block time.

For mixed-mode operations, the waiting time consists of two components: the queue waiting time and the runway waiting time due to arriving aircraft. The queue waiting time is determined similar to the waiting time for segregated operations. In order to determine the runway waiting time due to arriving aircraft, the runway availability is analysed. There are two possibilities to estimate the waiting time due to runway availability.

The first method is a deterministic model, which states that a departure is allowed to enter the runway until the moment that the arriving aircraft is at the required separation. The separation is measured from the runway threshold, the beginning of the runway, to the aircraft. The time that the departing flight is ready at runway entry is compared with the arrivals schedule to determine when the aircraft can start its take-off procedure.

The second method is a stochastic model, which analyses historical data to determine the runway availability. For every aircraft that arrives at the runway entry, there is a chance that the runway is not available, i.e. a server absence. This probability is multiplied with the distribution of runway waiting time determined from historical data to determine the runway waiting time due to arriving aircraft.

The final phase to be identified is the departure runway occupancy time. This phase includes the line-up and take-off procedure and is obtained from historical data. The total flight departure duration is determined by summing all the individual phases of the departure process.

The results for the case study at Vienna airport are generated by simulating six randomly chosen days and the busiest day of the data sample. A total of 1614 flights departed from Vienna airport during

those days. Roughly 75% of the flights departed from runway 29. A Monte Carlo simulation with 10,000 simulations is used to determine the results.

The model can estimate the flight departure duration for each flight, including confidence interval and standard deviation. The flight departure duration for flights departing from runway 29 (segregated operations) is estimated with a mean error of 0.54 minutes. For mixed-mode operations, the deterministic model estimates the flight departure duration with a mean error of 1.13 minutes, while the stochastic model provides these results with a mean error of 0.70 minutes.

The model is verified by testing increasing traffic samples of 10% and 20%, which show increasing queue waiting times, as expected. For validation, the model is tested by simulating seven different days. Since these results are similar to previously found results, the model is validated.

It is recommended to further research the service time, as it is expected that this will improve the model results. Furthermore, factors, such as weather and seasonal effects, should be analysed in order to improve the model.

In addition to that, the model should be extended to all runway configurations. It is also possible to extend the model with processes upstream of the departure process, in order to give an estimation of the take-off time earlier.

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Symbols and abbreviations

AABT	Actual On Block Time
ATOT	Actual Take-Off Time
ATA	Actual Time of Arrival
AOBT	Actual Off Block Time
D_{aTXOT}	Additional taxi-out time
D_{DROT}	Departure runway occupancy time
D_{PB}	Duration of push-back
D_{uTXOT}	Unimpeded taxi-out time
$P(A\|C)$	Probability of unavailable runway given that departing aircraft is at runway entry
R	Historical runway waiting time
S	Service time
T	Time between two consecutive aircraft arriving at queue
TOT	Estimated Take-Off Time
W	Estimated waiting time for aircraft n
$W_{Q,n}$	Estimated queue waiting time for aircraft n
$W_{R,n}$	Estimated runway waiting time due to arrivals for aircraft n

1

Introduction

One of the main bottlenecks in air transport operations is the runway capacity. Therefore, managing aircraft arrivals and departures is of great importance to maintain smooth and efficient airport operations. Current research mainly focuses on solving this problem by proposing deterministic optimisation models that either minimise delays or maximise throughput [5] [8]. However, during the actual operations, aircraft arrivals and departures are characterised by a high level of uncertainty. The duration of the taxi-out process can be influenced by the lay-out of the runways, the separation requirements, visibility, wind, type of aircraft and other random factors [10]. Also the decisions by pilots, air traffic control or airport staff can influence the departure process. These uncertainties are not captured in the deterministic models. An analysis on the influence of uncertainty is therefore relevant.

The research objective of this thesis is to model the airport departure process under the influence of uncertainty, where the duration of push-back, taxi-out and runway occupancy are modelled as stochastic variables.

The thesis is structured as follows. A description of the current literature on modelling of the departure process is given in chapter 2. The theoretical models for segregated operations and mixed-mode operations are explained in chapter 3. The model is applied in a case study at Vienna Airport, described in chapter 4. Chapter 5 shows and analyses the results. The conclusions and recommendations are given in chapter 7. Finally, the verification and validation are performed in chapter 6

2

Literature review

This chapter describes the literature closely related to the subject of airport departure processes and is divided into three sections. Existing models that describe (part of) the departure process using queuing theory are explained in section 2.1. Secondly, models that use statistical analysis to predict taxi-out times are described in section 2.2. This section describes various forms of statistical analysis, including machine learning. Finally, an elaborated explanation of the research questions that follow from the literature review is given in section 2.3

2.1. Models based on queue theory

This section describes the group of literature that models the airport departure process using queuing theory. Queuing theory is a way to determine the extra taxi-out time due to waiting time at the runway entrance. It has proven [7] that the take-off queue size is identified to be the main causal factor that effects the taxi-out time. Therefore a large part of the uncertainty can be explained by using queue theory.

To model the departure process using queuing theory, it is necessary to divide the process into smaller pieces. The simplest division that can be made is splitting the process into a travel time and a queue time. This is done to determine the estimated time that aircraft will enter the runway queue. The estimation of the travel time can be improved by making a distinction between the unimpeded taxi-out time and additional taxi-out time. Most models use the unimpeded taxi-out time, additional taxi-out and queue time to model the departure process. Therefore the focus in this literature is put on the differences between the papers. These exist in chosen distributions for arrival rate and service rate of the queue, calculation of unimpeded taxi time and calculation of the time due to interactions.

This section first explains several methods to calculate the unimpeded taxi-out time, one of which is the method used by Eurocontrol. After that, complete departure process models are described. The analytic models can be found in section 2.1.2, while the models based on simulation can be found in section 2.1.3.

2.1.1. Unimpeded taxi-out time

The common factor in most papers is the use of an unimpeded, or nominal, taxi-out time, which is calculated in a slightly different way in each paper. Next to that, the definition of unimpeded taxi-out time is not exactly the same in all papers. According to Eurocontrol, the unimpeded taxi-out time is the taxi-out time in non congested conditions at airports [2]. This definition is open to different interpretations, because it is difficult to asses when an airport is congested. This section states several methods used to determine the unimpeded taxi-out time.

First of all, Eurocontrol developed a method to calculate the unimpeded taxi-out time [2]. In this approach the unimpeded taxi-out time is based on statistical analysis of historical data. The taxi-out time is defined as the time between the Actual Off-Block Time (AOBT) and Actual Take-Off Time (ATOT). The unimpeded taxi-out time is the median of all taxi-out times in low traffic periods and it is calculated per departure runway and stand group combination, where the stand group is a virtual grouping of departure gates that are close to each other.

The first step in the calculation of the unimpeded taxi-out time is filtering of the data. The sample for calculation is one year of data, in which only flight with a taxi time less than 300 minutes are taken into account. Next, the congestion level is determined, which depends on the amount of departing and arriving flight in the preceding hour and the runway throughput. After that,the saturation level is determined. The saturation level describes the maximum amount of traffic that can be served when there is no congestion. A flight is categorised as unimpeded when the congestion level is lower than the saturation level multiplied with a congestion limit. This congestion limit equals 0.6 for major hubs and 0.5 for all other airports. The unimpeded taxi-out time is calculated, when there are more than ten flights left in the sample, by taking the median of the sample. If there are less than ten flights left in the sample, no unimpeded taxi time can be calculated.

Secondly, the FAA Aviation Policy and Planning Office (APO) has their own method to estimate the unimpeded taxi time [20]. This method is mainly based on a linear relationship between the aircraft on the ground and the taxi time. The first step in this method is to obtain the queue length for each flight in the data set. Next, all flights with a taxi time in the upper 25% are removed from the data set, such that extreme values do not influence the result. Then a linear regression for each subgroup, determined by airport, air carrier and season, is run, where the taxi-out time is a function of the number of aircraft taxiing out. The unimpeded taxi-out time is found by setting the number of aircraft taxiing out equal to 0. The APO method does not include other contributing factors, such as runway configuration, gate location or weather conditions.

In literature there are many more methods that are used to determine the unimpeded taxi-out time. One of those methods is the 20th percentile method (P20), where a cumulative distribution of taxi-out times for each group of flights, grouped by airline, season and runway configuration, is made. The 20th percentile of the distribution is taken as the unimpeded taxi-out time [20].

More simple methods include looking at the average taxi-out time in dull periods of the day, sometimes specified per gate-runway combination. The definition of ’dull periods of the day’ is vague, but this method is often used in research due to a limited amount of data availability. Since the papers described in this chapter all have their own method to determine the unimpeded taxi-out time, these methods they are explained more thoroughly in section 2.1.2 and 2.1.3, where the complete departure models are explained.

2.1.2. Analytical models

The first analytical model is created by Hebert in 1997 [6]. This paper models the departure process at LaGuardia Airport. The model is based on data collected during a single week in June 1994, of which only two days are found appropriate to use. During these two days, significant weather disruptions are experienced, which led to substantial delays.

The departure process is modelled by dividing it in a travel time and queuing time. The travel time is estimated by taking the average taxi-out time in quiet periods of the day, since it is assumed that there is no queue when little aircraft take off. Also, any delay caused by interactions in the taxiway system is assumed to be insignificant. The service demand time is modelled by a non-homogeneous Poisson process, since the amount of push-backs vary throughout the day. The intensity function of the Poisson process is different for every hour and equals the mean number of push-backs in that hour.

To model the runway service time, three different models are tested. The first model is an exponential model, in which all service times are represented by independent and identically distributed (i.i.d.) random variables with an exponential distribution. The model shows a reasonable fit on both days, although it is clear that the service rate varies during the day, since the roll-out time is overestimated in some parts of the day and underestimated in other parts.

The second model is an Erlang-2 model, in which all service times are represented by i.i.d. Erlang-2 random variables. Each service time can be seen as the sum of 2 exponentially distributed stages with mean completion rates 2μ, given that the mean service rate equals μ. When comparing the Erlang-2 model to the exponential model, the Erlang-2 model shows a better estimation of the expected roll-out time.

The third model is an Erlang model with service absence. In the analysis of times between take-off, it can be seen that usually the time between two consecutive aircraft taking-off is one, two or three minutes. However, in some cases there are between four and ten minutes between two aircraft. This indicates a server absence, in which the runway is not available due to arrivals or other external factors. With probability p, in this case $p \approx 0.2$, a server absence is experienced. Although this method seems to better represent reality, the results do not indicate an improvement compared to the Erlang-2 model. This can be explained by the fact that during the day a constant probability of runway availability is used, while this is highly dependent on the amount of arrivals and other factors interfering with the departure runway.

This paper does not provide a real validation of the model, since the model is built and tested on the same two days of data. Also, it uses a runway service rate which is derived from data from the same day. Normally, this information is not known at the start of the day. The paper does show an interesting way in dealing with runway availability. If the probability of absence is not held constant during the day, but for example made dependent on the amount of expected arrivals, this could be a suitable model to be used.

More recent and well-known researchers in the area are Simaiakis, Pyrgiotis and Balakrishnan as they published multiple articles involving research to the airport departure processes. They investigated both analytic models [17] [16] and models based on simulation [15]. The latest model [16] is the most detailed version. This model divides the departure process in two modules: the travel time and the queue, as can be seen in figure 2.1. The travel time consists of an unimpeded taxi time and a linear term to account for the extra travel time due to the interactions between departing aircraft on the ramp and taxiways. This term increases as the number of departing aircraft increases. The unimpeded taxi time is determined by creating a distribution for each airline and runway configuration. This distribution consists of data points where less than five aircraft are in the taxiway system, such that the interactions are minimal. A log-normal distribution is fitted through the empirical distributions. The total travel time is the sum of the expected value of the unimpeded taxi time distribution and the linear term which accounts for interactions.

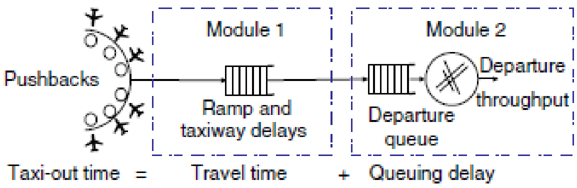


Figure 2.1: Departure process model as defined by Simaiakis[16]

The input of the queue is deterministic, as the expected travel time is added to the actual push-back time. The service rate of the queue is modelled with a time-dependent Erlang distribution with parameters k and $k\mu$. For every 15-minute interval, an empirical distribution is determined by looking at the route availability and arrival throughput by means of a regression tree. From this empirical distribution, the parameters k and $k\mu$ are estimated to obtain the Erlang distribution. By using a regression tree, this model includes interactions with the arrival flow in a simplified manner. The final take-off time is calculated by adding the expected travel time and the expected queue time to the actual push-back time.

The results of this model are compared to a deterministic model using data of the year 2011 at Newark International Airport. Both in high and low congestion, the deterministic model underestimates the mean taxi-out time compared to actual data. The stochastic model shows better results, especially in low congestion modes. In the deterministic model, average taxi-out times are underestimated by more than one minute, while the stochastic model is on average half a minute off.

Next to that, the predictive ability of the model is also tested by estimating the taxi-out times in the years 2007 and 2010, while the model parameters are identified using data from 2011. When looking at the average taxi-out time as function of the number of aircraft taxiing out, the model predicts the year 2010 as good as the year 2011. It is also possible to analyse a single day instead of yearly averages. This analysis shows that on days with a continuously high demand, the taxi-out time is more difficult to predict. Although the throughput is estimated quite accurately, each error propagates to every taxi-out time afterwards, since the queue is never empty. On days that there is a low demand, or occasionally high demand, the model shows excellent results compared to actual data. The year 2007 shows larger deviations from actual data, since in 2007 no information on route availability is known, which means that the distributions are less accurate.

This model gives a solid basis on how to discretise the departure process in smaller pieces, especially when no time stamps between push-back and take-off are known. However, since it does not include uncertainty in the push-back schedule, the predictive properties of the proposed model are only realistic in a short time horizon (roughly 15 minutes). To determine the confidence interval in take-off time one or two days in advance, the uncertainty in push-back must be included.

Simaiakis also developed an earlier version of this analytic model in [17]. This earlier version also splits the taxi-out time in three terms: the unimpeded taxi time, the interactions in the taxiway system and the departure queue. The difference between the two papers lies in the model assumptions. In [17], the unimpeded taxi time is estimated by plotting the taxi-out time against the take-off queue length, applying linear regression and taking the Y-intercept (take-off queue equals zero) as unimpeded taxi-out time. Only data points when the queue is smaller than eight aircraft is used in the regression. This method is different from the more recent paper of Simaiakis [16], where the unimpeded taxi-out time is determined from distributions obtained in low-traffic situations.

Furthermore, the main difference between the two papers can be found in the departure demand rate. While the most recent paper assumes a deterministic flow, the earlier version assumes a departure demand rate that can be modelled as a non-stationary Poisson process, as the inter-arrival times at the runway are assumed to be random. Both papers use an Erlang distribution to model the service rate of the runway queue, although the earlier version is much simpler, since it does not include a regression tree with information based on the amount of arrivals.

All analytic models provide a way to model the departure process with push-back time as given. The models from Simaiakis [16] [17] introduce a more detailed estimation of the travel time by splitting it in an unimpeded taxi time and added time due to interactions in the taxiway system. The first model [6] focuses mainly on the service rate of the departure queue. Although both model focus on a different aspect of the departure process, they can both be useful in model building.

2.1.3. Simulation models

Next to analytic models, there are also many models that use simulation to analyse the departure process. The first one is the Master thesis of Shumsky on the prediction of aircraft take-off times [14]. Since this thesis aims to predict take-off times, the delay at push-back is also included in this model, as can be seen in figure 2.2. The gate departure delay and the taxi-out times are seen as independent variables and therefore two separate models are created.

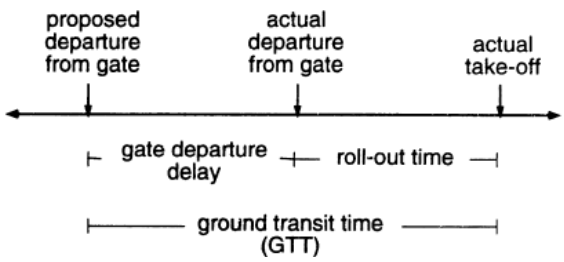


Figure 2.2: Timeline of the departure process as defined by Shumsky [14]

The first model tries to predict gate departure delay. This thesis describes two different ways to estimate the push-back delay. The first method is to analyse the influence of weather and runway configuration on push-back delay. It concludes that, although they are statistically relevant factors, the largest part of the push-back delay is not explained by these two factors. The second method is based on delay propagation in aircraft schedules. By simply looking at the arrival time of the previous flight and the minimum turnaround time, a prediction for the push-back delay can be made. This information is especially relevant for flights with large delays (over 30 minutes), since these delays are not random. Therefore they should not be included in the push-back distribution. However, this would limit the time horizon of the simulation to one to three hours before departure, since this information cannot be determined in an earlier phase. The output of the gate departure delay model is deterministic, therefore it does not include stochastic uncertainty.

The second part develops an aircraft flow model in which a deterministic flow is simulated from gate to the departure runway and into the air. The rate of flow onto the taxiway system is determined by the amount of push-backs in a fixed time period. The travel time to the queue is a fixed amount of time, which is determined from historical data. The service rate of the runway is limited by the airport capacity and modelled by a cumulative exponential capacity estimate. The model is simulated on Boston Logan International Airport and models all active runways as a single server with capacity equal to the total capacity of all runways.

According to Shumsky [14] the assumption of a deterministic process leads to a model which can be updated as real-time data arrives. To verify the model several empirical tests are performed to compare the forecasted amount of push-backs with the actual amount of push-backs in a ten-minute period. The forecast is produced 30 min in advance. The results of this analysis is that given perfectly accurate predictions of push-back times, it is possible to predict the number of aircraft on the airfield in the next ten minutes with a root-mean-square error (RMSE) of 1.4 aircraft. The RMSE for a one-hour prediction is 2.2 aircraft. Data of March and August 1991 is used from Boston Logan International Airport.

Although this model is quite extensive, the stochastic nature of the departure process is not captured by this model. It includes a possibility to update input when real-time information is available, but this does not mean that the uncertainty can be ignored. Also, the model does not simulate interactions between arriving and departing aircraft.

Next, a paper from Pujet, Delcaire and Feron [12] is discussed that models the departure process at Boston Logan International Airport from terminal to take-off as an input-output system, as shown in figure 2.3. Since there is no data available on push-back requests or push-back clearances, this model also takes the actual push-back time as input. Therefore only the last two blocks in figure 2.3 are included in the model. The time between push-back and take-off is split in a travel time and a queue time.

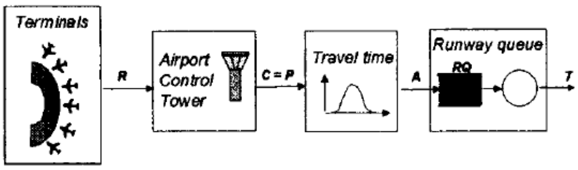


Figure 2.3: Structure of the departure process model as defined by Pujet [12]

The travel time is estimated from data in off-peak hours, when the number of aircraft in the taxiway system is very low. The distribution for the travel time is created for every runway configuration and airline pair by fitting a Gaussian distribution through the actual data. It is important to note that the travel time estimated by this distribution includes the take-off roll and the initial climb until the ACARS take-off message is sent.

When adding the travel time to the actual push-back time, the amount of arrivals in the departure queue in time period t can be determined. The queue is simulated by a simple balance equation of aircraft arriving to and leaving the queue. The take-off rate is determined in a similar way as suggested in [6]. The inter-departure times of periods when there are many aircraft in the taxiway system are analysed, since it is assumed that the queue is never empty in those periods. Then the server absence concept is used to simulate runway availability. This means that in each period of time, the runway is available with probability p. The probability p and the capacity c are chosen such that the probability distribution matches the histogram of actual data.

A computer simulation is used to compare the model outputs with actual data. One of the factors that is verified is the taxi-out time. It can be concluded that as the amount of traffic increases, the mean taxi-out time increases along with its variance. The model provides a good fit when light and medium traffic is observed, but when heavy traffic is observed the fit of the model is not as good. This can also be explained by the fact that situations with heavy traffic occurs much less often than situations with light or medium traffic.

This model is also validated using departure demand data from 1997. The model still provides reasonable good estimates of taxi-out times in most runway configurations. However, in some configurations the model overestimates the runway capacity and therefore underestimates the average taxi-out time. This is explained by the fact that these configurations are not used very often and most-likely only in bad weather situations, where the runway capacity is lower in general.

This paper shows that a simple simulation can provide many insights in the departure process, but in order to be more useful, the model must become more detailed. One of the things that can be approved is the fact that the taxi-out time includes the runway occupancy time and initial climb. When more detailed data is available, the output of this model can be improved.

Andersson, Carr, Feron and Hall [1] use the model from Pujet [12] to develop a model of the entire ground operations at an airport. The arrival process, the turnaround process and the departure process are combined in one model. The three processes are linked, but can be seen as three different models. The departure process is again modelled by splitting the travel time and the queue time. The difference with [12] is in several assumptions.

First of all, the unimpeded taxi time is determined by looking at the number of aircraft that take-off while the aircraft is taxiing out, instead of looking at the amount of aircraft in the taxiway system at time t. In this way, the data from aircraft that experience long taxi-out times due to reasons other than surrounding traffic are not used in the distribution of unimpeded taxi times, since the amount of aircraft that take-off while this aircraft is taxiing out is high. The distributions of unimpeded taxi times are approximated by fitting Gaussian or log normal distributions through the empirical results.

Secondly, the runway queue service rate is modelled by Poisson distributions for each level of departure congestion. As the level of congestion increases, the rate of the fitted Poisson distribution increases until a maximum throughput. Also, different distributions are obtained for each runway configuration and good and bad weather conditions. Compared to the model of [12], the runway service rate distribution does not include server absence, which was a clear identification of runway availability. However, since the Poisson distributions are fitted through actual data, these distributions also contain information about runway availability.

The departure process model is calibrated at Hartsfield-Jackson Atlanta International Airport at 1998 and at Dallas/Fort Worth International Airport at 1997. At both airports, the calibrated queuing model matches very well to the experimental data. A validation with data from a different period has not been performed.

Before developing its analytic models, Simaiakis also developed a model based on simulation [15]. This model is essentially equal to the analytic models explained in section 2.1.2, expect from the runway queue service rate. Instead of assuming an Erlang distribution, the service time is assumed to be a random variable with three possible outcomes. When analysing the inter-departure times at Boston Logan International Airport in 2007 in a histogram, it can be seen that in most cases there is a one- or two-minute separation between two successive aircraft. This are the first two possible outcomes of the random variable. The third outcome is the next increment such that the sum of the probabilities equals one. In the case of Boston Logan International Airport, the outcomes equal one, two and five minutes between two departures, where the probability of the first outcome is much higher than the probability of the second and third outcome.

This paper also explains in detail how the ramp and taxiway interactions are modelled. Since there are no specific operating conditions in which the interactions in the taxiway system are the dominant factor, it is first assumed that the model only includes an unimpeded taxi-out time and a queue time. When comparing the results of this model with the actual data, it can be seen that in medium traffic situations, the model differs from actual data. This is explained by the fact that the model overestimates the rate at which aircraft arrive at the runway, which results in a lower taxi-out time. A linear term $\alpha R(t)$ is used to counteract this phenomenon, where $R(t)$ is the number of aircraft that are currently in the taxiway system, but did not arrive at the queue yet and α is a parameter that depends on the runway configuration. α is chosen such that the fit between the actual and modelled number of aircraft on the ground is optimal.

This model is validated using data from Boston Logan International Airport in 2008, while model parameters are established with data from 2007. The models predicts the taxi-out time in two out of three runway configurations as well for 2008 as for 2007. In one runway configuration, the average taxi-out time in medium and heavy traffic is overestimated. There is no explanation given for this.

All papers based on simulation provide a different way to discretise the airport departure process. Shumsky [14] also includes gate departure delay, but cannot address stochastic uncertainty in his model. This model should be used for short-term analysis, since there is a possibility to update with real-time information. Pujet [12] and Andersson [1] both split the process into a travel time and a queue time, in where the travel time and runway queue service rate are stochastic variables. Simaiakis [15] assumes a deterministic flow entering the runway queue and a stochastic runway service rate.

2.2. Models based on statistical analysis

This section provides two types of models that estimate the taxi-out time. These models do not model all the small pieces of the departure process, as they analyse the duration of the complete taxi process. The first type of model tries to estimate the taxi-out time by using statistical analysis and finding out which factors influence the taxi-out time. The second type of models use machine learning to determine the taxi-out time, which is a more advanced and complex method.

2.2.1. Factors influencing the taxi-out time

The first paper that thoroughly analyses the influence of several factors is [7]. This paper finds that the main factor influencing the taxi-out time is the runway configuration. The runway configuration determines the flow of aircraft at the airport surface. The taxi-out time varies for different runway configurations since there is a variation in interaction between arriving and departing aircraft, there is a variation in distance between gate and active runway and there can be a difference in departure and arrival capacity between several configurations. This is also the reason that many papers in section 2.1 determine a queuing model for a particular runway configuration. Idris [7] clearly shows that at Boston Logan International Airport the difference in average taxi-out time between several runway configurations is large. He shows that both the capacity of a runway configuration and the distance between terminal and runway are explanatory factors.

The specific gate location also has an influence in the variability of taxi-out times. In many cases gate information is not known and therefore airline information is used, since airlines tend to use the same gates or group of gates. Idris et al. [7] perform a linear regression analysis to determine the correlation between airline and taxi-out time in a specific runway configuration, which resulted in a R^2-value of 0.02. This indicates that the distance is a positive factor, but it does not explain a significant amount of variability in taxi times.

Furthermore, the influence of weather and downstream restrictions is analysed in [7]. The weather is analysed by using Visual Flight Rule (VFR) and Instrument Flight Rule (IFR) information, however, this paper did not find a strong correlation between this information and the taxi-out time. Downstream restrictions do affect duration of the taxi-out time and its variability. Usually, these restrictions are imposed due to weather related factors.

Idris et al. [7] conclude that, within a runway configuration, the departure demand and queue size is the most important factor that causes long taxi-out times. The paper shows that the average taxi-out time increases when the number of aircraft that are on the airport surface at push-back increases. The R^2-value of the regression analysis between these two variables is 0.1927, which does not indicate a strong relation. However, Idris et al. mention that aircraft are able to pass each other in the taxiway system, which can explain the low R^2-value. Since the runway queue is found to have the largest influence, the paper develops a simple analytic queuing model that predicts the take-off time based on the number of aircraft that are present on the airport surface. Although it is called a queuing model, it cannot be compared with actual queuing models explained in section 2.1. This model estimates the taxi-out time from a regression plot of taxi time and take-off queue size. The queue size is determined from the number of aircraft on the surface. This model is tested for flights in August 1998, in which it predicted 66% taxi-out times within five minutes of the actual value. However, better results are found in actual queuing models explained in section 2.1.

Interestingly, Idris et al. [7] conclude that the amount of arrivals are of low influence on the taxi-out time. The number of arrivals has a low correlation, a R^2-value less than 0.02, with the taxi-out time. This is opposite to the findings of Clewlow et al. [3] that the number of arrivals are in fact significantly correlated with taxi-out times. Next to the number of arriving aircraft, this paper finds that the number of departing aircraft, the runway configuration, weather and originating terminal are key variables that affect the taxi-out time. Although it should be noted that the influence of arriving aircraft is much larger when the runway configuration is a mixed-mode operation.

Since this paper uses the same data set as [7], the findings from that paper can be verified. Clewlow et al. [3] discovers that the definition of the number of arrivals can be of great importance. When using the definition that the number of arrivals equals all aircraft that are taxiing in when aircraft i is pushed back from the gate, the R^2-value indeed equals 0.02. By using this definition, all arrivals that occur after push-back but before take-off of aircraft i are not taken into account. A different definition proposed in this paper is the number of aircraft that landed and arrived at their gate while aircraft i was taxiing out. If this definition is used in a regression model, for Boston Logan International Airport the R^2-value equals 0.6773 and for John F. Kennedy International Airport it equals 0.7470. Although using this definition, the number of arrivals is difficult to calculate, since an assumption about the taxi-in time would be needed.

This paper also analyses which definition of the number of departures has the highest influence on the taxi-out time. If the number of departures is defined as the number of take-offs that take place between push-back of aircraft i and take-off of aircraft i, R^2-values of 0.6380 and 0.7599 are found for BOS and JFK respectively. A downside of this definition is that it assumes knowledge of the order in which aircraft take-off. For example, when an aircraft has an earlier push-back time than aircraft i, but has a later take-off time, this aircraft is not assumed to interfere with aircraft i. However, knowledge of its actual take-off time is not known in advance.

Lastly, another paper that identifies main influential factors in taxi time estimations is written by Ravizza [13]. This paper uses multiple linear regression to identify the most relevant factors affecting both taxi-in and taxi-out times. Interesting about this paper is the fact that it uses two European airports: Stockholm-Arlanda Airport and Zurich Airport. This is in contrast to most other papers, which focus on American airports. The multiple linear regression is based on data of an entire day's operation, 7th of September 2010 at Stockholm and 19th of October 2007 at Zurich.

This paper focuses on correctly predicting the average taxi speed, from which the taxi time can be derived. The first factor that is analysed is the influence of the distance that an aircraft was taxiing. In order to calculate the distance, the authors modelled the airport layout as a graph, where the shortest path is assumed to be the distance travelled. From the analysis, it is concluded that, in general, the average taxi speed is higher for aircraft that had a longer taxi distance. Next, the influence of the total amount of turning that an aircraft has to perform is analysed, since aircraft will have to slow down to make a turn. This factor also significantly improved the forecast of the average speed. Lastly, the amount of traffic is also found to be of great importance, which is found in [7] and [3] as well. Around 13% of the variability is not explained by the model. This model stands out from other models, since it uses detailed information on the airport lay-out.

2.2.2. Machine learning

Machine learning is different from statistical analysis, since these models are not only analysing the historical data, but also detecting patterns that can be used in predictions for the future. There are several papers that use machine learning to estimate the taxi-out time, as explained in this section.

The first paper to be discussed is the paper from Ravizza et al. [18], which follows from the paper discussed in the previous section. The research done in [18] tests different statistical regression methods and machine learning techniques to predict taxi times more accurately. Methods that are tested include multiple linear regression, least median squared linear regression, support vector regression, M5 model trees and two different fuzzy rule-based systems. Fuzzy rule-based systems are used to combine human knowledge with mathematical models, since if-then statements are used.

The comparison between the different models is made by using several metrics, such as the root mean-squared error, mean-absolute error, relative errors and prediction accuracy. The prediction accuracy indicates what percentage of flights are predicted within a fixed time-span. Conclusions drawn from this research state that the fuzzy rule-based models provide the best results compared to other methods.

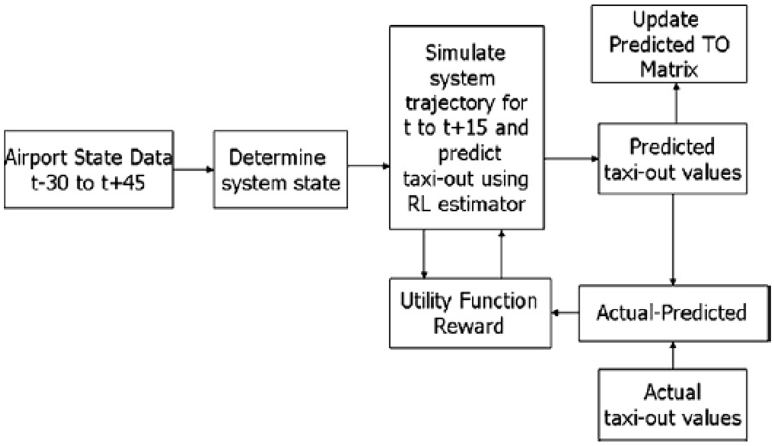


Figure 2.4: Functional block diagram of Markov Decision Process combined with reinforcement learning [11]

Another interesting paper written by Balakrishna et al. [11], where the taxi-out time is predicted using reinforcement learning (RL) algorithms. The paper states that the decision making process for departures and arrivals, performed by air traffic controllers, can be seen as a stochastic control problem. Uncertainties in the process arise due to congestion, weather and the probabilistic nature of the arrival and departure demands. Furthermore, the airport system is modelled as a discrete-time Markov chain. Together, the system state space and the Markov chain form a Markov Decision Process (MDP), where actions and rewards are added to the regular Markov chain.

In this case, the actions are the predicted taxi-out values and the reward equals the absolute error between actual and predicted taxi-out time. The state variables for taxi-time prediction are found after analysing data and literature. These variables are: (1) the runway queue length, (2) the number of departing aircraft that are taxiing out at the same time, (3) the number of arrival aircraft in the taxiway system, (4) the average taxi-out time of the last 30 minutes and (5) the time of day. The fourth variable incorporates a change in taxi-out time due to changing weather, runway configuration, etc. These changes are applicable to all aircraft taxiing out, therefore the taxi-out time of previous aircraft is a good indication.

The model block diagram, found in figure 2.4, shows clearly the learning process where the goal is to optimise the utility reward function. The model is trained using three months of data, after which it simulates one week.

It is concluded that the RL method is a suitable approach to model the airport departure process in the near future. The benefit of using this method compared to other, more simple methods, is the fact that this model is able to capture the trend in taxi-out times by looking at actual data from the last 30 minutes. Especially in airports where there is a huge uncertainty, this can be beneficial, since it is difficult to establish a trend without including recent data.

Finally, the paper of Herrema et al. [4] compares four different machine learning techniques to predict the taxi-out time at Charles de Gaulle airport. The neural networks, regression tree, reinforcement learning and multilayer perceptron methods are tested and compared based on the root-mean-squared error (RMSE) metric. The regression tree method and the reinforcement learning method performed equally well when looking at the RMSE, but the computational time for the regression tree is smaller. Therefore, the regression tree method is found to be the best option.

2.3. Research questions

This section provides the research questions that followed from the literature review. The main question is: “How to model the airport departure process under the influence of uncertainty?”. This question can be divided into several sub questions, which are explained below.

Representation
The first sub question is related to the representation of the departure process. As found in literature, there are several ways to split the process into several pieces. The departure process can be modelled much more specific than current models, since they only used two timestamps, push-back and take-off, and had to make assumptions about everything in between. With more detailed data available for Vienna Airport, it should be possible to make a clear representation of the departure process. Therefore, the first sub question is: “How to represent the departure process, taking into account the push-back, travel time and queue time?”.

Simulation
The simulation of the departure process is the largest part of the thesis and therefore this question is divided into several smaller questions. The sub question related to this subject is: “How to simulate the departure process?”. To answer this question, further knowledge on the moment of arrival in the runway queue and how to model the runway queue is needed. Therefore, the following set of questions has to be answered:

- How to determine the moment of arrival in the runway process?
  - What is the distribution of the push-back time?
  - How to determine the unimpeded taxi time?
  - What is the relation between the amount of traffic in the taxiway system and the extra travel time until the departure queue?
- How to model the runway queue?
  - What is the service time of the queue?
  - How to determine the runway availability (in a mixed-mode operation)?

Analysis
After the simulation, several key performance indicators can be analysed, but focus is put on the expected take-off time. The sub question related to this is: “What is the confidence interval of the expected take-off time?”.

Validation
The final sub question is related to the validation of the proposed model. The model is built for the case study at Vienna Airport, therefore the question is: “How to validate the model using a case study at Vienna Airport?”.

3
Model

This chapter describes a model to simulate the airport departure process at Vienna International Airport, which is the main airport of Austria. The airport consists of two runways, runway 11/29 and runway 16/34, as can be seen in figure 3.1. There are multiple runway configurations possible, but the configuration departing flights on runway 29 and mixed-mode operations on runway 34 is used most frequently in peak hours [1]. For this reason, the model is created for this runway configuration.

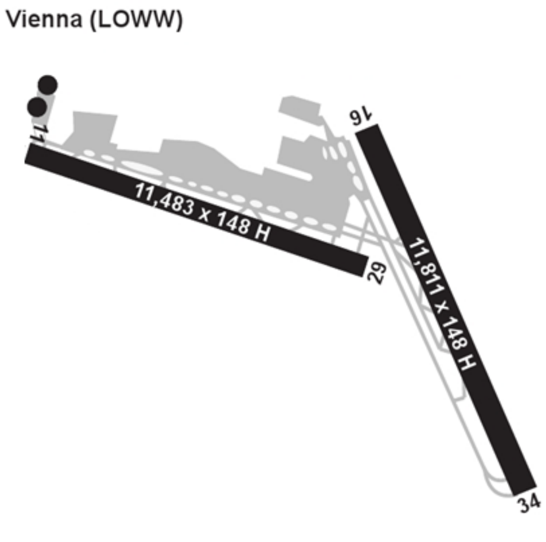


Figure 3.1: Lay-out of Vienna International Airport [2]

The model is created in two steps. As a first step, the model concentrates on runway 29, which is only used by departing aircraft. This model can be used to simulate aircraft departures from a single runway. Section 3.2 explains how this model is created and what input is needed.

The second step is to extend the first model to be able to simulate multiple runways and mixed-mode operations. This is done by adding runway 34 in the model, which is used by departures and arrivals. This results in a model with two runways, of which one is used in segregated mode and one is used in mixed-mode. This step is described in section 3.3.

Before describing the theoretical model, the model assumptions are given in section 3.1. These assumptions are applicable to both model types.

[1] `https://ext.eurocontrol.int/airport_corner_public/LOWW`

[2] Adjusted from `https://acukwik.com/Airport-Info/LOWW`

3.1. Assumptions

Several assumptions are made to create a mathematical model. These assumptions are listed below:

1. The model simulates the departure process from off-block time until take-off time, therefore the uncertainty of gate departure time is not included in the model.
2. The departure process is divided into parts, which are added together to obtain the estimated total duration of the departure process. All parts are assumed to be independent from each other.
3. The service time of the queue and the runway occupancy time are modelled as independent random variables.
4. The model assumes independent service times in the simulation of the queue.

The first assumption is made in order to define the research area. By only investigating the process between actual off-block time and take-off time, factors such as gate delays due to passengers, baggage and other external factors do not influence the model. Those factors are hard to analyse, because there is no or very limited data available on the processes that occur before the aircraft leaves the gate. This also means that the actual off-block time (AOBT) can be taken as input for the model. The AOBT is registered for each flight and therefore available in this research.

Assumption 2 states that every part of the departure process is independent from each other. This means that for example an aircraft with a slow push-back process does not automatically have a slow taxi process as well. It can only influence the time an aircraft arrives in the runway queue and therefore its waiting time in the queue.

The third assumption involves the service time and the runway occupancy time. In reality, these two random variables are linked, since a long runway occupancy time leads to a longer service time. The service time can be seen as the sum of the departure runway occupancy time and the additional separation time between to aircraft. It is impossible to determine the stochastic distribution for the additional separation time between aircraft, therefore it is decided to use two separate distributions for service time and runway occupancy time, as these variables can be determined by analysing the data.

The last assumption states that the service times in the queue are independent. In reality, the service time can depend on the flight directions of two consecutive flights and the aircraft type.

The flight direction is important in determining the service time, since aircraft have to respect the ICAO separation minima. For two consecutive aircraft that will fly in diverging directions, these minima are easier to satisfy than for aircraft that will continue to fly in the same direction. Therefore, the service time between two consecutive aircraft that will fly in diverging directions is smaller.

Also, the aircraft type can lead to a different service time, since heavy aircraft generate wake vortex turbulence that prevents light and medium aircraft to follow directly, which results in a larger service time between heavy and medium or light aircraft.

Although it is known that these factors influence the service time, they are not taken into account in the case study. The direction of flight is difficult to asses from the data, thus not considered as an input to the model. Also, the available data proved that 92% of the departing aircraft is categorised as medium weight, 6% as heavy weight and 2% as light weight. This means that extra service time due to wake vortex turbulence does not occur often and therefore has a small influence in the simulation.

3.2. Segregated operations on a single runway

This section described the model that is used for segregated operations on a single runway. The model is created to simulate the aircraft departures from runway 29 at Vienna Airport. Section 3.2.1 discusses the representation of the model. An overview of the required input is given in section 3.2.2.

3.2.1. Representation of the departure process

The departure process can be divided into several parts, being push-back, taxi, queue and take-off. The structure of the model is graphically displayed in figure 3.2. Here, the taxi phase is divided in an unimpeded taxi-out time and an additional taxi-out time. The duration of each of the stages is found by drawing a random value from a distribution, expect the queue duration, which is found by using queue theory. An explanation of each phase is given below.

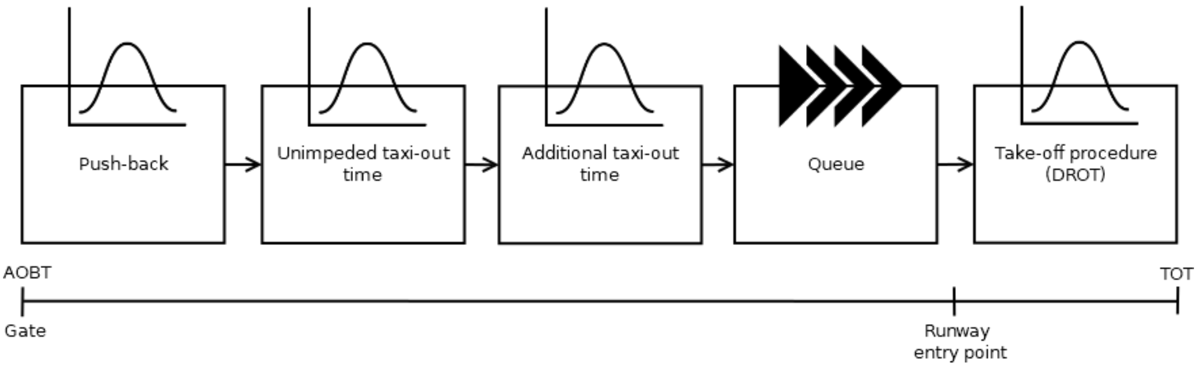


Figure 3.2: Representation of the departure process with a single runway

Push-back

The duration of push-back is defined as the process between actual off-block time (AOBT) and the moment that the aircraft starts taxiing to the runway. The push-back is characterised by the backwards motion from the gate and the aircraft is pushed by a push-back truck. The AOBT is a timestamp that is recorded by the ACARS system (Aircraft Communication Addressing and Reporting System). The AOBT is seen as the beginning of the departure process.

There are two different kind of parking spots for aircraft at Vienna Airport. The first one is located next to a gate and has a passenger loading bridge connected to the gate. The second type is a parking spot on the apron, which is not connected to a gate. In the first case, a push-back is always necessary before the aircraft can start its taxi-out process. However, when a parking spot is not connected to a gate, it might be possible for the aircraft to start the taxi-out process without push-back. This depends on the location of the parking spot, since in some parking spots the aircraft faces a wall and thus also needs a push-back. Using the ICAO map of the airport, see appendix A, and satellite images, it is determined which parking spots require a push-back.

In the simulation, the push-back duration, D_{PB}, is modelled as a random variable with a distribution based on historical data. Every flight in the data is analysed to extract the push-back duration. Together, these durations form the distribution that is used as input to the simulation.

Unimpeded taxi-out time

The taxi process is divided in an unimpeded taxi-out time and an additional taxi-out time. The unimpeded taxi-out time is defined as the time that is needed to reach the runway when there are no interruptions on in the taxi system. The stage of unimpeded taxi-out time starts directly after the push-back process.

The duration of unimpeded taxi-out time, D_{uTXOT}, depends on the distance between the gate and the runway [7]. This distance is taken into account when creating the distribution of unimpeded taxi-out time, since the distribution is determined for each combination of runway and group of gates. A group of gates is defined as several gates that are close to each other and prove to have similar unimpeded taxi-out times.

Additional taxi-out time

The additional taxi-out time is defined as any duration that the aircraft is interrupted during the taxi-out process. These interruptions are mainly caused by other traffic in the taxi system and bad weather [7]. For example, de-icing an aircraft is seen as additional taxi-out time, since the aircraft is interrupted during the taxi-out phase.

In the simulation, the additional taxi-out time, D_{aTXOT}, is determined by drawing a random value from a distribution that is created by analysing historical data. Since Vienna airport is a relatively simple airport that is not too busy, it is expected that in many cases there is no additional taxi-out time.

Runway modelling - Queue waiting time
The queue waiting time is defined as the time that an aircraft has to wait in the runway queue, because previous aircraft are still occupying the runway. The waiting time, W, for a runway that only serves departing flights is determined by queuing theory. In this case, a $G/G/1$ queue is used, since the input of the queue is random, the service time is modelled by a general distribution and there is only one server. The queue is served on a first-in-first-out (FIFO) basis.

The waiting time depends on the demand and the service time of the queue. The demand is related to the departure schedule and determines the incoming flow of aircraft. The service time is of great importance to the queue waiting time, as it controls how fast the aircraft can leave the queue. The service time is modelled as a distribution based on historical data.

To determine the service time distribution, the duration between two consecutive take-offs is analysed. According to [16], this is a good indication to determine the service time. All the flights in the data sample are sorted based on actual take-off time (ATOT) and the difference in ATOT is determined. This method can only be used when it is certain that the two consecutive aircraft take-off immediately after each other. Otherwise, the time between take-offs is much larger than the service time, because there was simply not enough demand at the runway. Therefore, the service time is defined as difference in ATOT between consecutive aircraft, given that the following aircraft has been waiting in queue.

The input of the queue module can be calculated using equation 3.1, where $T_{\text{queue entry},n}$ equals the time that aircraft n enters the runway queue and AOBT is the actual off-block time. The random variables $D_{\text{PB},n}$, $D_{\text{uTXOT},n}$ and $D_{\text{aTXOT},n}$ equal the duration of the push-back process, the unimpeded taxi-out time and the additional taxi-out time, respectively.

$$T_{\text{queue entry},n} = \text{AOBT} + D_{\text{PB},n} + D_{\text{uTXOT},n} + D_{\text{aTXOT},n} \tag{3.1}$$

Next, the waiting time of the $(n+1)^{th}$ aircraft, W_{n+1}, is recursively calculated using the Lindley equation [9] given by equation 3.2. The initial waiting time is zero, $W_1 = 0$, since the first aircraft never has to wait.

$$W_{n+1} = \max(0, W_n + U_n) \tag{3.2}$$

U_n is defined as in equation 3.3.

$$U_n = S_n - T_n \tag{3.3}$$

T_n is the time between the n^{th} and the $(n+1)^{th}$ aircraft arriving in the queue and S_n is the service time between the n^{th} and the $(n+1)^{th}$ aircraft. The service time is determined by randomly drawing from the service time distribution. T_n is computed using equation 3.4.

$$T_n = T_{\text{queue entry},n} - T_{\text{queue entry},n+1} \tag{3.4}$$

The runway entry time, $T_{\text{runway entry},n}$ is determined by equation 3.5.

$$T_{\text{runway entry},n} = T_{\text{queue entry},n} + W_n \tag{3.5}$$

Lastly, the take-off time, TOT, is calculated by adding the random variable $D_{\text{DROT},n}$, the runway occupancy time (DROT), to the runway entry time as seen in equation 3.6

$$TOT_n = T_{\text{runway entry},n} + D_{\text{DROT},n} \tag{3.6}$$

Take-off procedure
The final phase of the departure process is the take-off procedure. The take-off procedure includes line-up and take-off roll. The departure runway occupancy time (DROT) is the duration that an aircraft spends on the runway. This is measured by taking the difference between the runway entry time and the actual take-off time. The distribution for DROT is created for each ICAO weight category, since heavy aircraft generally need more time to take-off. The distribution for DROT is created by analysing historical data. Currently there are three weight categories, light (L), medium (M) and heavy (H), determined by the maximum take-off weight.

The distribution for departure runway occupancy time is determined for every ICAO weight category. For each flight in the data sample, the weight category is known. It is chosen to make separate distributions based on weight category, because heavy aircraft generally need more time to take-off.

3.2.2. Required input

The required input for the departure process model is described in this section. The input is divided in two types of input, variables that should be included in the traffic sample and distributions of the random variables that are used in the model.

Table 3.1 summarises the required input for the model that simulates segregated operations on a single runway. The traffic sample is used as input for the simulation and should contain at least the actual off-block time, the runway from where the aircraft will take-off, the gate and the ICAO weight category. The actual off-block time is used as starting point of the departure process. It is also necessary to know to which runway the aircraft will taxi, since the aircraft has to enter the queue for that runway. Next to that, the gate information is necessary to determine if a push-back is required, since this is not necessary at all gates. Finally, the ICAO weight category is needed to determine which distribution to use to simulate the departure runway occupancy time.

The distributions that are required are push-back, unimpeded taxi-out time, additional taxi-out time, service time and departure runway occupancy time. As an extra requirement, the unimpeded taxi-out time requires a distribution for each gate-runway combination. To be more exact, for each group of gates and runway combination, since adjacent gates are assumed to have similar taxi-out times. The distribution for departure runway occupancy time is specified for each ICAO weight category, since the time spend on the runway relates to the weight class of the aircraft.

Table 3.1: Required input for the model that simulates segregated operations on a single runway

Data type	Variable	Extra requirements
Traffic sample	AOBT	
	Runway	
	Gate	
	ICAO weight category	
Distributions	Push-back	
	Unimpeded taxi-out time	specified for each gate-runway combination
	Additional taxi-out time	
	Service time	
	Departure runway occupancy time	specified for each ICAO weight category

3.3. Mixed-mode operations and multiple runways

This section explains how the model from section 3.2 can be extended to multiple runways and mixed-mode operations. The model is created to simulate the aircraft departures from runway 29 and runway 34 at Vienna Airport. The model for two runways is visualised in figure 3.3. Compared to the single runway, segregated operations model, there are two differences. First of all, the taxi system is now shared between flights departing from both runways. Next to that, there are also arriving flights in the taxi system. The second difference is that runway 34 is added, which is the runway that is used for mixed-mode operations. The model extensions needed to model these two differences are explained in this section.

Section 3.3.1 discusses how the shared taxi system is modelled. Afterwards, two methods to simulate mixed-mode operations are explained in section 3.3.2. Finally, an overview of the required input is given in section 3.3.3.

3.3.1. Shared taxi system

Figure 3.3 shows that the first part of the model remains the same as for a single runway model. The push-back process, the unimpeded taxi-out time and the additional taxi-out time take place in the taxi

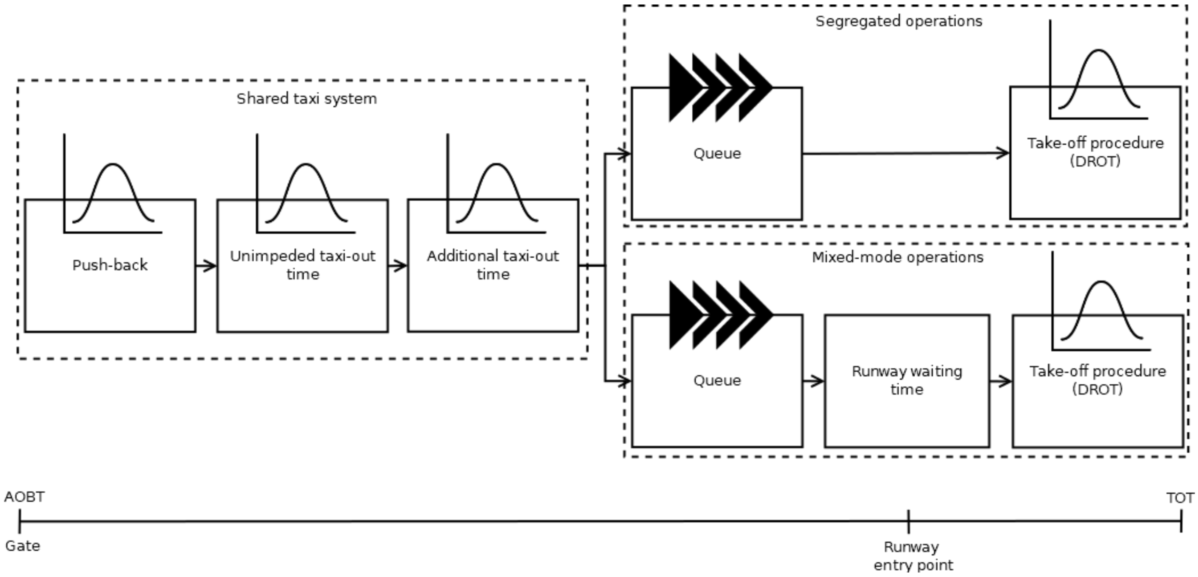


Figure 3.3: Representation of the departure process with multiple runways

system. However, the taxi system is now shared between flights that depart from runway 29 and flights that depart from runway 34.

The push-back duration and the unimpeded taxi-out time are determined in the same way as in the model for segregated operations on a single runway, as the push-back process and the unimpeded taxi-out time are not influenced by other aircraft. The additional taxi-out time does change, since this a way to model the interactions between all flights in the system. The additional taxi-out time should increase when the system becomes more complex. This is the part of the taxi-out time that represents any extra taxi-out time due to interactions with other aircraft.

For every 15 minutes, it is determined how many aircraft are present in the taxi system. This is done by adding the number of departures with an actual off-block time in those 15 minutes and the number of arrivals with an actual time of arrival in the 15-minute time period. This is an estimate of the actual number of aircraft in the system, as the duration aircraft spend in the taxi system is not taken into account.

Figures 3.4 and 3.5 show that there is a trend visible between the additional taxi-out time and the number of aircraft in the system. It can be seen that the CDF moves to the down-right corner for increasing number of aircraft in the system. This shift indicates a higher average additional taxi-out time and less flights that do not encounter any additional taxi-out time. This relation is visible for flights departing from both runways, but there appears to be a stronger relations for flights departing at runway 34. This can be explained by the graphical lay-out of the airport, see appendix A, where flights taxiing to runway 34 have to pass the entry of runway 29.

It is decided to model the additional taxi-out time based on the number of aircraft in the system. For the six groups displayed in figures 3.4 and 3.5 a distribution is created.

3.3.2. Mixed-mode operations

When aircraft leave the shared taxi system, the model splits into two directions. The first flow of aircraft takes off at runway 29, while the second flow of aircraft departs from runway 34. This means that there are two separate queues, one for each runway. For Vienna Airport, segregated operations are simulated on the first runway, as runway 29 is used for departures only. This part is modelled as explained in section 3.2. Mixed-mode operations are modelled on the second runway, since runway 34 is used by arriving and departing aircraft simultaneously.

The model for mixed-mode operations is created by extending the model for segregated operations. The waiting time for segregated operations is defined in equation 3.2, where the waiting time depends on the waiting time of the previous aircraft and the service time between two departing aircraft. For mixed-mode operations, the waiting time does not only depend on the previous aircraft, it also depends on the runway availability. Therefore, this equation needs to be adjusted. Equations 3.1 and 3.3-3.6,

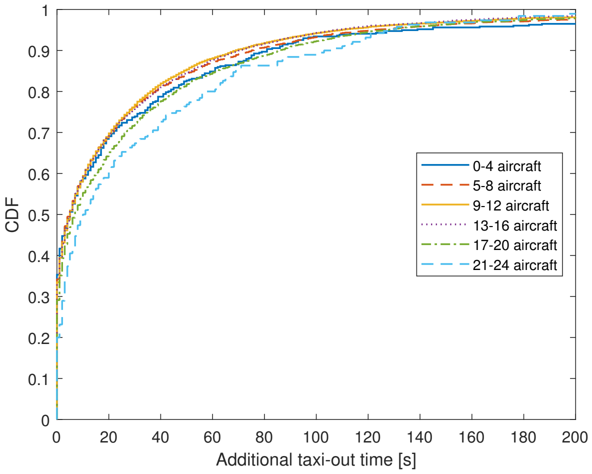


Figure 3.4: CDF of additional taxi-out time for increasing number of aircraft in the system for flights departing at R29

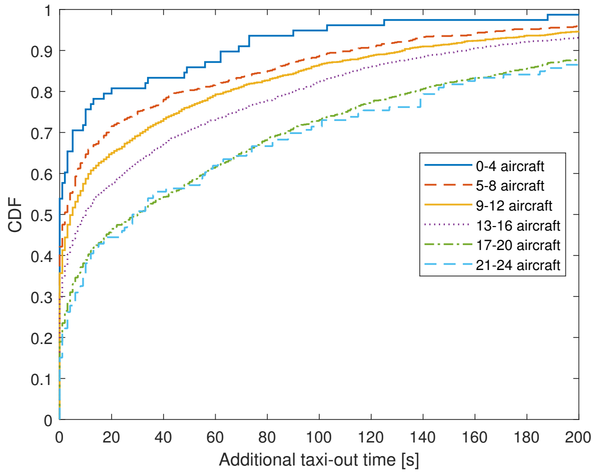


Figure 3.5: CDF of additional taxi-out time for increasing number of aircraft in the system for flights departing at R34

given in section 3.2.1 are still valid in the model for mixed-mode operations.

The calculation of the waiting time, given by equation 3.2, has to be extended to incorporate waiting time due to an unavailable runway. This is because in mixed-mode operations, the runway does not only serve departures, it also serves arrivals. This means that the runway is not always available for aircraft that are in front of the departure queue. This server absence can be modelled in two different ways. Firstly, it is possible to use the information on arriving flights to determine when the runway is available. The second option is to obtain a probability when the runway is available by analysing historic data. Both options are discussed below.

Model 1: Modelling runway availability using information on arriving flights

This section explains how to model mixed-mode operations using the arrival schedule. When this information is available, this method probably gives a better estimate on runway availability than historical data. The method states that a departure is allowed to enter the runway until the moment that the arriving aircraft is at the required separation. The separation is measured from the runway threshold, the beginning of the runway, to the aircraft. For simplicity, the required separation is set to 2 minutes. The value of 2 minutes is often used by EUROCONTROL in capacity studies at various European airports.

As long as the arriving aircraft is more than 2 minutes from the runway threshold, the departing aircraft can enter the runway. This means that there is a timeframe measured from the moment when the arriving aircraft is 2 minutes from the threshold until the moment that the aircraft touches down, where a departure cannot enter the runway.

The waiting time for departing aircraft consists of two components, the queue waiting time, W_Q, and the runway waiting time, W_R, as defined in equation 3.7.

$$W_n = W_{Q,n} + W_{R,n} \tag{3.7}$$

In this equation, $W_{Q,n}$ is computed using the Lindley equation given by equation 3.2. This waiting time is used to determine the moment when the departing aircraft leaves the queue and is ready to enter the runway, as seen in equation 3.8.

$$T_{\text{queue exit},n} = T_{\text{queue entry},n} + W_{Q,n} \tag{3.8}$$

Next, the queue exit time, $T_{\text{queue exit},n}$, is compared with the arrival schedule to find the arriving flight after which there could be a possibility to enter the runway. This is the flight that is less than 2 minutes from the runway threshold at the time of queue exit. The next arrival is more than two minutes from the runway threshold at the queue exit time. This can be defined mathematically by equation 3.9, where $T_{a_m}^{\text{2min}}$ and $T_{a_{m+1}}^{\text{2min}}$ equal the times that arrivals m and $(m+1)$ are exactly 2 minutes from the runway threshold.

$$T_{a_m}^{\text{2min}} \leq T_{\text{queue exit},n} < T_{a_{m+1}}^{\text{2min}} \tag{3.9}$$

The mathematical definition of $T_{a_m}^{\text{2min}}$ and $T_{a_{m+1}}^{\text{2min}}$ is given in equation 3.10 and 3.11. Here, S_n is the arrival schedule that is known from live information.

$$T_{a_m}^{\text{2min}} = \max_{m \in S_a} \left\{ T_a^{\text{2min}}(m) | T_a^{\text{2min}}(m) \leq T_{\text{queue exit},n} \right\} \tag{3.10}$$

$$T_{a_{m+1}}^{\text{2min}} = \min_{m \in S_a} \left\{ T_a^{\text{2min}}(m) | T_a^{\text{2min}}(m) > T_{\text{queue exit},n} \right\} \tag{3.11}$$

The next step is to analyse whether it is possible for the departing aircraft n to enter the runway between arriving aircraft m and $(m+1)$. This is done by comparing the time that aircraft m has landed with the time that aircraft $(m+1)$ is exactly 2 minutes from the runway threshold. The time that an aircraft lands is registered in the A-SMGCS system as Actual Time of Arrival (ATA).

When the ATA of arriving aircraft m is smaller than the time that aircraft $(m+1)$ is 2 minutes from the runway threshold, the departing aircraft is allowed to enter the runway. In that case, the runway entry time for departing aircraft n is given by equation 3.12. The waiting time due to an unavailable runway is given by equation 3.13.

$$T_{\text{runway entry},n} = \max\left(T_{\text{ATA},m}, T_{\text{queue exit},n}\right) \tag{3.12}$$

$$W_{R_n} = T_{\text{runway entry},n} - T_{\text{queue exit},n} \tag{3.13}$$

When aircraft $(m+1)$ is closer than 2 minutes from the runway threshold at the time that aircraft m leaves the runway, there is no possibility for a departure. In that case, the next possibility to depart is after aircraft $(m+1)$. This process continues until aircraft n can depart. Figure 3.6 summarises this process by means of a flowchart.

The take-off time is determined by adding every phase of the departure process to the AOBT, as done in equation 3.14. The waiting time, W_n, consists of queue waiting time, $W_{Q,n}$ and runway waiting time, $W_{R,n}$.

$$TOT_n = \text{AOBT} + D_{\text{PB},n} + D_{\text{uTXOT},n} + D_{\text{aTXOT},n} + W_n + D_{\text{DROT},n} \tag{3.14}$$

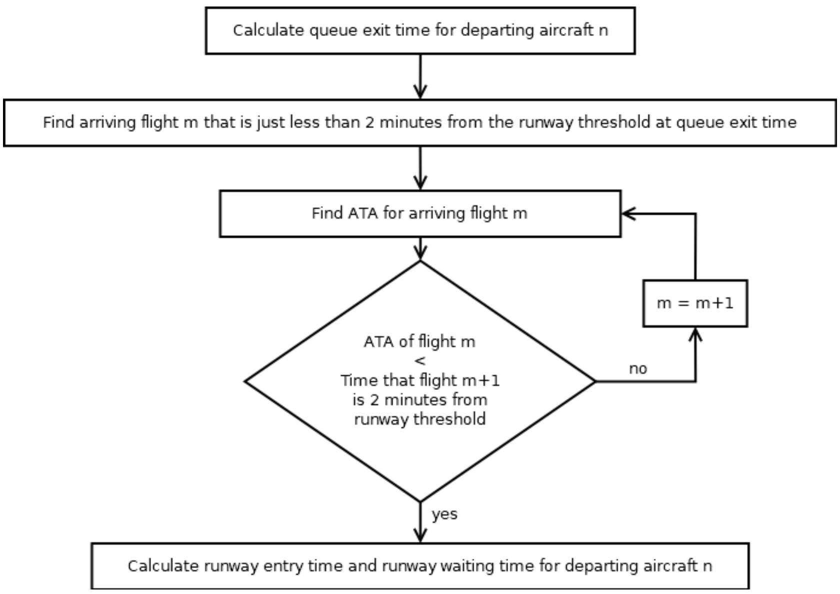


Figure 3.6: Flowchart on how to determine the runway waiting time, W_{R_n}

Model 2: Modelling runway availability by analysing historical data
It is also possible to model the runway availability by analysing historic data. For every aircraft that arrives at the runway entry, there is a chance that the runway is not available, a server absence. This can be defined as a conditional probability given by equation 3.15. This conditional probability can be determined from historic data.

$$P\,(A|C) = P\,(\text{Runway is not available}|\text{Departing aircraft arrives at runway entry point}) \tag{3.15}$$

The time an aircraft has to wait before the runway becomes available, the runway waiting time R, is modelled as a random variable. The runway waiting time is defined by any duration that the aircraft is waiting at the runway entrance, while there is no other departure on the runway. It is assumed that the aircraft is then waiting for an arrival. The distribution is obtained from historic data. A benefit of analysing the historic waiting time of departing aircraft is that it is not necessary to include information on arriving aircraft in the model.

The waiting time, W_{n+1}, is found by extending equation 3.2 as defined in equation 3.16, where R_n equals the runway waiting time and $P\,(A|C)$ equals the probability of a server absence, given that the aircraft is at the runway entry. In this case, W_1 is not equal to zero, it is equal to $P\,(A|C) \cdot R_1$.

$$W_{n+1} = P\,(A|C) \cdot R_n + \max\,(0, W_n + U_n) \tag{3.16}$$

The take-off time is again determined by adding every phase of the departure process to the AOBT, as done in equation 3.17. The waiting time, W_n, is defined as in equation 3.16.

$$TOT_n = \text{AOBT} + D_{\text{PB},n} + D_{\text{uTXOT},n} + D_{\text{aTXOT},n} + W_n + D_{\text{DROT},n} \tag{3.17}$$

3.3.3. Required input

The input that is required for both type of mixed-mode operations models is discussed in this section. Table 3.2 gives an overview of the required input for model 1. It can be seen that next to a traffic sample for departures, a traffic sample for arrivals is necessary. The arrivals schedule needs at least the time that the aircraft is at the runway threshold and the actual time of arrival as input. The input is used to determine when runway 34 is available for departures.

Additional distributions that are required for mixed-mode operations model 1 are also stated in table 3.2. The distributions for push-back, unimpeded taxi-out time and service time are determined in the same way as for the model that simulates segregated operations on a single runway. The additional taxi-out time is used to model runway interactions and is created for increasing number of aircraft in the system.

Table 3.2: Required input for mixed-mode operations model 1

Data type	Variable	Extra requirements
Traffic sample departures	AOBT	
	Runway	
	Gate	
	ICAO weight category	
Traffic sample arrivals	ATA	
	Time at runway threshold	
Distributions	Push-back	
	Unimpeded taxi-out time	for each gate-runway combination
	Additional taxi-out time	for increasing number of aircraft in the system
	Service time	
	Departure runway occupancy time	for each ICAO weight category

Table 3.3 summarises the input that is required for mixed-mode operations model 2. This model does not require an arrival schedule. Compared to the model that simulates segregated operations on a single runway, it only requires an additional distribution of runway waiting time. Next to the distribution, this model also requires the probability that a runway is available, given that the departing aircraft has arrived at the runway entry. Furthermore, to model interactions in the shared taxi system, an additional taxi-out time distribution is required for increasing number of aircraft in the system.

Table 3.3: Required input for mixed-mode operations model 2

Data type	Variable	Extra requirements
Traffic sample	AOBT	
	Runway	
	Gate	
	ICAO weight category	
Distributions	Push-back	
	Unimpeded taxi-out time	for each gate-runway combination
	Additional taxi-out time	for increasing number of aircraft in the system
	Service time	
	Departure runway occupancy time	for each ICAO weight category
	Runway waiting time	
Probability	Probability runway availability	

4
Case study: Vienna Airport

The theoretical model from chapter 3 is applied to a case study. This case study is performed at Vienna International Airport, which is the main airport of Austria. This airport consists of two runways, being runway 11/29 and runway 16/34, as can be seen in figure 4.1. There are multiple runway configurations possible, but the configuration with segregated mode (departures only) on runway 29 and mixed-mode (both arrivals and departures) on runway 34 is used most frequently in peak hours [1]. For this reason, the case study only focuses on this runway configuration (D29M34).

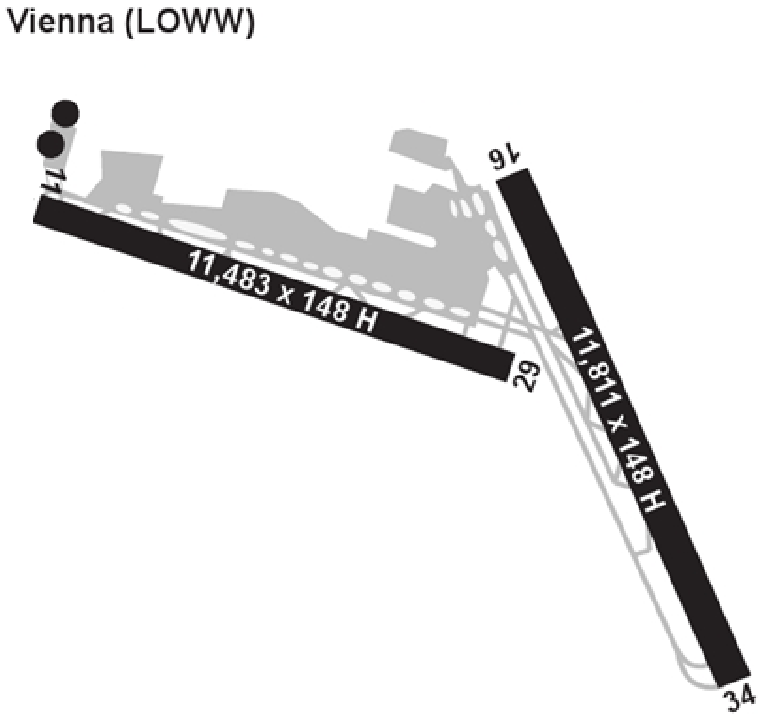


Figure 4.1: Lay-out of Vienna International Airport [2]

This chapter first elaborates on the data availability in section 4.1, as this is the main reason for choosing Vienna Airport. Next, a thorough analysis of the data is performed in section 4.2. This section explains the data preparation and analyses the flight profiles. The resulting distributions that are used

[1] https://ext.eurocontrol.int/airport_corner_public/LOWW
[2] Adjusted from https://acukwik.com/Airport-Info/LOWW

for segregated operations on a single runway are determined in section 4.3. The distributions that are used when modelling multiple runways and mixed-mode operations are described in section 4.4. Finally, the process of outlier removal is explained in section 4.5.

4.1. Data availability

Vienna International Airport is chosen as case study due to the large data availability. Section 4.1.1 shows some statistics on the available data, while section 4.1.2 explains what data is available and from what source this data is extracted.

4.1.1. Statistics on the data

This research uses data that is provided by Eurocontrol as part of the European research project ‘Safe-Clouds’. Austrocontrol, the ANSP at Vienna Airport is one of the participating stakeholders in that project. The data consists of six months, from 1^{st} of July until 31^{st} of December, in 2015. The data includes all flights departing from and arriving at runway 29 and runway 34. Data from the other two runways is not available. In total, the data sample contains roughly 80,000 flights.

Table 4.1 shows the total number of flights in the data sample. It can be seen that the total sample contains 58% departures and 42% arrivals. Normally, the number of incoming and outgoing flights should be equal. However, the data sample only contains flights from runway 29 and runway 34. The other two runways are not available in the data. Especially runway 16 is used often for arriving aircraft in combination with departing flights at runway 29. The airport dynamics are different if runway 16 is used instead of runway 34, therefore it is important to filter flights that arrive or take-off while the airport is in D29M34 configuration.

The number of flights in configuration D29M34 is also stated in table 4.1. It can be seen roughly two-third of the flights in the data sample belong to runway configuration D29M34, thus it can be concluded that this configuration is indeed used often. Furthermore, the number of arrivals and departures are almost equal when considering this runway configuration, which means that the inbound and outbound flow is balanced.

Table 4.1: Percentage of departures and arrivals for all flights and for flights in configuration D29M34

	All flights		**Configuration D29M34**	
	Number	Percentage	Number	Percentage
Departures	46670	58%	27453	52%
Arrivals	33945	42%	25823	48%
Total	80615	100%	53276	100%

The number of flights divided per runway is given in table 4.2. The flights in this table are performed when the airport was in runway configuration D29M34. It can be seen that 77% of the flights depart from runway 29, while the other 23% departs from runway 34. This 23% depart from a runway in mixed-mode configuration. Almost all arriving flights are, as required by the configuration, landing on runway 34.

For the model that simulates segregated operations on a single runway, runway 29 at Vienna Airport, there are 21138 flights available as input for the distributions. For mixed-mode operations, additional distributions are created from 6315 departing flights.

Table 4.2: Number of flights per runway in configuration D29M34

	Departures		**Arrivals**	
	Number	Percentage	Number	Percentage
Runway 29	21138	77%	84	0.3%
Runway 34	6315	23%	25739	99.7%
Total	27453	100%	25823	100%

Other important statistics are found in table 4.3 and are determined by calculating the number of days and number of hours that configuration D29M34 is in use. This gives an idea about the number of hours per day that this configuration is used. The airport is open 24 hours per day. Out of six months of data, 120 days used the D29M34 configuration for at least one hours. As the total number of hours where the configuration is used equals 1280, the average duration per day that the configuration is used, equals 10 hours and 40 minutes. This average holds if it is known that the configuration is used during that day.

Table 4.3: Number of days and hours that configuration D29M34 is in use

Configuration	Number of days	Number of hours
D29M34	120	1280
Other	64	3136
Total	184	4416

4.1.2. Explanation of the available data

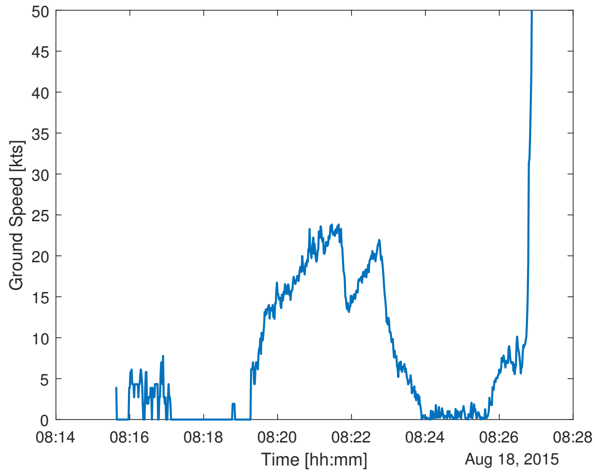
Table 4.4 presents an overview of the available data. The first category of data is general flight information. For each flight, this consists of the flight date, call sign, aircraft type and ICAO weight category. The flight date and call sign are used to merge all data sets.

Table 4.4: Available data for Vienna International Airport

Category	Variable	Description
Flight information	Flight date	Date of flight
	Call sign	Call sign of the flight
	Aircraft type	ICAO code for aircraft type
	ICAO weight category	Weight category according to ICAO standards. Three categories specified: Heavy, Medium, Light
Radar track data	Time	Time of day [hh:mm:ss]. For each flight the time consists of a vector with an entry for every second.
	Latitude	Vector with a recorded latitude in degrees for every second
	Longitude	Vector with a recorded longitude in degrees for every second
	Flight level	Vector with a recorded flight level (=100ft) for every second
	Ground speed	Vector with a recorded groundspeed in kts for every second
	On runway Boolean	Vector with a 0/1 indicating when the aircraft is on the runway
A-SMGCS	Time	Time of day [hh:mm:ss] when the milestone occurs
	Milestone	Milestone events recorded by the A-SMGCS system, such as AOBT, ATOT, ATA, AABT.
	Gate / Runway	Shows gate when milestone equals AOBT or AABT. Shows runway when milestone equals ATOT and ATA.

The second group of data is obtained from radar information. After adding this source of data, the complete flight profile for every flight is known, since the latitude, longitude, groundspeed and flight level are measured every second. The flight profile is measured from gate location until 30 NM out of the airport, or in the opposite direction, from 30 NM out until the gate location, for arriving flights. Figure 4.2 shows an example flight profile and ground speed curve, which can be created for all flights using the available data. As this model only focuses on the departure process, the profile is only drawn until the end of the runway. The runway Boolean that is available in the data indicates when the aircraft is on the runway.

(a) Departure flight profile.



(b) Ground speed.

Figure 4.2: Departure flight profile and ground speed of flight NLY170F departing from runway 29 - Vienna airport, 18^{th} August 2015.

Finally, the last group of data is obtained from Advanced Surface Movement Guidance and Control Systems (A-SMGCS) information. This source adds important information about the Actual Off Block Time (AOBT), the Actual Take Off Time (ATOT), the Actual Time of Arrival (ATA) and the Actual On Block Time (AABT). This information is needed to determine the start of the airport departure process. It is also used to compare the estimated take-off time with the actual take-off time.

4.2. Data analysis

The data analysis is done in two steps, which are explained in the following sections. Section 4.2.1 explains the data preparations that are needed for data analysis, which is explained in section 4.2.2.

4.2.1. Data preparation

The data preparation part merges the different data sources together and determines important information about the flights or group of flights. The flowchart depicted in figure 4.3 shows the process of data preparation.

The first step in the process consist of combining the general flight information with the radar track data. This step has to be performed for every movement type and runway combination, resulting in four traffic files (departing and arriving flights for runways 29 and 34). Combining the data sources is done based on date, call sign and aircraft type. This step also includes basic calculations to determine the runway entry time and the distance until runway entry, using the 'on-runway' variable, as these variables are needed in further analysis.

The following two steps combine all four traffic files and add important timestamps from the A-SMGCS data. For departing flights, the Actual Off Block Time and the Actual Take Off Time are added, as these two timestamps mark the beginning and end of the departure process. Since for departing flights this data source includes the actual gate information, this information is also included in the traffic files. For arriving flights, the Actual Time of Arrival and Actual On Block Time are added.

Next, for departing flights the geographical location of the start of the process, at AOBT, is determined and compared with the location of the gate obtained from the A-SMGCS date. The coordinates for all the gates at Vienna International Airport are obtained via Google Maps and are therefore subjected to small measurement errors. Inspection of the data shows that the start of the flight profile from the

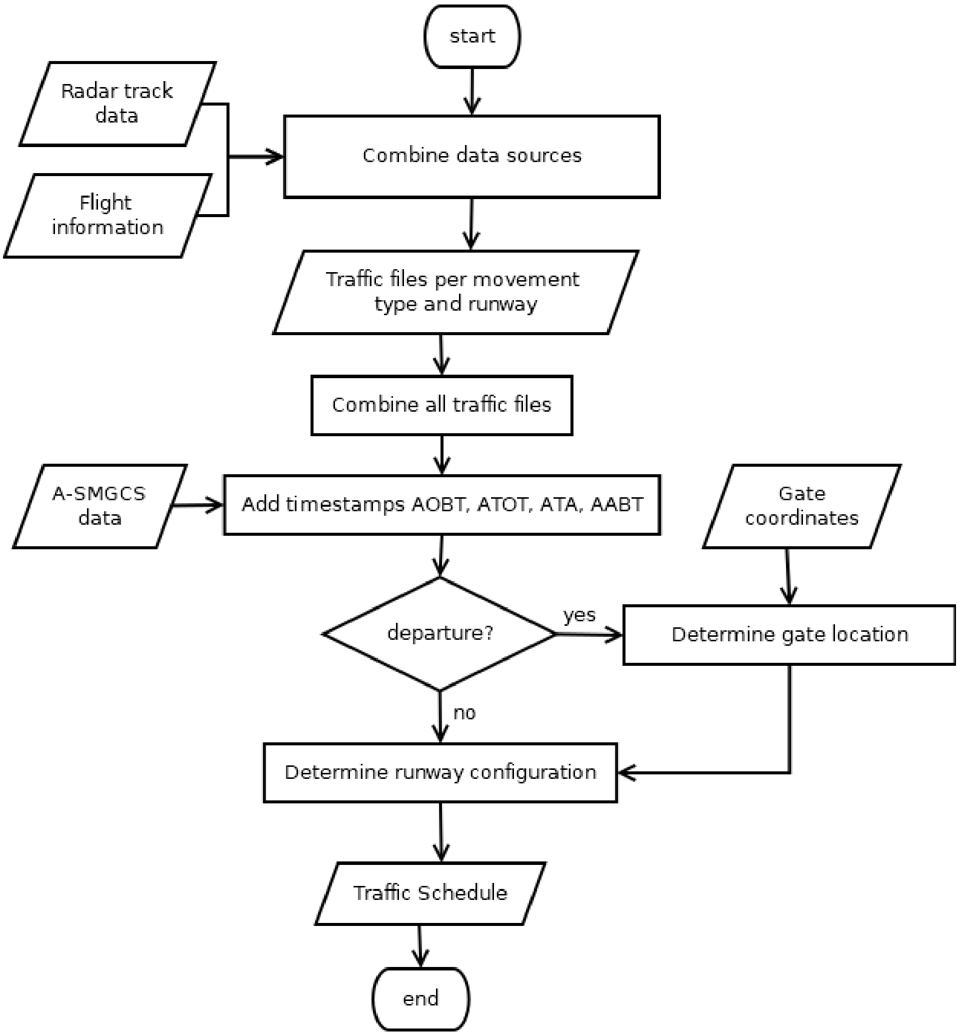


Figure 4.3: Flowchart of data preparation

radar track data does not always coincide with the known departure gate. This may be explained by the fact that a pilot did not turn on the transponder when leaving the gate. Other explanations, such as inaccuracies in the A-SMGCS data, are also possible.

To ensure that only flights with the right gate information are included in the data sample, flights where the distance between the geographical location of the start of the profile and the location of the gate is more than 200 meters are not taken into account when analysing the data. A non-coinciding gate location occurs at roughly 2.5% of the flights. Although these flights are not taken into account when analysing the data, they remain in the data sample, since they should be included in the model when simulating a traffic sample.

The final step in data preparation is the determination of the runway configuration. Since the model is only applicable to a single runway configuration, it is important to only filter the operations that occurred in a specific runway configuration. As explained in the beginning of this chapter, for Vienna International Airport the most frequently used runway configuration in peak hours is D29M34. There is no data available on when the airport was using this configuration in 2015, thus it must be determined from the available data.

This can be done by calculating the amount of flights departing and arriving per hour for each runway. An example is shown in table 4.5. This example shows the number of flights arriving and departing on each runway per hour during a part of the 2nd of September 2015. To determine whether the airport is operating in runway configuration D29M34, there are several conditions to satisfy:

1. The number of departing aircraft from runway 29 should be larger than 2
2. The number or arriving aircraft on runway 29 should be smaller or equal to 2
3. The number of arriving aircraft on runway 34 should be larger than 2

The first and the third requirements are most important to determine the runway configuration. The second condition is implemented to prevent having too much aircraft landing on runway 29, while the configuration requires only departing aircraft at runway 29. It does however allow one or two aircraft to land on runway 29, since such a small number of aircraft will not have a large influence on the runway operations.

Table 4.5: Table to determine runway configuration per hour

Time begin RWY	DEP29	ARR29	DEP34	ARR34	Total	Configuration D29M34
02-Sep-2015 16:00:00	14	0	0	30	44	1
02-Sep-2015 17:00:00	22	0	0	29	51	1
02-Sep-2015 18:00:00	29	1	10	16	56	1
02-Sep-2015 19:00:00	10	24	0	0	34	0
02-Sep-2015 20:00:00	18	15	0	0	33	0

The output of the data preparation is a traffic schedule with important timestamps, information on the gate location and information about the runway configuration. The traffic schedule consist of all flights departing and arriving from runway 29 and runway 34.

4.2.2. Flight profile analysis

This section provides the analysis of the flight profiles in order to create distribution of each state of the departure process. This analysis is done separately for runway 29 and 34. However, since the analysis is almost equal for both runways, the method is only explained once. Figure 4.4 shows the flowchart that represents this process.

The first three steps are to initialise the data for the analysis. It is important that only flights that are departing in configuration D29M34 are taken into account. Next, the flights are sorted based on actual take-off time, since calculations made later in the model require knowledge about the previous flight.

After the initialisation, the model iteratively determines every state that a flight encounters during the departure process. Figure 4.2 shows the flight profile and ground speed for a random flight. Using this information, it is determined which phases of the departure process the flight encounters, and the duration the flight spends in each phase. It can be seen that the ground speed is a good indicator to determine the duration of each phase of the departure process, as the push-back process and the unimpeded taxi-out time can be clearly distinguished in the profile.

Waiting at the gate

The first state that a flight encounters in the departure process is waiting at the gate, which ends at actual off-block time. This state is not considered to be a part of the departure process and therefore not further analysed.

Push-back

The push-back duration is found from the historical data by calculating the difference between the time between AOBT and the moment that the groundspeed exceeds 7 kts for more than 10 consecutive seconds, as at that moment it can be assumed that the aircraft has started taxiing to the runway. The threshold of 7 kts is chosen, because the threshold should be higher than the typical groundspeed during push-back and lower than a typical taxi speed. Analysing data revealed that a typical taxi speed at Vienna Airport is 15 kts. Therefore, a threshold of 7 kts should distinguish the phase of push-back from the phase of taxiing.

The push-back duration is found by analysing the time between AOBT and the moment that the groundspeed exceeds 7 kts for more than 10 consecutive seconds, as at that moment it can be assumed that the aircraft has started taxiing to the runway. The threshold of 7 kts is chosen, because the threshold should be higher than the typical ground speed during push-back and lower than a typical

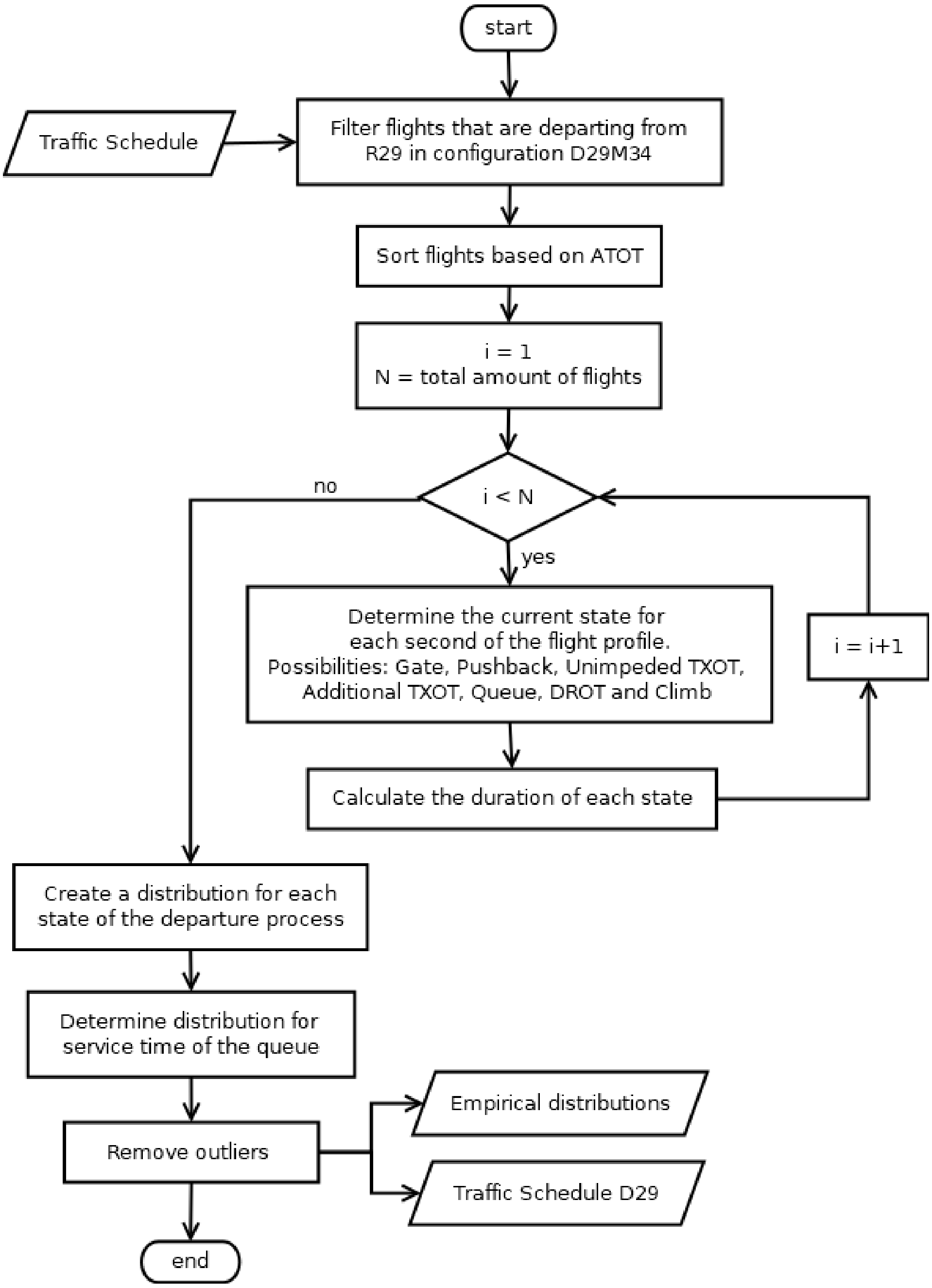


Figure 4.4: Flowchart of flight profile analysis

taxi speed. As a push-back is usually performed with two wing walkers, who check for clearance, thus a typical groundspeed equals 3-4 kts, as this equals a fast-pace walking speed. When looking at the ground speed in figure 4.2a, it can also be seen that the speed during push-back does not exceed 7 kts. At the same time, the graph of the ground speed shows that, for this flight, the average taxi speed equals 15 kts. Therefore, a threshold of 7 kts should distinguish the phase of push-back from the phase of taxiing.

Taxi to runway entry

The next phase of the departure process is taxiing to the runway entry, this phase consists of unimpeded taxi-out time, additional taxi-out time and waiting time in the queue. For mixed-mode operations, a fourth stage takes place, which is the runway waiting time.

When the groundspeed is higher than the threshold value of 7 kts, it is assumed that the aircraft is taxiing unimpeded (without interruptions) to the runway entry. To obtain the unimpeded taxi-out time, every second that the groundspeed is higher than 7kts is added.

Furthermore, when the aircraft is interrupted during its taxi process, the duration of this interruption is considered as additional taxi-out time. An interruption occurs when the groundspeed is reduced below 7 kts. Since Vienna airport is a relatively simple airport that is not often in saturation, thus in many cases there is no additional taxi-out time.

Finally, when (1) the groundspeed is lower than 7 kts, (2) the aircraft is within 300 meters of entering the runway and (3) the previous aircraft is departing on the runway or also waiting in the queue, the aircraft is waiting in queue. In this case, this duration is not considered as additional taxi-out time, since an aircraft can only be in one state at the time. The requirement of 300 meters is chosen after geographical analysis of the airport, mainly focused on the entry to runway 29 and the fact that at Vienna airport the queue normally is quite short, because it is not very busy. The third requirement is to make sure that the aircraft is actually waiting in the departure queue and not waiting anything else.

However, for mixed-mode operations the runway waiting time is determined by searching for flights where the aircraft was waiting at the runway entrance. In this case, the aircraft is not waiting for the previous aircraft, it is waiting for an arrival. Therefore, this stage occurs when (1) the ground speed is lower than 7 kts, (2) the aircraft is within 300 meters of entering the runway and (3) the aircraft is not waiting for other departing aircraft.

Take-off procedure

The final phase of the departure process is the take-off procedure, or departure runway occupancy time (DROT). The DROT is calculated by subtracting the time of runway entry from the actual take-off time (ATOT). Anything that happens after ATOT is considered as climb, but this phase is not part of the departure process and therefore not further analysed.

4.3. Distributions for segregated operations

After analysing each flight profile separately and calculating the duration of each state, it is possible to create a distribution for each phase of the departure process. As explained in section 3.2, distribution for push-back, unimpeded taxi-out time, additional taxi-out time and runway occupancy time are needed as input to the model. Next to these distributions, a distribution for the service time is needed to model the runway queue.

Each empirical distribution is fitted with a parametric distribution that is assumed to be the best fit, which is decided based on visual analysis. The distributions that are used for fitting is the normal distribution, the exponential distribution and the gamma distribution.

Literature also suggests an Erlang distribution to describe the service time of the runway queue, which is a particular case of the gamma distribution. The benefit of using an Erlang distribution is its applicability in analytic models, since the shape parameter, k, is a positive integer. However, the gamma distribution will give a better fit than an Erlang distribution, because the shape parameter can have any positive real value. This model is not analytic, therefore the gamma distribution is preferred over the Erlang distribution.

The exponential distribution is also a particular case of the gamma distribution, but has the memoryless property as benefit. This means that the waiting time until a certain event does not depend on how much time has elapsed already. Due to this property, the exponential distribution can be a useful distribution to use in the model.

When none of the parametric distributions result in a good fit, the kernel distribution is an option. The kernel distribution is a non-parametric representation of the probability density function of a random variable, which can be used to describe an empirical distribution without making assumption about the distribution of the data. A kernel distribution is defined by a smoothing function and a bandwidth value, which control the smoothness of the resulting density curve.

To fit a distribution to the data, the `fitdist()` function from MATLAB® is used. Each of the proposed distributions can be fitted using `fitdist()`. This function finds the best fit for each distribution using the maximum likelihood estimation. There is one exception, the normal distribution, where the maximum likelihood estimation is not used. The estimated value of the sigma parameter equals the square root of the unbiased estimate of the variance.

The goodness-of-fit is tested using a one-sample Kolmogorov-Smirnov test, `kstest()` in MATLAB®. The Kolmogorov-Smirnov test measures the maximum vertical distance, D, between the empirical CDF and the parametric CDF and compares this distance to a critical value. A visual representation of the Kolmogorov-Smirnov test can be seen in figure 4.5.

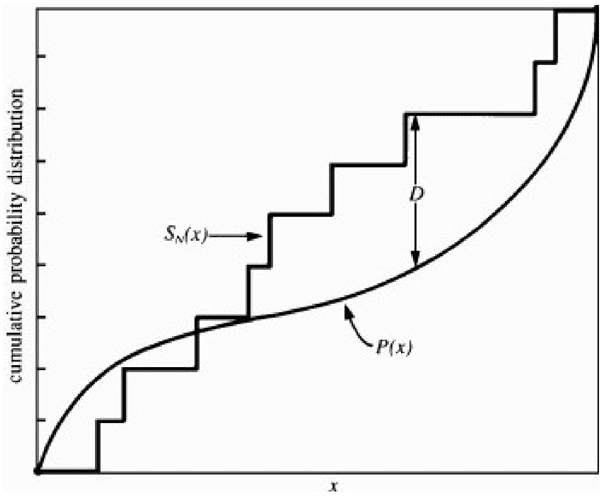


Figure 4.5: Kolmogorov-Smirnov test [19]

The test returns a test decision for the null hypothesis that the empirical comes from a parametric distribution, against the alternative that it does not come from such a distribution. The result h is 1 if the test rejects the null hypothesis at the 5% significance level, or 0 otherwise. Note that the algorithm of `kstest()` does not actually compare the distance, D, to the critical value, since the critical value is also an estimate. Instead, it compares the p-value to the significance level α. p is the probability, given the null hypothesis, of observing a test statistic as extreme as, or more extreme than, the observed value. Small values of p question the validity of the null hypothesis. Thus, when the p-value is lower than the significance level, the null hypothesis is rejected.

4.3.1. Data-driven parameter estimation for push-back

The first distribution to be determined is the duration of push-back, D_{PB}. This distribution is created by combining the obtained push-back duration from all flights that are analysed. The distribution is determined using flights that departed from a push-back gate, as explained in section 4.2.2. Flights where the gate location deviated more than 200 meters from the actual start location are not included in the distribution. In this case, the pilot probably turned on the transponder too late and the aircraft is already taxiing.

The push-back process is assumed to be a process that is normally distributed. The histogram with a distribution fit and cumulative distribution function (CDF) for the empirical distribution and the normal fit is found in figures 4.6 and 4.7.

The Kolmogorov-Smirnov test rejects the null hypothesis, thus it can be concluded that the push-back distribution is not a normal distribution. Since the normal distribution does not accurately describe the push-back process, it is possible to use a Kernel probability distribution instead. Figures 4.8 and 4.9 show the kernel fit compared with the empirical data. The result of the Kolmogorov-Smirnov test with a 5% significance level states that the kernel fit and the empirical data are equal.

4.3.2. Data-driven parameter estimation for unimpeded taxi-out time

Next, the distribution for unimpeded taxi-out time, D_{uTXOT} is created. The unimpeded taxi-out time depends on the distance between the gate and the runway [7]. Hence, the unimpeded taxi-out time should be calculated for each combination of gate and runway. On the other side, it is important to have enough data points to create a distribution. When taking these two requirements into account, it is best to make a distribution of the unimpeded taxi-out time for a group of gates. A group of gates

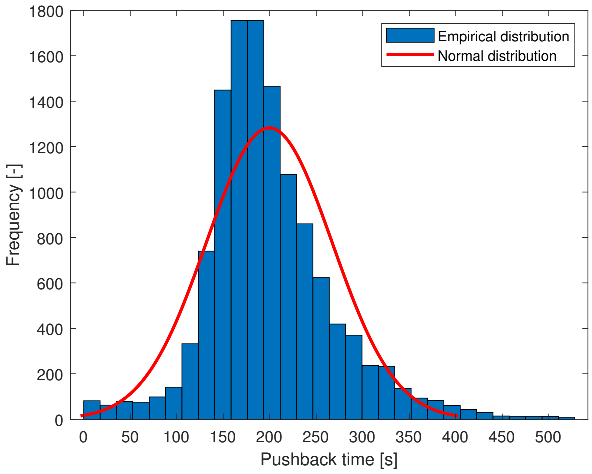


Figure 4.6: Histogram of push-back duration with a normal distribution

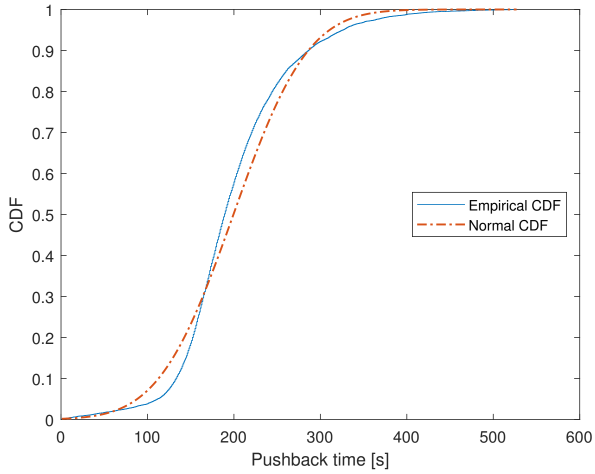


Figure 4.7: CDF of push-back duration with a normal distribution

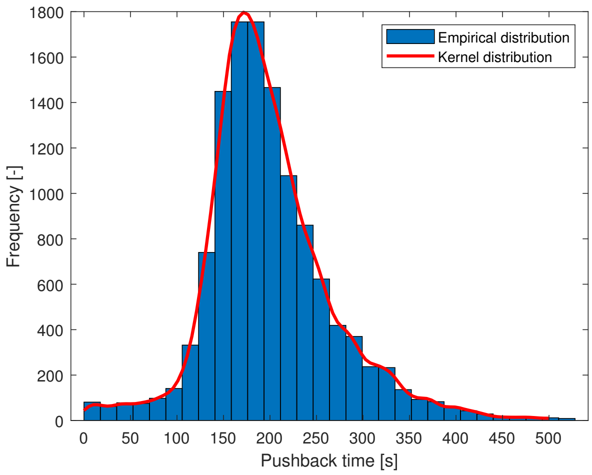


Figure 4.8: Histogram of push-back duration with a kernel distribution

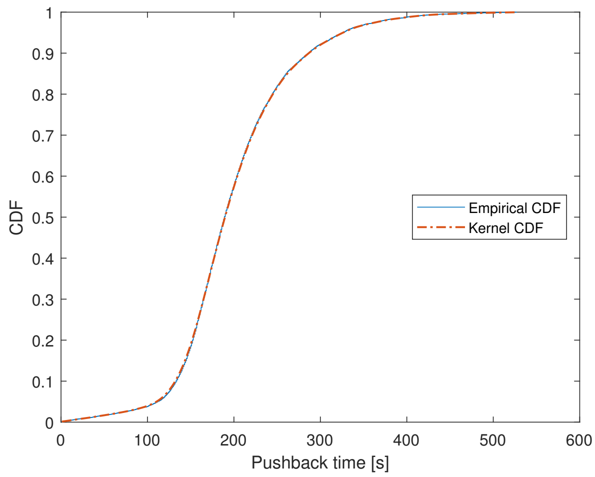


Figure 4.9: CDF of push-back duration with a kernel distribution

is defined as several gates that are close to each other and prove to have similar unimpeded taxi-out times. An analysis of the median unimpeded taxi-out time is performed to decide which gates should be combined in a gate group. The table containing the median unimpeded taxi-out time for each gate is found in appendix B. This appendix also contains two airport maps in which the gate groups are defined. The gates are divided in 13 groups that each have their own distribution for unimpeded taxi-out time. A 14$^{\text{th}}$ group is created from flights that have no gate information.

The empirical distribution for unimpeded taxi-out time is fitted with a normal distribution, as can be seen in figure 4.10. Figure 4.11 shows the CDF for both the empirical and fitted distribution. These figures are made for gate group C1, which consists of seven adjacent gates on the West Pier of the airport. The unimpeded taxi-out time distributions for all gate groups is found in appendix C.

When visually comparing the empirical and normal distribution, the normal distribution seems to be a good fit. This is not only the case for gate group C1, but also the gate groups that is found in appendix C. The goodness of fit is again determined using the Kolmogorov-Smirnov test with a 5% significance level. The results for all gate groups is found in table 4.6, which shows that for nine groups the Kolmogorov-Smirnov test concludes that the sample belongs to the normal distribution. Although the test results for the other five groups suggest that those distributions are not normal, it is decided to still use a normal fit for all gate groups.

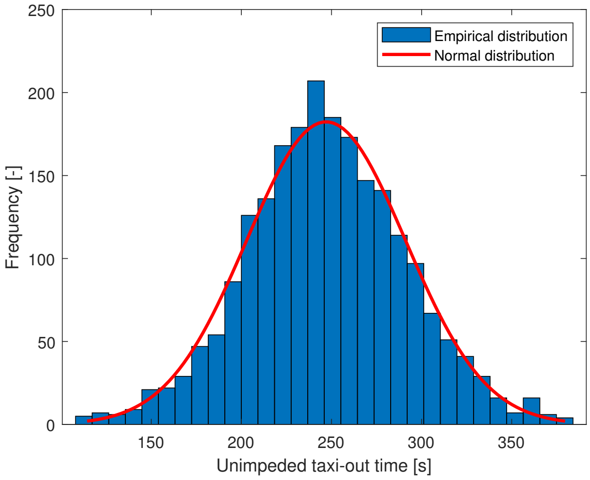


Figure 4.10: Histogram of unimpeded taxi-out time - Group C1

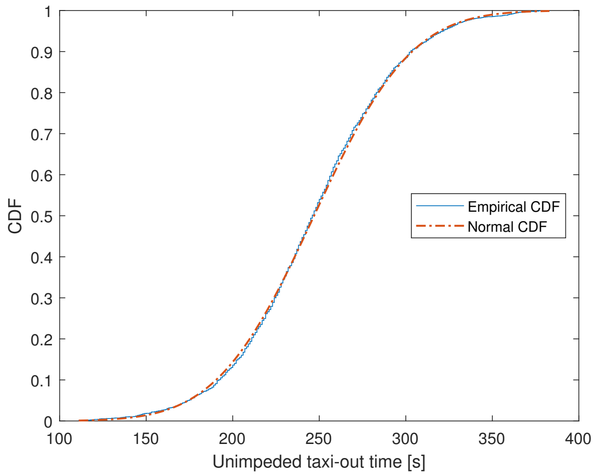


Figure 4.11: CDF of unimpeded taxi-out time - Group C1

Table 4.6: Results of Kolmogorov-Smirnov test for each group of gates

Gate group	KS-test result	Gate group	KS-test result
AB	h = 1	F1	h = 1
C1	h = 0	F2	h = 1
C2	h = 0	F3	h = 0
D1	h = 0	GAW	h = 0
D2	h = 0	H	h = 0
E1	h = 1	K	h = 0
E2	h = 1	none	h = 0

4.3.3. Data-driven parameter estimation for additional taxi-out time

Furthermore, the distribution for additional taxi-out time is determined. Many flights departing from Vienna airport, do not encounter additional taxi-out time, since they are not interrupted during the taxi process. Therefore, the percentage of flights that have no additional taxi-out time is first determined. For the available data sample this percentage equals 33.1% of the flights. For the percentage of flights that do encounter an additional taxi-out time, a distribution is created. This distribution has a shape most similar to an exponential distribution, which is why this distribution is chosen as fit. Figures 4.12 and 4.13 show the empirical distribution and exponential fit for the additional taxi-out time. The percentage that have no additional taxi-out time and the distribution can be combined as in equation 4.1, where the random variable D_{aTXOT} represents the duration of the additional taxi-out time of a flight. The rate parameter of the exponential distribution, given by λ, equals 36.

$$D_{\text{aTXOT}} = \begin{cases} 0 & \text{with} \quad p = p_{\text{No aTXOT}} \\ exp(\lambda) & \text{with} \quad p = 1 - p_{\text{No aTXOT}} \end{cases} \tag{4.1}$$

According to the Kolmogorov-Smirnov test with a 5% significance level, the empirical distribution cannot be modelled as an exponential distribution, since the test rejects the null hypothesis. As an alternative the kernel distribution can be used, as is done for the push-back distribution. Figures 4.14 and 4.15 show the empirical distribution of the additional taxi-out time in combination with a kernel distribution.

Although the CDF of the kernel distribution is a perfect fit, the histogram in figure 4.14 indicates that the kernel distribution does not accurately represent the empirical distribution. When looking at low values for the additional taxi-out time, the exponential fit is a more realistic fit, as the additional taxi-out time cannot contain negative values. Therefore, it is decided to model the additional taxi-out time as an exponential distribution with λ equal to 36.

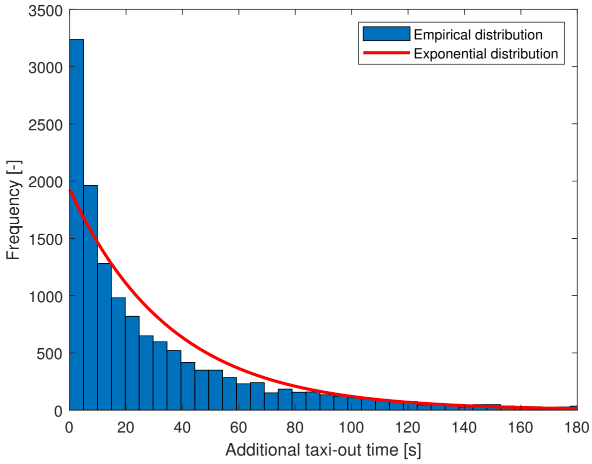


Figure 4.12: Histogram of additional taxi-out time and an exponential fit

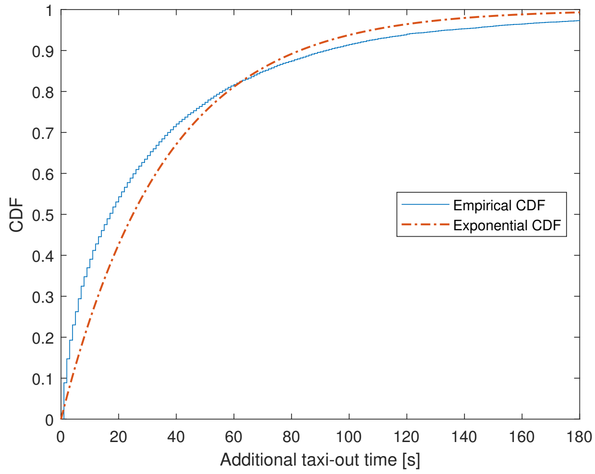


Figure 4.13: CDF of additional taxi-out time and exponential fit

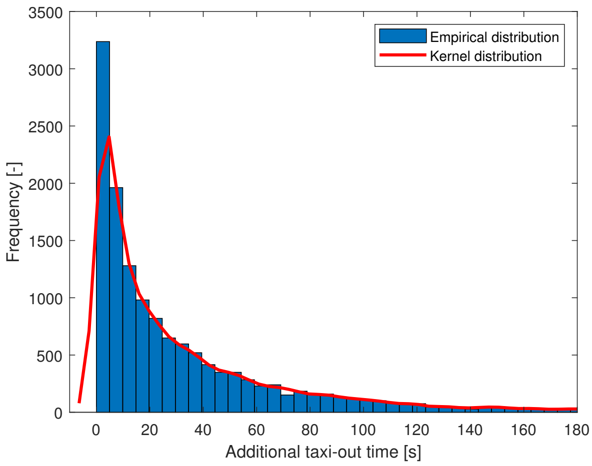


Figure 4.14: Histogram of additional taxi-out time and kernel fit

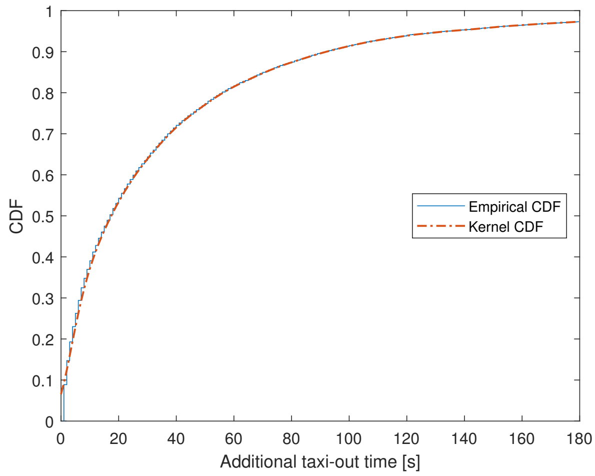


Figure 4.15: CDF of additional taxi-out time and kernel fit

4.3.4. Data-driven parameter estimation for departure runway occupancy time

The distribution for departure runway occupancy time is determined for every ICAO weight category. Currently there are three weight categories, light (L), medium (M) and heavy (H), determined by the maximum take-off weight. For each flight in the data sample, the weight category is known. It is chosen to make separate distributions based on weight category, because heavy aircraft generally need more time to take-off. Figures 4.16 and 4.17 show the histogram and CDF of the departure runway occupancy time for medium aircraft, since more than 90% of the flights that depart from Vienna Airport are medium weight aircraft. The distribution that is chosen as fit is the gamma distribution, because it outperforms the normal and exponential distribution when comparing the distributions visually.

The distributions for all three weight categories are found in figures D.1 until D.6 in appendix D. When looking at figure D.5 in the appendix, it can be seen that the histogram for light aircraft does not follow the same shape of distribution as medium and heavy aircraft. It actually consists of two separate distributions. This may be explained due to the fact that light aircraft can enter the runway halfway, since they do not need the entire runway to take-off. The departure runway occupancy time will therefore be different, as this probably is a rolling take-off, which takes less time than a normal take-off where the aircraft first has to wait for clearance on the runway. In a rolling take-off, the clearance is already given before the aircraft enters the runway. The exact reason for the occurrence of two different distributions for light aircraft is not investigated, since only 2% of the flights consists of light aircraft. Therefore, the distribution of light aircraft only has a small influence in the total simulation.

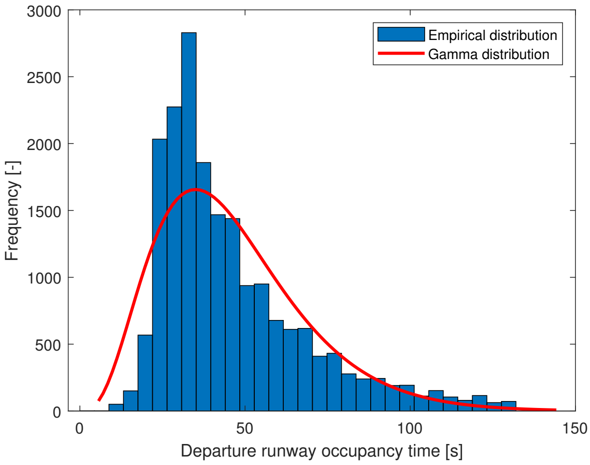


Figure 4.16: Histogram of departure runway occupancy time for medium aircraft. Empirical distribution with a gamma fit.

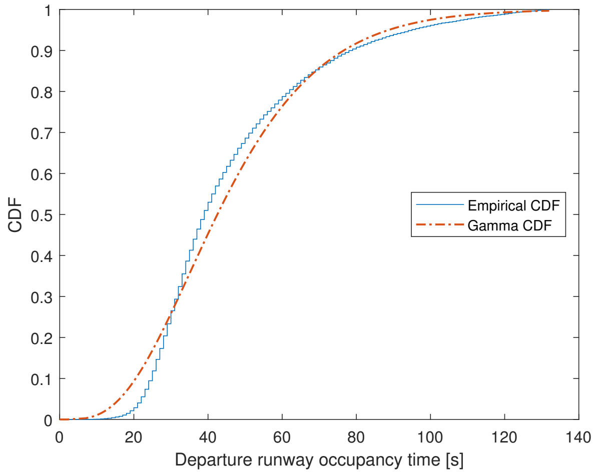


Figure 4.17: CDF of departure runway occupancy time for medium aircraft. Empirical data and a gamma fit.

The Kolmogorov-Smirnov test with a 5% significance level states that the empirical distribution for medium aircraft is not equal to the gamma distribution that is fitted through the data. This is also the case for light and heavy aircraft. Again, the alternative option is to fit the non-parametric distribution, the kernel distribution, through the data. The distributions for medium aircraft with a kernel fit are shown in figures 4.18 and 4.19. The distributions with a kernel fit for all weight categories are found in figures D.7 until D.12 in appendix D. For modelling purposes, the gamma distribution does not have a benefit over the kernel distribution and since the kernel estimation shows a better fit, it is decided to use this distribution in the model.

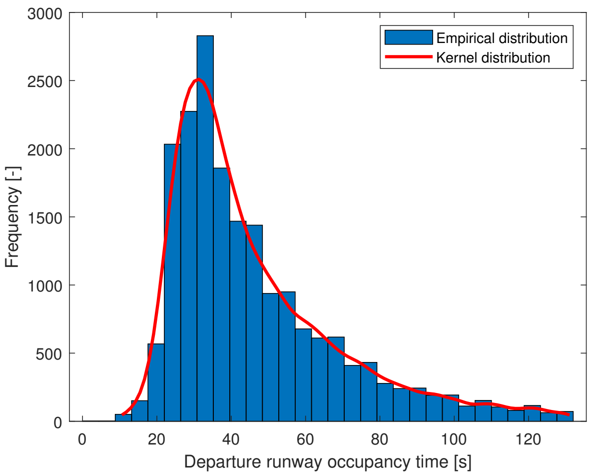


Figure 4.18: Histogram of departure runway occupancy time for medium aircraft. Empirical distribution with a kernel fit.

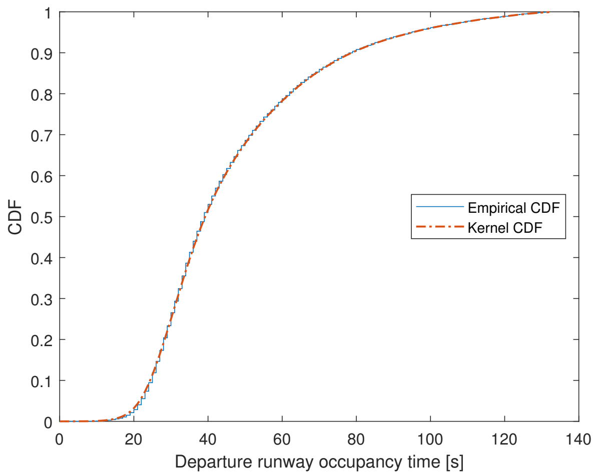


Figure 4.19: CDF of departure runway occupancy time for medium aircraft. Empirical data and kernel distribution.

4.3.5. Data-driven parameter estimation for service time

The service time between two aircraft is of great importance to the queue waiting time, as it controls how fast the aircraft can leave the queue. To determine the service time, the duration between two consecutive take-offs is analysed. According to Simaiakis[16], this is a good indication to determine the service time. All the flights in the data sample are sorted based on actual take-off time (ATOT) and the difference in ATOT is determined. This method can only be used when it is certain that the two consecutive aircraft take-off immediately after each other. Otherwise, the time between take-offs is much larger than the service time, because there was simply not enough demand at the runway. Therefore, the service time is defined as difference in ATOT between consecutive aircraft, given that the following aircraft has been waiting in queue.

The resulting distribution is found in figure 4.20. The service time is fitted with a gamma distribution, since it is found in chapter 2 that it is common to use a gamma or Erlang distribution. As explained before, the Erlang distribution is a special case of the gamma distribution and thus the gamma distribution will result in a better fit. The cumulative distribution function of the empirical data and the gamma distribution is shown in figure 4.21.

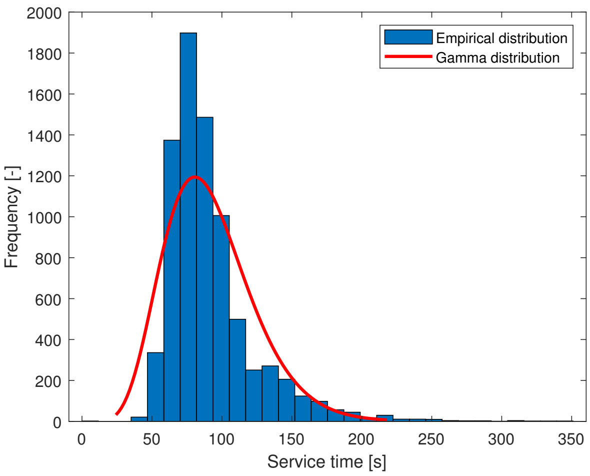


Figure 4.20: Histogram of service time

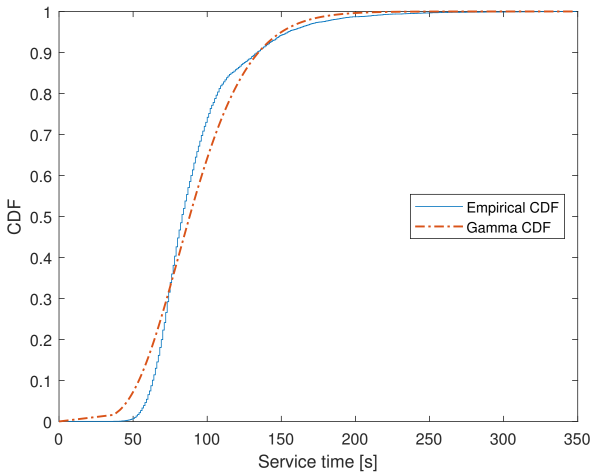


Figure 4.21: CDF of service time

The Kolmogorov-Smirnov test with a 5% significance level rejects the null hypothesis that the empirical distribution is equal to the gamma distribution. However, it is common to model the service time as a gamma distribution and a visual comparison of the CDF shows that the empirical distribution is very similar to the gamma distribution. It is also possible that the empirical data is not perfect, since it is determined from the data by using some assumptions. Therefore, it is decided to use the gamma distribution as input to the simulation model.

4.4. Distributions for multiple runways and mixed-mode operations

This section describes the distributions that are needed when extending the model to facilitate mixed-mode operations on the second runway. When modelling two runways, there is a shared taxi system that is used by flights from both runways. The distributions that are needed to model the shared taxi system are push-back, unimpeded taxi-out time and additional taxi-out time. Furthermore, the multiple runways model also requires a distribution for departure runway occupancy time for the second runways. Section 4.4.1 explains how the interactions in the taxi system are modelled and what distributions are used as input to the simulation. Section 4.4.2 provides the distributions that are needed when modelling mixed-mode operations.

4.4.1. Data-driven parameter estimation for distributions in shared taxi system

As explained in section 3.3, the interactions between aircraft are modelled by analysing the additional taxi-out time. This part of the taxi-out time should increase when the system becomes more complex. Figures 4.22 and 4.23 show that there is a trend visible between the additional taxi-out time and the number of aircraft in the system. It can be seen that the percentage of flights that do not encounter any additional taxi-out time decreases when the number of aircraft in the system increases. Also, the mean additional taxi-out time of flights with an additional taxi-out time increases as the system becomes busier. These relations are visible for flights departing from both runways, but there appears to be a stronger relation for flights departing at runway 34. This can be explained by the graphical lay-out of the airport, see appendix A, where flights taxiing to runway 34 have to pass the entry of runway 29.

It is decided to model the additional taxi-out time based on the number of aircraft in the system. For the six groups displayed in figures 4.22 and 4.23 a distribution is created in the same way as explained in section 4.3.3. First, the percentage of flights without an additional taxi-out time is determined, then the distribution of additional taxi-out time of the other flights is fitted with an exponential distribution. The

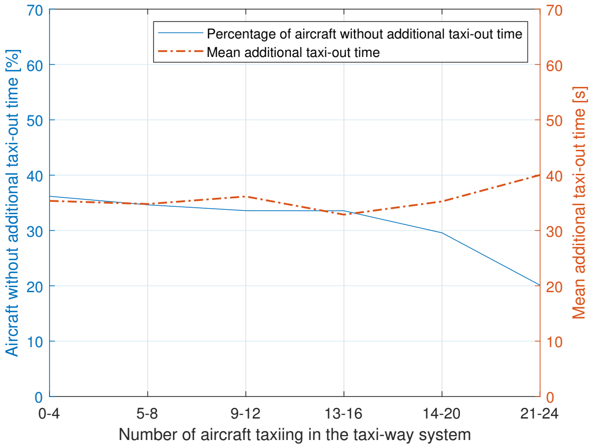


Figure 4.22: Relation between the number of aircraft in the system and the additional taxi-out time for flights departing at R29

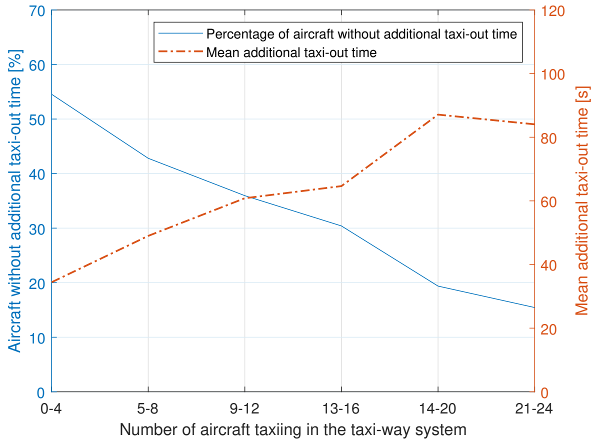


Figure 4.23: Relation between the number of aircraft in the system and the additional taxi-out time for flights departing at R34

probability that a flight does not encounter additional taxi-out time is displayed in table 4.7.

The probability that a flight does not encounter additional taxi-out time varies quite a lot for flights departing from runway 29 and flights departing from runway 34. Also figure 4.22 indicates that the relation is stronger for aircraft taxiing to runway 34. Therefore, it is decided to separate the probabilities and the distributions per runway. The distributions, with the exponential fit, are found in figures E.1 until E.24 in appendix E. These distributions are used as input to the model when both runways are simulated.

Table 4.7: Probability that a flight does not encounter additional taxi-out time for increasing number of aircraft in the system

Number of aircraft	**Probability that a flight does not encounter additional taxi-out time**	
	Departing from runway 29	**Departing from runway 34**
0-4	0.362	0.597
5-8	0.346	0.511
9-12	0.336	0.451
13-16	0.336	0.397
14-20	0.296	0.297
21-24	0.201	0.246

When looking back to the representation of the departure process for multiple runways in figure 3.3, it can be seen that push-back and unimpeded taxi-out time also take place in the shared taxi system. It is expected that the push-back process for aircraft that depart at runway 29 is comparable with the push-back process for aircraft that depart at runway 34, since the departure runway does not influence the push-back duration. Also, it is expected that the unimpeded taxi-out time distributions for aircraft departing at both runways show a similar shape, with an offset for flights departing at runway 34, since these flights need to travel a longer distance before they reach the runway. A Kolmogorov-Smirnov test is executed to test these expectations.

Figure 4.24 shows cumulative distribution functions of the push-back duration for flights departing from runway 29 and flights departing from runway 34. Visually, both distribution functions are almost equal. The result of the Kolmogorov-Smirnov test with a 5% significance level states that the null hypothesis is not rejected, therefore the distributions are equal to each other. The data of both distributions is added together, after which the Kernel distribution is fitted through the data. The resulting distribution and CDF are shown in figures E.25 and E.26 in appendix E.

Figure 4.25 shows the cumulative distribution functions of the unimpeded taxi-out time for flights departing from runway 29 and runway 34. This figure is created from all available data, so there is no distinction between gate groups, because the goal is to check for a similar shape. The distributions for all gate groups in section 4.3.2 are modelled by a normal distribution, which is the typical S-shape visible in figure 4.25. As expected, there is an offset visible between the two cumulative distribution functions. The offset equals roughly 3.5 minutes, which means that the unimpeded travel time to runway 34 is on average 3.5 minutes longer. It is concluded that the unimpeded taxi-out time for flights departing at runway 34 should also be modelled by a normal distribution.

Appendix E shows the distributions for each group of gates for R34 flights. These distributions, shown by figures E.27 until E.54, are used as input to the simulation. Table 4.8 states the test results of the Kolmogorov-Smirnov test with a significance level of 5%. The results show that the normal distribution is indeed a good fit for the unimpeded taxi-out time.

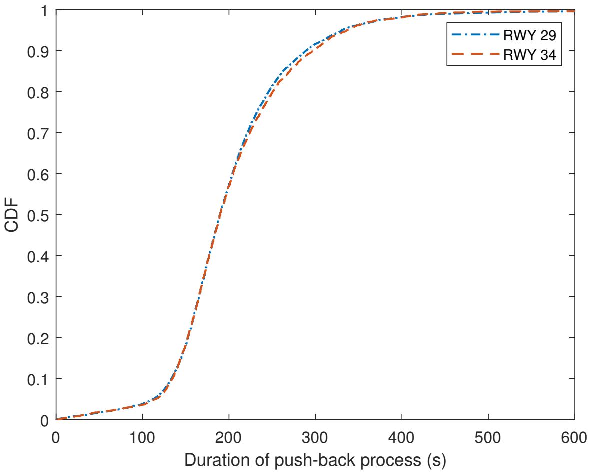


Figure 4.24: CDF of push-back duration for flights departing at runway 29 and runway 34

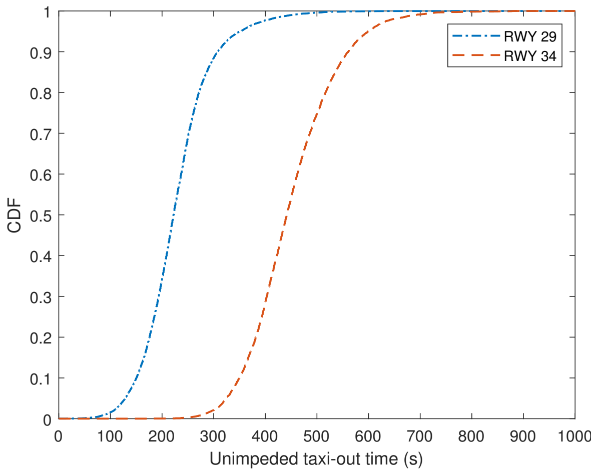


Figure 4.25: CDF of unimpeded taxi-out time for flights departing at runway 29 and runway 34

Table 4.8: Results of Kolmogorov-Smirnov test for each group of gates for flights departing from runway 34

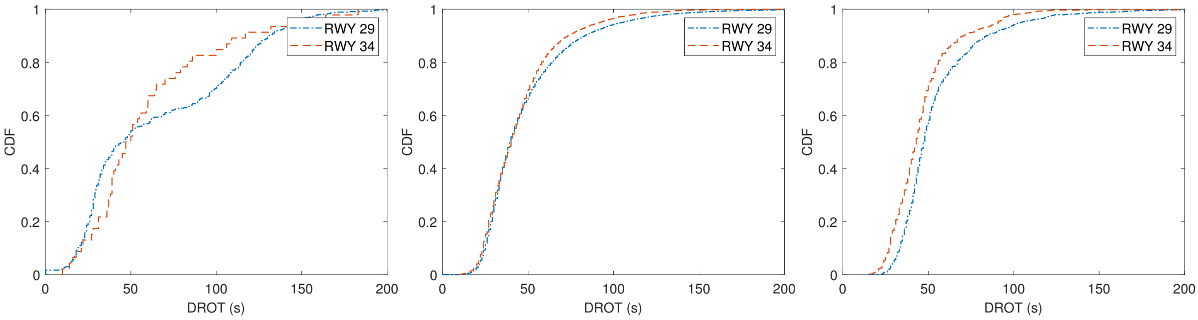
Gate group	KS-test result	Gate group	KS-test result
AB	h = 0	F1	h = 0
C1	h = 0	F2	h = 1
C2	h = 0	F3	h = 0
D1	h = 0	GAW	h = 0
D2	h = 0	H	h = 0
E1	h = 0	K	h = 0
E2	h = 0	none	h = 0

Finally, the representation of the departure process in figure 3.3 shows that the distribution of the departure runway occupancy time is needed for both runways. To check whether it is possible to combine the DROT distributions from runway 29 and runway 34, a two-sample Kolmogorov-Smirnov test with a 5% significance level is performed. The test states that for all three weight categories the null hypothesis is rejected. This means that the take-off procedures at both runways are slightly different and should be modelled by different distributions. The CDF comparison is given in figure 4.26.

The distributions of the departure runway occupancy time for runway 34 are modelled similar to the distribution for runway 29, as explained in section 4.3.4. The distributions are fitted with a Kernel distribution. The CDF of each of the distributions is presented in figures E.55 until E.60 in appendix E.

4.4.2. Data-driven parameter estimation for distributions required for modelling mixed-mode operations

When modelling mixed-mode operations using the second model, a distribution of the runway waiting time is required. This section describes this distribution is obtained from the data. The runway waiting time is determined by analysing historic data to determine the runway waiting behaviour. First, the



(a) Light (b) Medium (c) Heavy

Figure 4.26: CDF of departure runway occupancy time for flights departing at runway 29 and runway 34 for each weight category

probability that aircraft have to wait, given that they are not waiting in queue, is determined. Next, the duration of the runway waiting time is determined and used to create a distribution.

The probability that an aircraft has to wait at runway entry is determined by analysing the flight profile. When an aircraft meets all the requirements to be in queue, given in section 4.2.2, except the previous aircraft is not in service or waiting in queue, it is assumed that the aircraft is waiting at the runway entry for an arriving aircraft. Using the definition from section 4.2.2, this means that aircraft is waiting for runway entry when the groundspeed is lower than 7 kts, the aircraft is within 300 meters of entering the runway and the aircraft is not waiting for previous departures. The available data proves that the probability equals 0.76. This means that roughly 75% of the flights do not encounter runway waiting time.

The distribution for runway waiting time is given in figure 4.27. It is chosen to use an exponential fit, since other parametric and non-parametric distributions include negative values in the fit. Since the waiting time is always equal or larger than zero, the exponential distribution is the best option. Even though the Kolmogorov-Smirnov test rejects this distribution. This distribution is used as input when mixed-mode operations are modelled without using information on arrivals.

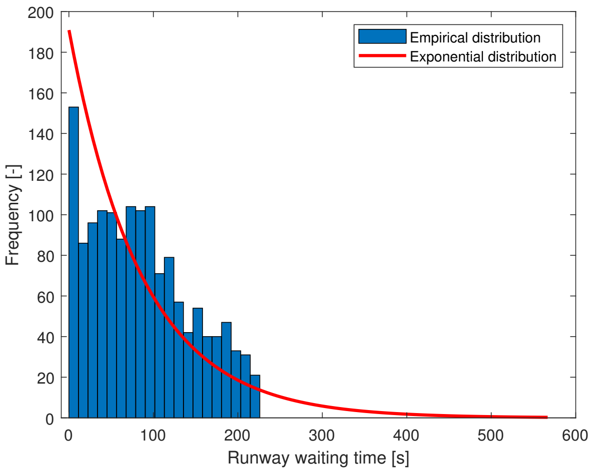


Figure 4.27: Histogram of runway waiting time for departing flights that are ready at runway entry 34

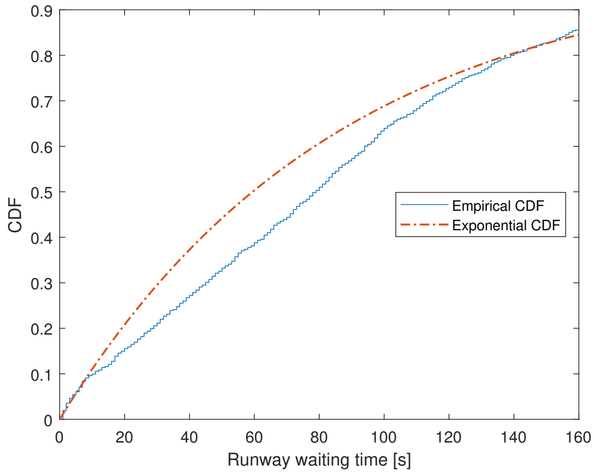


Figure 4.28: CDF of runway waiting time for departing flights that are ready at runway entry 34

4.5. Outlier removal

In sections 4.3 and 4.4 it is defined how the data is grouped in order to obtain the distributions needed in the model. For each group of data, outliers are removed from the empirical distribution before it is fitted with a parametric or non-parametric distribution. This is also visualised in the flowchart depicted in figure 4.4. This section explains the method of outlier removal and gives the amount of outliers that are removed in the process.

Outliers are removed from the data by using the function `isoutlier()` from MATLAB®. The method for detecting outliers is to identify all elements that deviate more than three standard deviations from the mean. The standard deviation, S, is given by equation 4.2, where A is a vector of N observations. The mean of A, μ, is defined in equation 4.3.

$$S = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(A_i - \mu)^2} \tag{4.2}$$

$$\mu = \frac{1}{N}\sum_{i=1}^{N}A_i \tag{4.3}$$

The results of the outlier removal process for the distributions used in the segregated operations model are given in table F.1 in appendix F. The method of outlier detection is especially useful for data that is normally distributed, because three standard deviations from the mean includes 99.7% of the data sample. For a standard normal distribution, the outlier removal method should therefore delete 0.3% of the data. It can be seen in table F.1 that for unimpeded taxi-out time, which is modelled by a normal distribution, between 0 and 2% of the data is removed. For data that is not normally distributed this method is less suited. However, when analysing the percentages of push-back, additional taxi-out time, departure runway occupancy time and service time, it can be seen that this method does not remove more than 2% of the data.

Table F.2 in appendix F shows the amount of outliers that is removed from data that is used in the mixed-mode operations model. The table includes additional data, specified by 'R34', and data that is used instead of data used in the segregated model, specified by 'R29'. The data used for the push-back distribution is merged for both runways.

5
Results

This section presents and analyses the results of the case study at Vienna Airport. The distributions that are determined in chapter 4 are used as input in the theoretical model from chapter 3. The model simulates seven days. Six of those seven days are chosen randomly from the data sample, while the seventh day is the busiest day of the sample. During these days, the configuration D29M34 is used for at least 7 hours. This indicates that the airport is using this configuration for at least half of the daytime period. The days that are simulated are given in table 5.1. This table also presents the average hourly throughput, determined by dividing the total amount of flights, arrivals and departures, by the number of hours that the D29M34 configuration is in use. It can be seen that the 18th of September is the busiest day on average.

Table 5.1: Random days for simulation with their average hourly throughput (arrivals and departures)

Date	Average hourly throughput
18-08-2015	41.6
18-09-2015	48.1
28-09-2015	44.2
04-11-2015	38.8
09-11-2015	38.6
27-11-2015	41.7
10-12-2015	40.7

A Monte Carlo simulation with 10,000 simulations is used to determine the results presented in this chapter. Section 5.1 presents the results for segregated operations on a single runway. Section 5.2 gives the results for mixed-mode operations and multiple runways. Finally, the results of the two runways combined are presented in section 5.3.

5.1. Segregated operations on a single runway

This section presents the result of the segregated operations model discussed in section 3.2. For the case study at Vienna Airport, this means that only departing flights from runway 29 are simulated. Over seven days there are 1152 flights that depart from runway 29.

5.1.1. Flight specific information

The first result that is obtained from the simulation is flight specific information. This information is useful for air traffic controllers who would like know with how much certainty they can estimate the take-off time. Figure 5.1 shows a histogram of the duration of the departure process for a flight departing at the 18th of September from runway 29. The take-off time is determined by adding the flight departure duration to the actual off-block time.

The expected duration of the departure process is given by the mean value in table 5.2. This table also shows the lower and upper limits of the confidence interval. The confidence interval states that

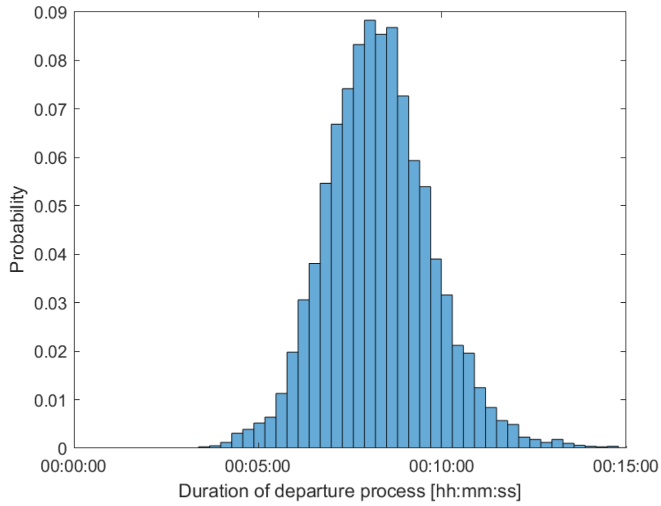


Figure 5.1: Probability density function of the duration of the departure process of a flight departing from runway 29 at the 18th of September

with 95% confidence, the expected value lies between 8 minutes and 15 seconds and 8 minutes and 19 seconds. The confidence interval depends on the standard deviation and the number of simulations, as stated in equation 5.1. In this equation, $\overline{X}$ is the mean value, s is the standard deviation and n equals the number of simulations.

$$CI = \overline{X} \pm 1.96 \frac{s}{\sqrt{n}} \tag{5.1}$$

Table 5.2: Mean, confidence interval and standard deviation of duration of departure process

Metric	**Duration [hh:mm:ss]**
Mean	00:08:17
Lower limit confidence interval	00:08:15
Upper limit confidence interval	00:08:19
Standard deviation	00:01:28

The standard deviation is a good way to give an indication about the spread of the distribution. For normal distributions, two standard deviations from the mean states that 95% of the distribution is included. For this flight, it would mean that in 95% of the cases, the duration of the departure process lies between 00:05:19 and 00:11:11. However, note that this only holds if the distribution is normal.

5.1.2. Comparison with actual data

The comparison with actual data is made to see how well the model can predict the duration of the departure process. Figures 5.2 and 5.3 show the probability density function and cumulative distribution function of the total flight departure duration. The distribution with the actual duration is found by computing the process duration for each flight. The distribution with the estimated duration is determined by combining all simulation results for all flights. For 10,000 simulations and 1152 flights, this adds up to 11.5 million data points, which are used to create the PDF and CDF.

It can be seen that the actual and estimated distributions are similar, although the simulation slightly overestimates the actual duration. Since this overestimation is constant throughout the results, it is most-likely related to an assumption. One of the assumptions that could result in overestimation is related to the service time. As explained in section 4.3.5, the service time is determined by the time between two take-offs, given that the following aircraft was waiting in queue. If this assumption results in an overestimation of the service time, it will automatically result in a higher queue waiting time. This

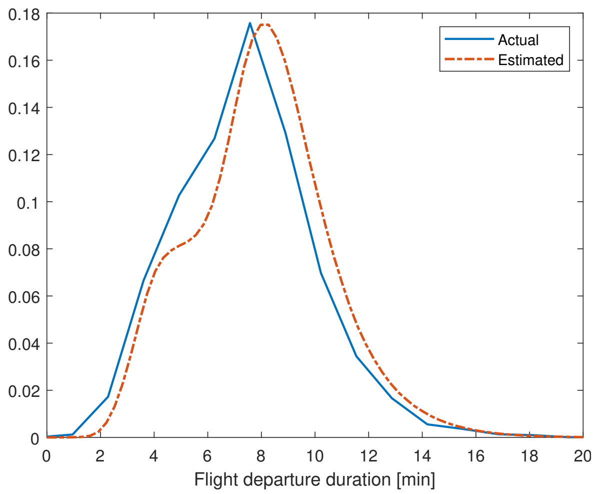


Figure 5.2: PDF of actual and simulated duration of departure process

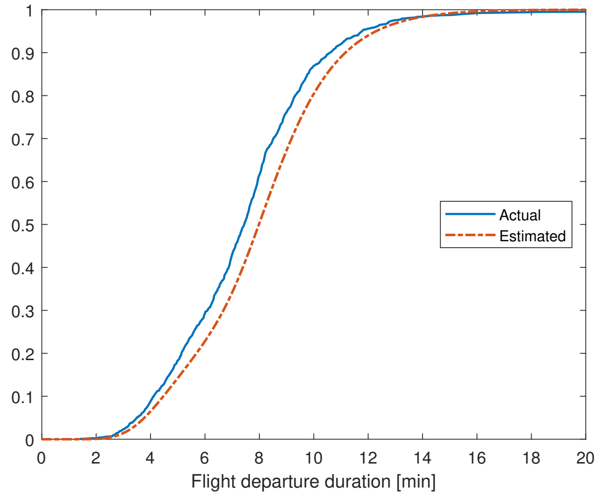


Figure 5.3: CDF actual and simulated duration of departure process

can be checked by plotting the cumulative distribution function of the queue waiting time.

Figure 5.4 shows the CDF for actual and simulated queue duration. The graph immediately shows that the percentage of flights that have no waiting time is roughly 15% lower in the simulation, compared with actual data. Therefore, the average waiting time for in simulation is higher than in the actual data. This graph shows that the queue waiting time is indeed overestimated in the simulation, which can be explained by an overestimation of the service time. Since there is no other distribution involved in the queue module, this is the most-likely cause of the difference between actual data and the simulation.

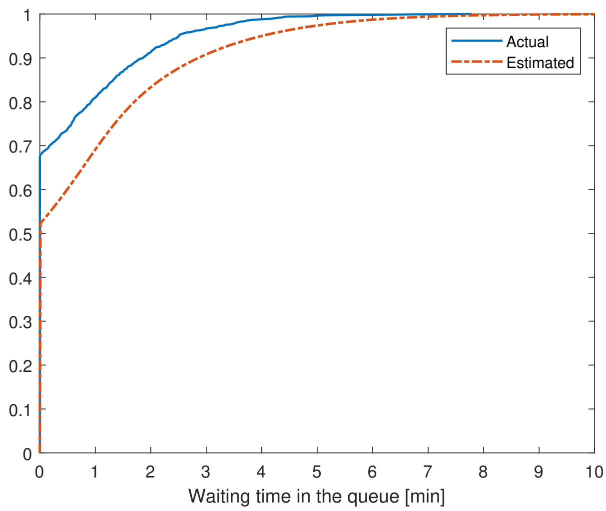


Figure 5.4: CDF actual and simulated queue duration

Next to comparing the entire distribution of the simulation with the distribution of the actual data, it is possible to compare the expected process duration with the actual process duration. This comparison is made per flight and results in an error. For a single flight, this error is usually quite large, but the average error shows how well the model is performing. Table 5.3 states the mean error, the mean absolute error and the root mean square error for the duration of the entire departure process and the waiting time in the queue.

It can be seen that the simulation overestimates the actual duration by 0.55 minutes. This is in line with the overestimation displayed in figures 5.2 and 5.3. Furthermore, the mean absolute error shows that the simulation is on average 1.57 minutes off, either due to a lower estimate or due to a higher estimate.

Table 5.3: Error between the estimated duration and the actual duration of the flight departure from gate to take-off - runway 29, segregated operations, 7 days.

	ME	MAE	RMSE
Departure duration from gate to take-off (min)	0.55	1.57	2.08
Waiting time in the queue (min)	0.41	0.76	1.19

Figure 5.5 shows the cumulative error of the take-off time. The S-shape indicates that the error is normally distributed. Errors smaller than -2 minutes and larger than 4 minutes do not occur often. The cumulative error is located more to the right, with respect to zero, which indicates that the simulation overestimates the actual take-off time.

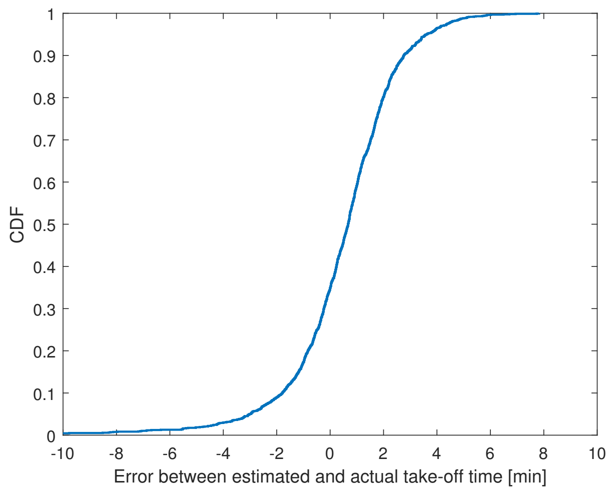


Figure 5.5: CDF of error between estimated and actual take-off time, runway 29

Figure 5.6 shows the departure actual and estimated departure throughput per 15 minutes on 18th of September. 18th of September is the busiest day in the data sample, since the average hourly throughput (both arrivals and departures) is highest on this day. From 4:00AM until 7:00PM, the D29M34 configuration is used. It can be seen that the model estimation and the observed number of departures per 15 minutes match well.

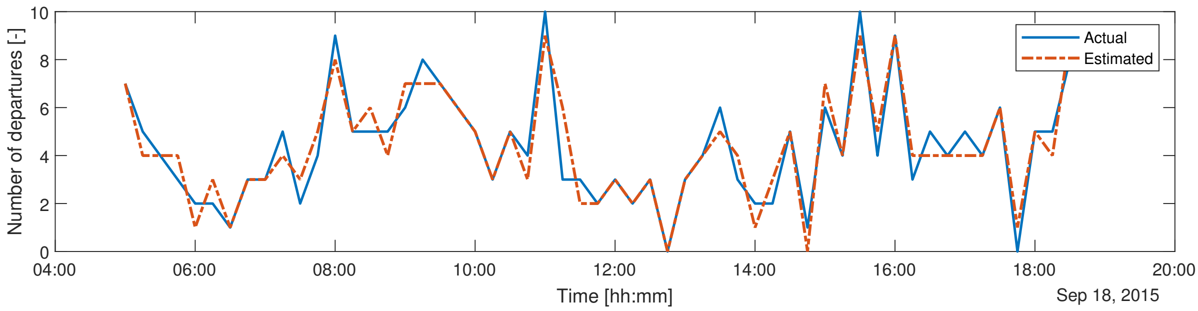


Figure 5.6: Actual and estimated number of departures per 15 min, 18th Sept 2015.

Figure 5.7 shows the actual and estimated mean duration of the departure process per 15 minutes on the 18th of September. The actual and estimated values are in line with each other, although sometimes differences of a couple of minutes exist. This is explained by the fact that in quiet periods, where only one or two aircraft depart, the average is also only based on one or two flights. This can result in large deviations in the graph.

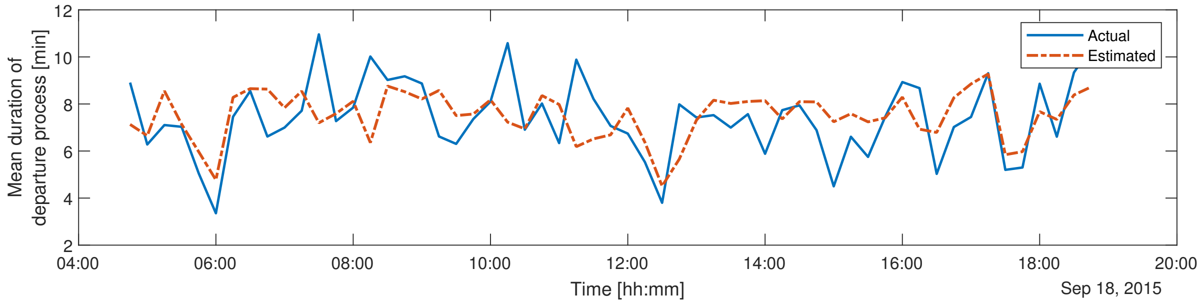


Figure 5.7: Actual and estimated mean flight departure duration per 15 min, 18th Sept 2015.

5.2. Mixed-mode operations

This section presents the results of the two models for mixed-mode operations discussed in section 3.3. The first model uses the arrival schedule to determine the runway availability. The second model uses historical data to determine the runway availability. For the case study at Vienna Airport, runway 34 is used for mixed-mode operations. Over seven days there are 462 flights that depart from runway 34.

5.2.1. Flight specific information

Figures 5.8 and 5.9 show the probability density function of a randomly chosen flight that departs from runway 34. These figures depict the difference between both models. The histogram of the first model has a gap around 14 minutes. This gap is created due to an unavailable runway, based on the arrival schedule. This means that when the aircraft would arrive at the runway just after the runway became unavailable, it has to wait for a few minutes. The largest part of the simulations could depart before the arrival blocked the runway, but as soon as the travel time would be a bit too long, the total duration of the departure process would immediately increase by a few minutes.

The histogram of the second model, depicted in figure 5.9 shows a regular distribution. Since the waiting time depends on historically available data, the probability of encountering an unavailable runway is equal for every simulation. This results in a smooth distribution.

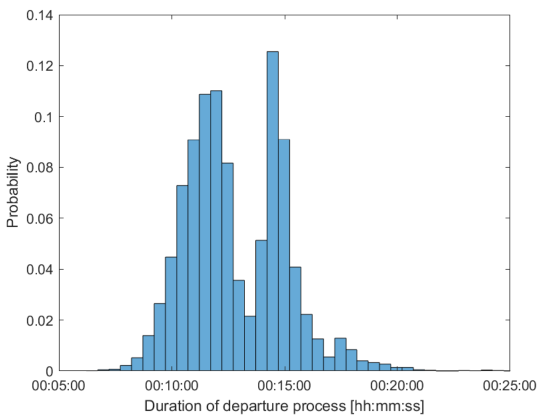


Figure 5.8: Probability density function of the departure process duration of a flight departing from runway 34 at the 4th of November. Simulation results of model 1.

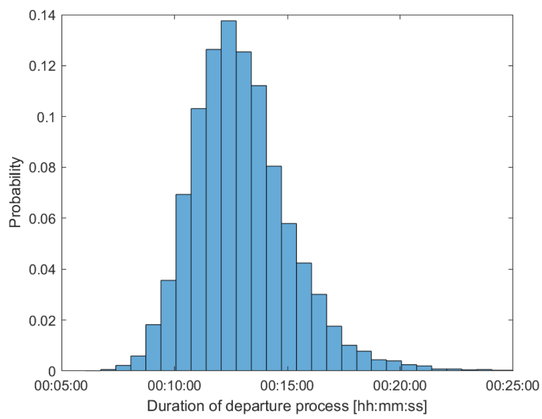


Figure 5.9: Probability density function of the departure process duration of a flight departing from runway 34 at the 4th of November. Simulation results of model 2.

5.2.2. Comparison with actual data

Figures 5.10 and 5.11 show the probability density functions for both models. It can be seen that there is little difference in PDF between the two models. Both models overestimate the actual duration, as was the case for the segregated model as well. Since the same service time distribution is used in all model, this is still a probable reason.

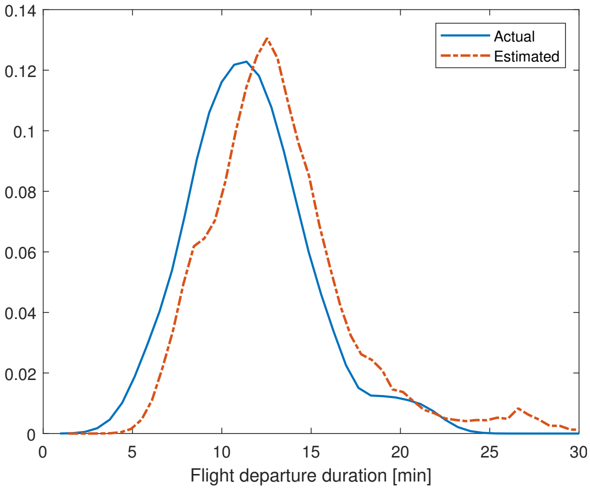


Figure 5.10: PDF of actual and simulated duration of departure process with mixed-mode model 1

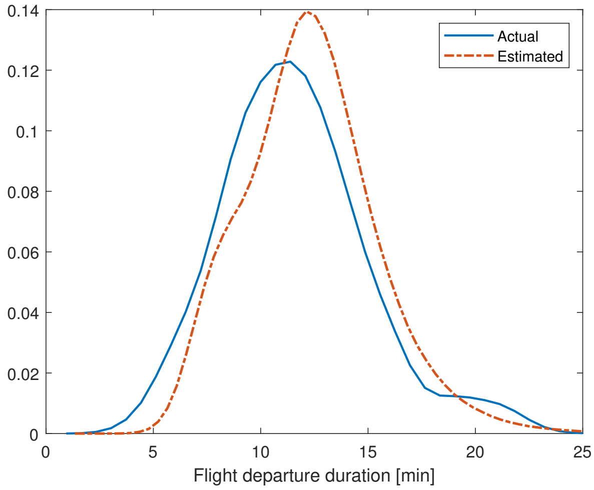


Figure 5.11: PDF actual and simulated duration of departure process with mixed-mode model 2

When comparing the two probability density functions, the distribution of the second model is a bit closer to the actual data. This is also suggested by the calculated errors, stated in table 5.4. The second model has a mean error of 0.70 minutes, while the first model has a mean error of 1.13 minutes. Also the MAE and RMSE are lower for the stochastic model.

Table 5.4: Error between estimated and actual flight duration of the departure process and waiting time in the queue, respectively - runway 34, mixed-mode operations, 7 days.

	Departure durations (min)			**Waiting time in queue (min)**		
	ME	MAE	RMSE	ME	MAE	RMSE
Model 1	1.13	2.23	2.91	0.57	1.15	1.70
Model 2	0.70	2.07	2.68	0.14	0.98	1.28

Figures 5.12 and 5.13 show the cumulative error between the estimated and the actual take-off time for model 1 and 2, respectively. Compared to model 2, model 1 has more positive errors, since 5% of the errors is larger than 10 minutes. Both cumulative errors are located to the right of zero, which indicates overestimation of the model.

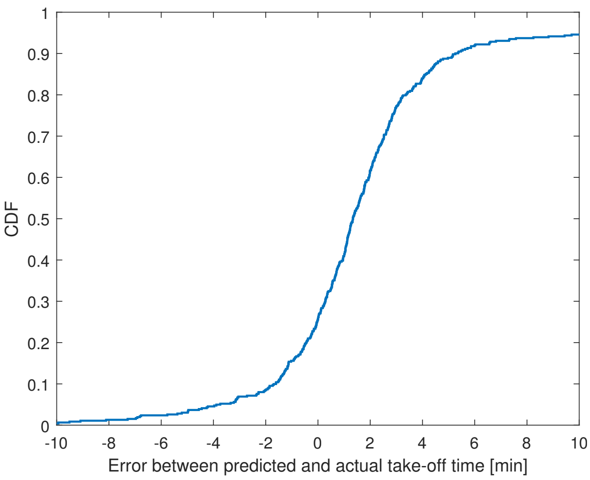


Figure 5.12: CDF of error between estimated and actual take-off time - runway 34, mixed-mode model 1.

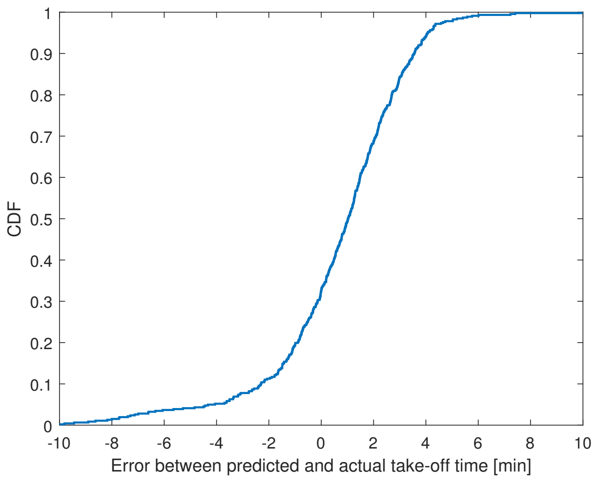


Figure 5.13: CDF of error between estimated and actual take-off time - runway 34, mixed-mode model 2.

Figure 5.14 shows the actual and estimated number of departures per 15 minutes on the 18th of September 2015. It can be seen that runway 34 is not used constantly throughout the day. This runway is used for departures during an outbound peak on the airport, where there are more departing flights than arriving flights. In these periods, runway 34 is also used for departures, since the capacity of runway 29 is not sufficient.

Furthermore, figure 5.14 shows that the actual and estimated number of departures are similar. Both models estimate the actual number of departure well, with a maximum difference of two aircraft.

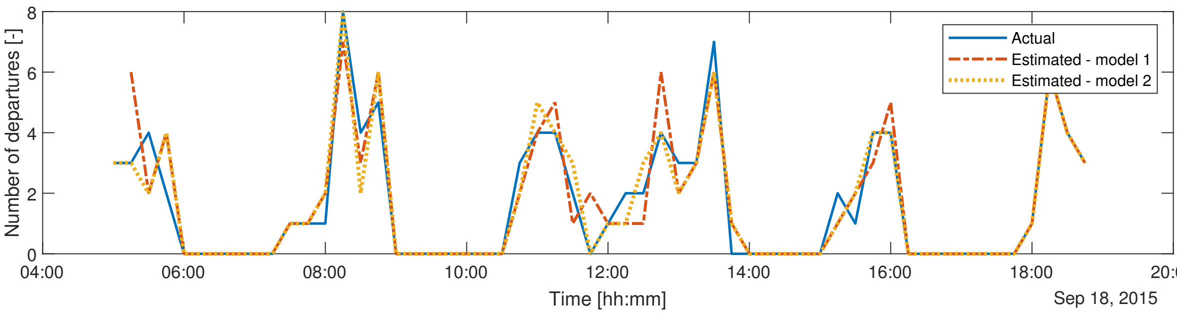


Figure 5.14: Actual and estimated number of departures per 15 min, 18th Sept 2015 - runway 34.

Figure 5.15 shows the actual and estimated mean flight departure duration. The actual data clearly contains an outlier, since a flight departure duration of 40 minutes is not realistic. Furthermore, for the periods when there are no aircraft departing, there is also no average to be shown, which explains the gaps in the graph.

When comparing model 1 and 2, it can be seen that model 1 usually provides higher estimates than model 2. Model 2 is closer to the actual mean departure duration compared to model 1.

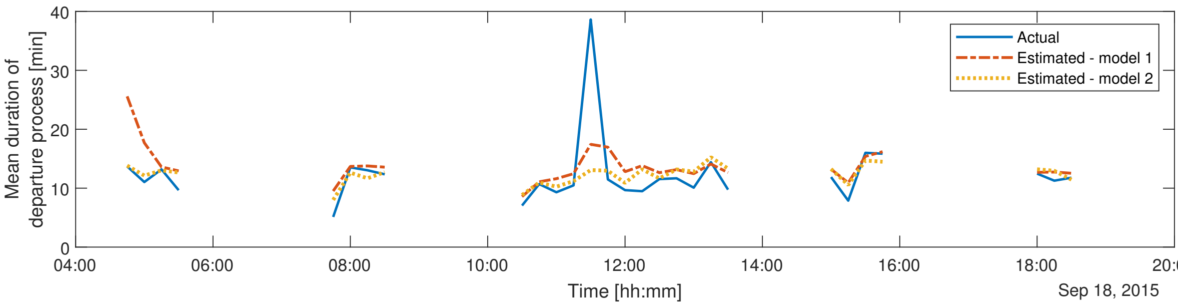


Figure 5.15: Actual and estimated mean flight departure duration per 15 min, 18th Sept 2015 - runway 34.

5.3. Both runways combined

This section presents the results of both runways combined. These results are determined by combining the simulation results for flights to runway 29 and runway 34. In the simulation of runway 34, the second model is used, since this model provided better results. In total, there are 1614 flights departing over the 7 days simulated.

Table 5.5 shows the error between the estimated and actual duration of the flight departure and the queue waiting time for the two runway system. The mean error for the flight duration is 0.59, which is only slightly higher than the mean error for runway 29, stated in table 5.3. This is explained by the fact that roughly 75% of the departing flights take-off from runway 29, thus the combined results are closer to the results for runway 29.

Figures 5.16 and 5.17 shows the PDF and CDF of the actual and estimated flight departure duration for both runways combined. The actual and estimated graphs are similar, with a small overestimation. The PDF has a gradually decreasing left side of the curve, which is the influence of the flights departing from runway 34. These flights have, on average, a 3 minute longer taxi time than flights departing from runway 29.

Table 5.5: Error between the estimated duration and the actual duration of the flight departure from gate to take-off - 7 days, both runways combined, mixed-mode operations model 2.

	ME	MAE	RMSE
Departure duration from gate to take-off (min)	0.59	1.69	2.23
Waiting time in the queue (min)	0.35	0.81	1.21

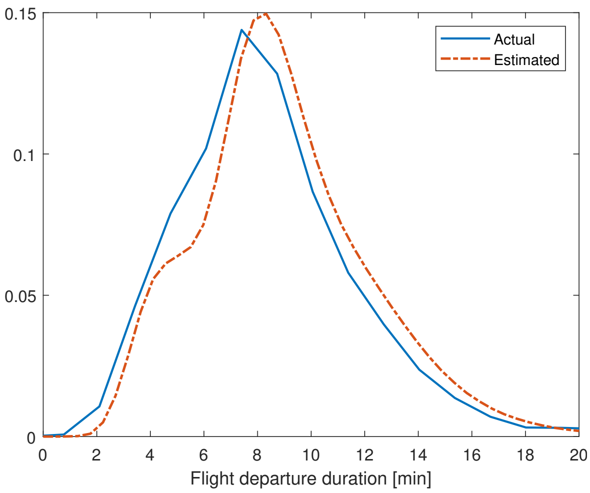


Figure 5.16: PDF of actual and simulated duration of departure process - 7 days, both runways combined.

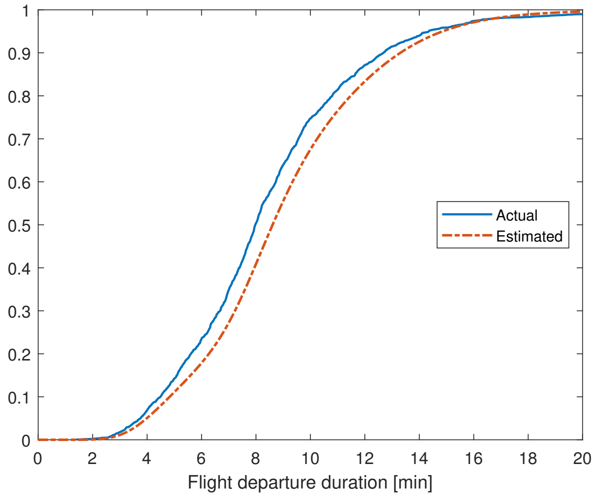


Figure 5.17: CDF actual and simulated duration of departure process - 7 days, both runways combined.

Figures 5.18 and 5.19 show the actual and estimated number of departures and mean flight departure duration per 15 minutes, respectively, In both graphs, it can be seen that the actual and estimated curve are similar, except for the outlier in the actual data in figure 5.19.

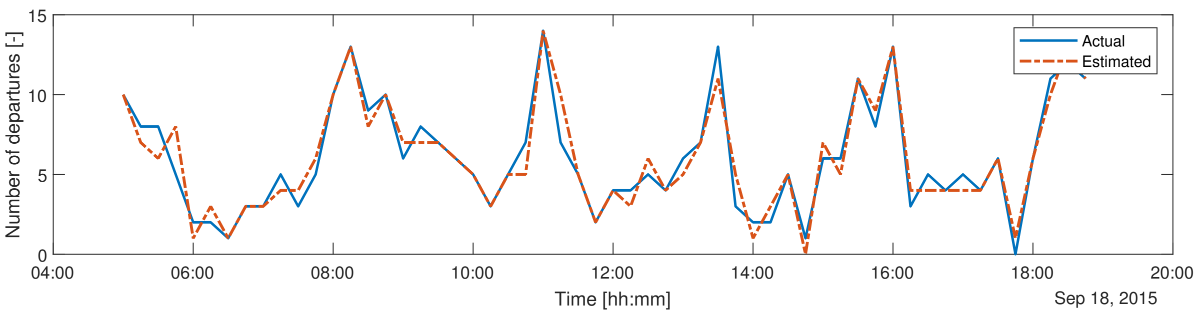


Figure 5.18: Actual and estimated number of departures per 15 min, 18th Sept 2015 - both runways combined.

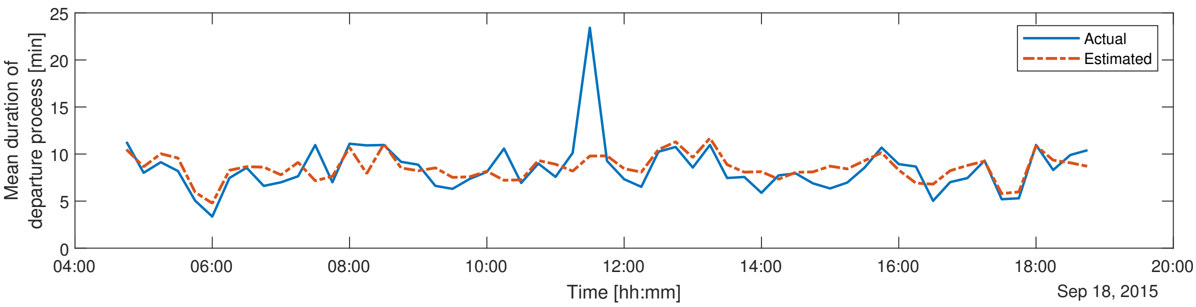


Figure 5.19: Actual and estimated mean flight departure duration per 15 min, 18th Sept 2015 - both runways combined.

6
Verification and Validation

This chapter discusses the methods used to verify and validate the model. Section 6.1 explains the verification process, while the validation process is explained in section 6.2.

6.1. Verification

This section gives an overview of the methods that are used to verify the model. Verification means checking whether the written code is solving the problem in the right way. This includes both code verification and computation verification of part of the model, followed by a test of the entire model.

The model consists of several steps, being the data preparation, data analysis and the simulation. These three steps are verified by analysing the input and output of each step to make sure there are no programming mistakes and that every step provides the expected output. For each step, there is a list of verification tasks listed below. These verification tasks are performed while programming, thus each step in the model is verified.

1. **Data preparation**
    (a) *Input*: check if the input data is available, correct and complete.
    (b) *Combine data sources*: check for NaN values after combining the three data sources. When NaN values occur, remove flight from sample.
    (c) *Determine gate location:* check flights where the start of the profile does not coincide with the gate location (> 200m). Verify with flight profile plot if aircraft is indeed already in the taxi system.
    (d) *Determine runway configuration*: visually inspect the runway configuration table to see how often the configuration changes. Decide if rules need to be adjusted.
    (e) *Output*: check if the output file consists of all necessary data.
2. **Data analysis**
    (a) *Input*: check if the input data is available, correct and complete.
    (b) *Determine state for each second in flight profile*: check if every second of the flight profile has a state.
    (c) *Calculate duration of each state*: check per state if the outcome makes sense. For example, unimpeded taxi-out time cannot equal zero, the push-back duration should be around 3-5 minutes. Look for extremes and, if necessary, visually check the flight profile to see what happened.
    (d) *Create distribution*: check if the amount of data in the distribution equals the amount of flights.
    (e) *Remove outliers*: check what percentage of the data is removed.
    (f) *Output*: check if the output file consists of all necessary data.

3. **Simulation**
   (a) *Input*: visually inspect the distributions that are used as input in the simulation.
   (b) *Travel time module*: check if the travel time consists of random variables that are drawn from the right distribution.
   (c) *Moment of arrival in the queue*: check if the flights are sorted based on moment of arrival in the queue.
   (d) *Queue*: check if the right method is applied and if the method works as it should do.
   (e) *Queue probabilities*: check if the probabilities used in the queue equal 1.
   (f) *Output*: check if the output of the simulation is as expected.

The complete model can be verified by increasing the traffic sample. In this way, it is tested if the model performs as it should do. More flights should result in an increase in queue time, since the demand on the runway increases. The total duration of the departure process should also increase if the demand increases. Figures 6.1 and 6.2 show the PDF and CDF of the departure process duration for increasing traffic samples. As expected, a 10% and 20% increase in flights results in a higher process duration. With this results, the model is considered verified.

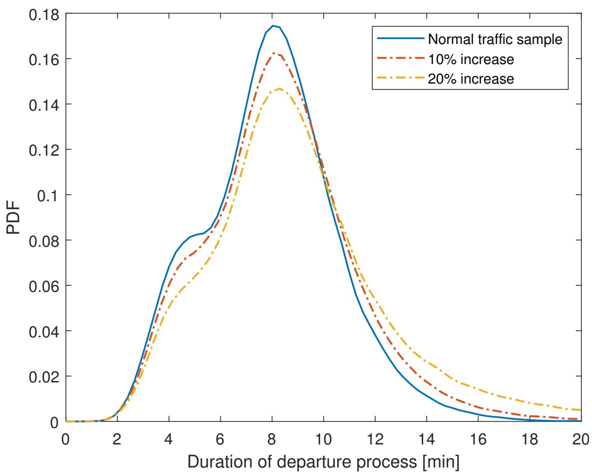


Figure 6.1: PDF of departure process duration for increasing traffic samples

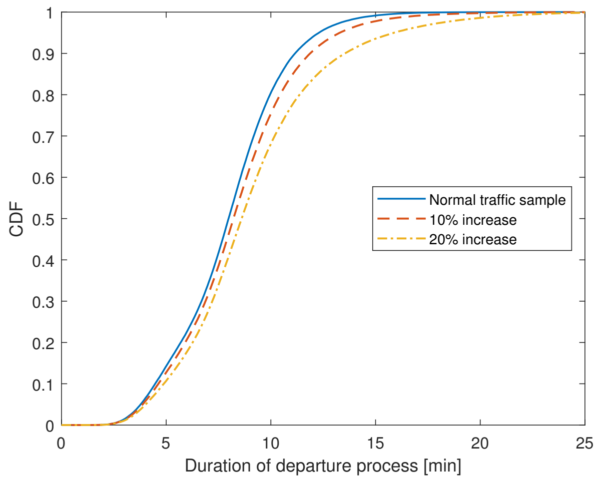


Figure 6.2: CDF of departure process duration for increasing traffic samples

6.2. Validation

The model is validated by comparing the model results to actual data. This is done to see how well the model performs compared to actual data. In chapter 5, the comparison with actual data is already made. Here it is established that the simulation result is similar to the actual data, which means that the model is validated.

However, to show that the model is not adjusted in order to obtain perfect results, the simulation is also performed for seven new days. The days that are simulated for validation purposes are: 17 Jul, 5 Aug, 22 Aug, 18 Sept, 23 Sept, 12 Oct and 21 Nov.

Table 6.1 shows the mean error, mean absolute error and the root mean square error for the validation data. It can be seen that the errors are of the same order of magnitude as in table 5.3 and 5.4. Since the model results and the simulation results are similar for these seven random days, and for the seven random days simulated in chapter 5, the model is considered to be validated.

Table 6.1: Error between estimated and actual flight duration of the departure process and waiting time in the queue, respectively. Validation data based on 7 different days.

	Duration departure (min)			**Waiting time in queue (min)**		
	ME	MAE	RMSE	ME	MAE	RMSE
Runway 29	0.28	1.53	2.02	0.35	0.79	1.22
Runway 34 (Model 1)	1.44	2.23	2.93	1.02	1.43	2.20
Runway 34 (Model 2)	0.80	1.99	2.46	0.26	1.06	1.39

The probability density function and cumulative distribution function that are created for flights departing from runway 29 during the days used for validation are given in figures 6.3 and 6.4. The PDF for both models simulating runway 34 are depicted in figure 6.5 and 6.6. It can be seen that the actual data and the simulation results are almost equal, which means that the model performs as expected.

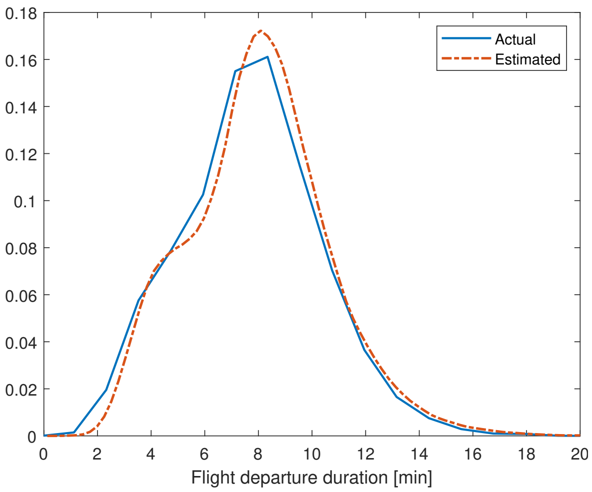


Figure 6.3: PDF of actual and estimated departure process duration using validation data, runway 29

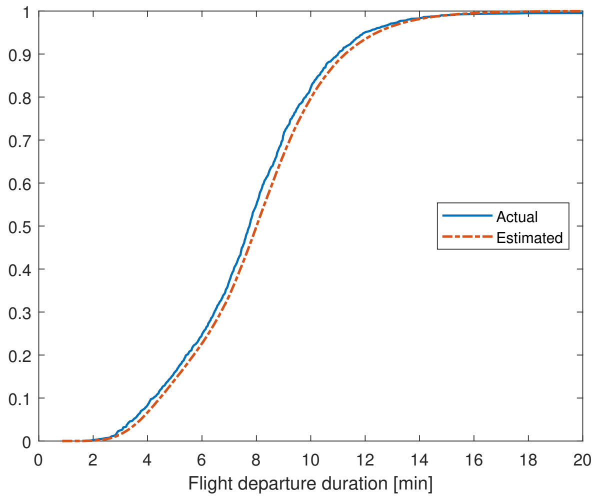


Figure 6.4: CDF of actual and estimated departure process duration using validation data, runway 29

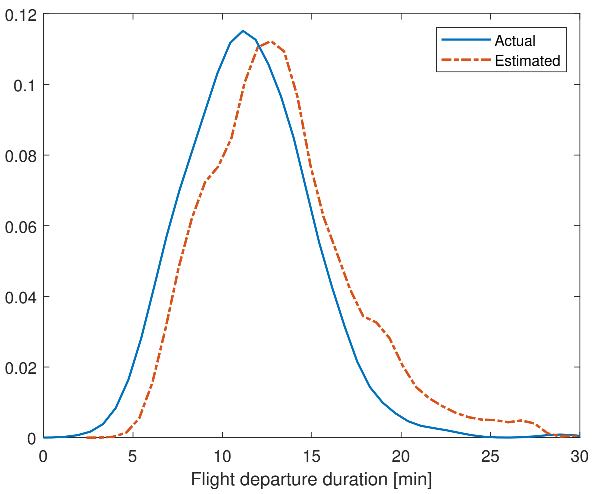


Figure 6.5: PDF of actual and estimated departure process duration using validation data, runway 34, model 1

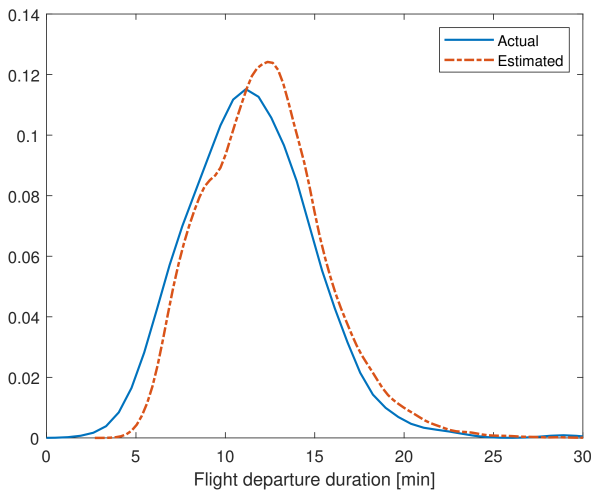


Figure 6.6: PDF of actual and estimated departure process duration using validation data, runway 34, model 2.

7

Conclusion and Recommendations

This chapter states the conclusions that are drawn from the results in section 7.1. Furthermore, section 7.2 provides recommendations for further research.

7.1. Conclusions

The main research question of this research “How to model the airport departure process under the influence of uncertainty?” is answered by providing a model that simulates the airport departure process at Vienna Airport.

It is concluded that the model for segregated operations on a single runway can estimate the duration of the departure process for each flight, including confidence interval and standard deviation. For runway 29 at Vienna Airport, using data of July until December 2015, the expected take-off time is predicted with a mean absolute error or 1.5 minutes. The duration of the departure process is overestimated with 0.5 minutes compared to the actual data, which makes the model conservative. However, the distribution of the simulation and the actual data prove to have a similar shape, which shows that the characteristics of the departure process are captured in the model.

For mixed-mode operations, there are two types of models developed, a deterministic and a stochastic model. Both types of models are suitable to predict the take-off time, however, the stochastic model provides a better estimate for the duration of the departure process. Using the stochastic model, the duration is predicted with a mean absolute error of 2 minutes. The simulation slightly overestimates the actual distribution with 0.7 minutes, while the deterministic model overestimates the actual distribution with roughly 1 minute.

The main research question is divided into several sub questions. The first sub question is related to the representation of a departure process. The question “How to represent the departure process, taking into account the push-back, travel time and queue time?” is answered by the theoretical model that is created in chapter 3. The departure process is divided into a push-back duration, unimpeded and additional taxi-out time, waiting time and departure runway occupancy time. Each of the phases is represented by a distribution obtained from historical data, except the waiting time, which is determined using queue theory.

The second group of questions is related to simulating the departure process. The most important questions to answer are “How to determine the moment of arrival in the runway process?” and “How to model the runway queue?”. The moment of arrival in the queue is found by adding the push-back duration, the unimpeded taxi-out time and the additional taxi-out time to the actual off-block time. The push-back duration is found from historical data, where the ground speed is used to determine when the push-back process ended. The unimpeded taxi-out time is defined as the nominal duration to travel to the runway entry, given that the aircraft is not interrupted. The additional taxi-out time is the duration that an aircraft is interrupted while taxiing. The additional taxi-out time increases for increasing number of aircraft in the system.

The runway queue is modelled by a G/G/1 queue, since the input is random, the service time is modelled by a gamma distribution and the queue has one server, which is based on the first-in-first-out principle. The queue model provides the queue waiting time for each flight. For aircraft departing from a runway in mixed-mode operations, an additional runway waiting time is calculated based on the runway availability.

The question “How to determine the runway availability (in a mixed-mode operation)?” is answered developing two different models. The first model is deterministic and uses live information from the arrivals schedule to determine when the runway is available. It states that a departure can enter the runway, as long as the arriving aircraft is more than 2 minutes from the runway threshold. The second model uses historical data to determine if the runway is available.

7.2. Recommendations

This section provides recommendations for further research. The results in chapter 5 showed that the model is capable of estimating the flight departure duration, although the model is conservative, since it overestimates the actual duration. As explained in the analysis of the results, a possible reason for overestimation is the service time assumption.

Therefore, the first recommendation is to perform a thorough analysis of the service time, since it is expected that a better estimation of the service time will improve the results. This research assumes independent service times, while the service time depends on the type of aircraft (both leader and follower). Also, the model has a service time that is not related to the departure runway occupancy time of the leading aircraft. In reality, the DROT is related to the service time, together with the separation requirements.

In addition to that, the model results may be improved by adding the influence of external factors to the model. For example, weather related effects and seasonal effects should be analysed to determine if it has potential to improve the model estimation.

Another recommendation is to test this model at a different airport, preferably a busier airport. Since Vienna Airport is quite small and it is not saturated often, there are no large queues in front of the runway. At airports that have problems with queue forming, the queue module can be tested more extensively.

Furthermore, the model should be extended to all possible configurations before it can be used in daily operations. It is not necessary to change the model completely, as only the input distributions should be changed. These distributions should be created with historical data from flights in that specific configuration.

Finally, the model can be extended by adding the processes upstream from the departure process. To be able to create an estimate of the take-off time well in advance, the turn-around process should be included in the model. Also, the taxi-in procedure can be added to the model.

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A

ICAO map Vienna International Airport

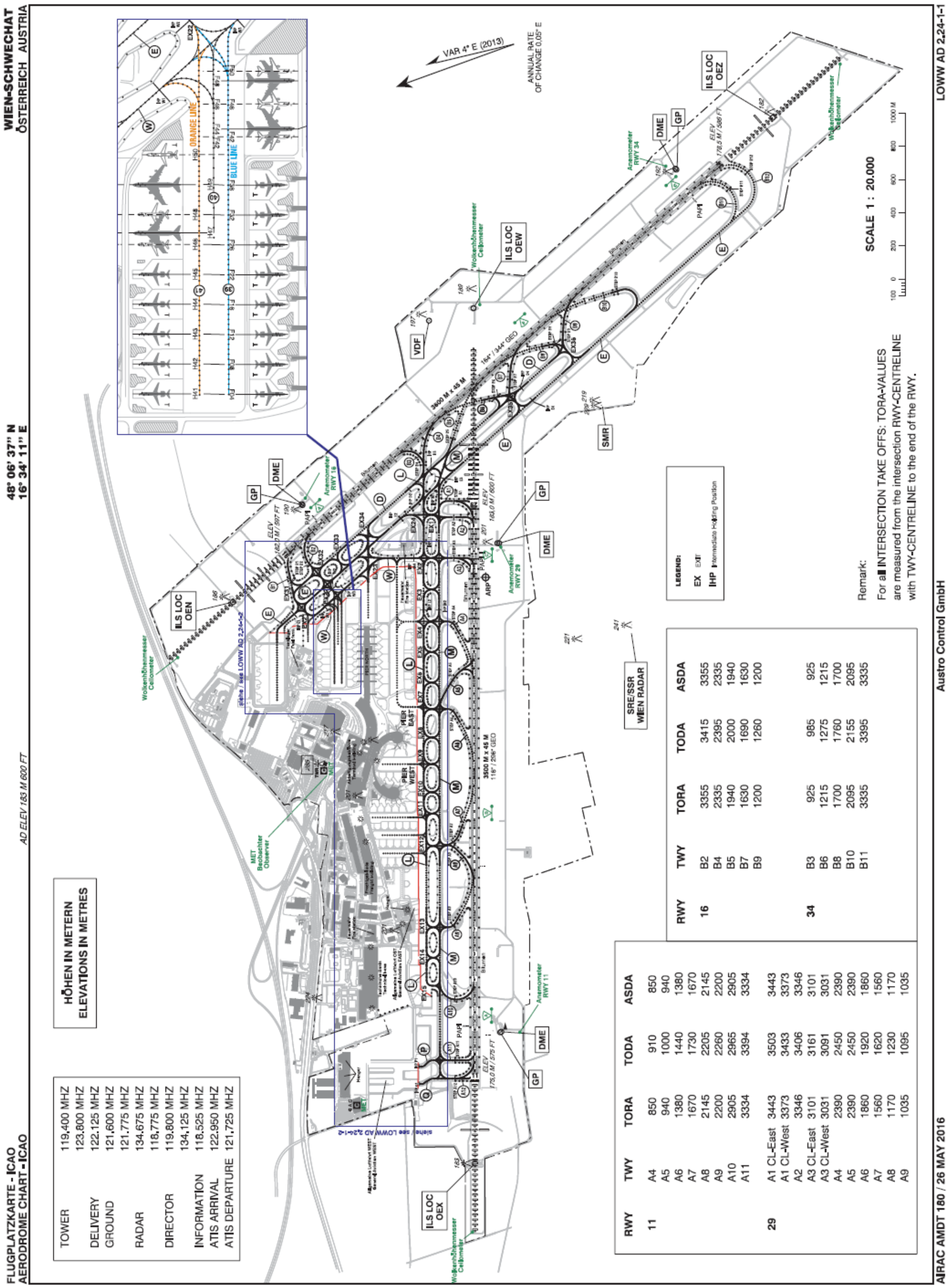

Figure A.1: ICAO map of Vienna Airport

B

Definition of gate groups

Table B.1: Median of unimpeded taxi-out time for each gate

Gate	Median unimpeded taxi-out time	Gate	Median unimpeded taxi-out time	Gate	Median unimpeded taxi-out time
(null)	331	C40	238	F33	223
A91	377	C41	229	F36	237
A92	374	C42	234.5	F37	200
A93	368.5	D21	259	F41	223.5
A94	334	D22	274	F42	213.5
A95	374	D23	287.5	F43	261
A96	343	D24	224.5	F44	296
A97	333	D25	227.5	F45	215.5
A98	314	D26	269.5	F46	212
A99	323	D27	243	F49	200
AUA	328	D28	245.5	F50	210
B51	393	D29	235	F51	203.5
B52	399	E41	202.5	F53	230.5
B53	286	E42	205	F55	194
B61	254	E43	205	F57	203
B62	338	E44	198	F59	186
B63	404	E45	188	GAE	263
B71	285	E46	181.5	GAW	372
B72	356	E47	181	H03	270
B73	296	E48	155	H41	254
B74	266.5	E49	148	H42	249
B75	244	E50	145	H43	250
B81	288.5	E51	145	H44	228
B82	296.5	E52	136	H45	221
B83	308	F01	266	H46	228
B84	305	F03	272	H47	305
B85	285	F04	264	H48	230
B91	306	F05	296	H49	231
B92	285	F08	263	H50	221
B93	294	F09	260	K41	278
B94	291.5	F11	258	K42	280.5
B95	291	F12	269	K43	265
B96	285	F13	288.5	K44	260
C31	270	F16	254	K45	302
C32	272.5	F17	253	K46	238
C33	264.5	F21	226.5	K47	289
C34	263.5	F22	238	K48	194
C35	248	F23	263	K49	186.5
C36	251	F26	248	K50	276
C37	250	F27	225	K51	242
C38	234	F31	205		
C39	226	F32	240.5		

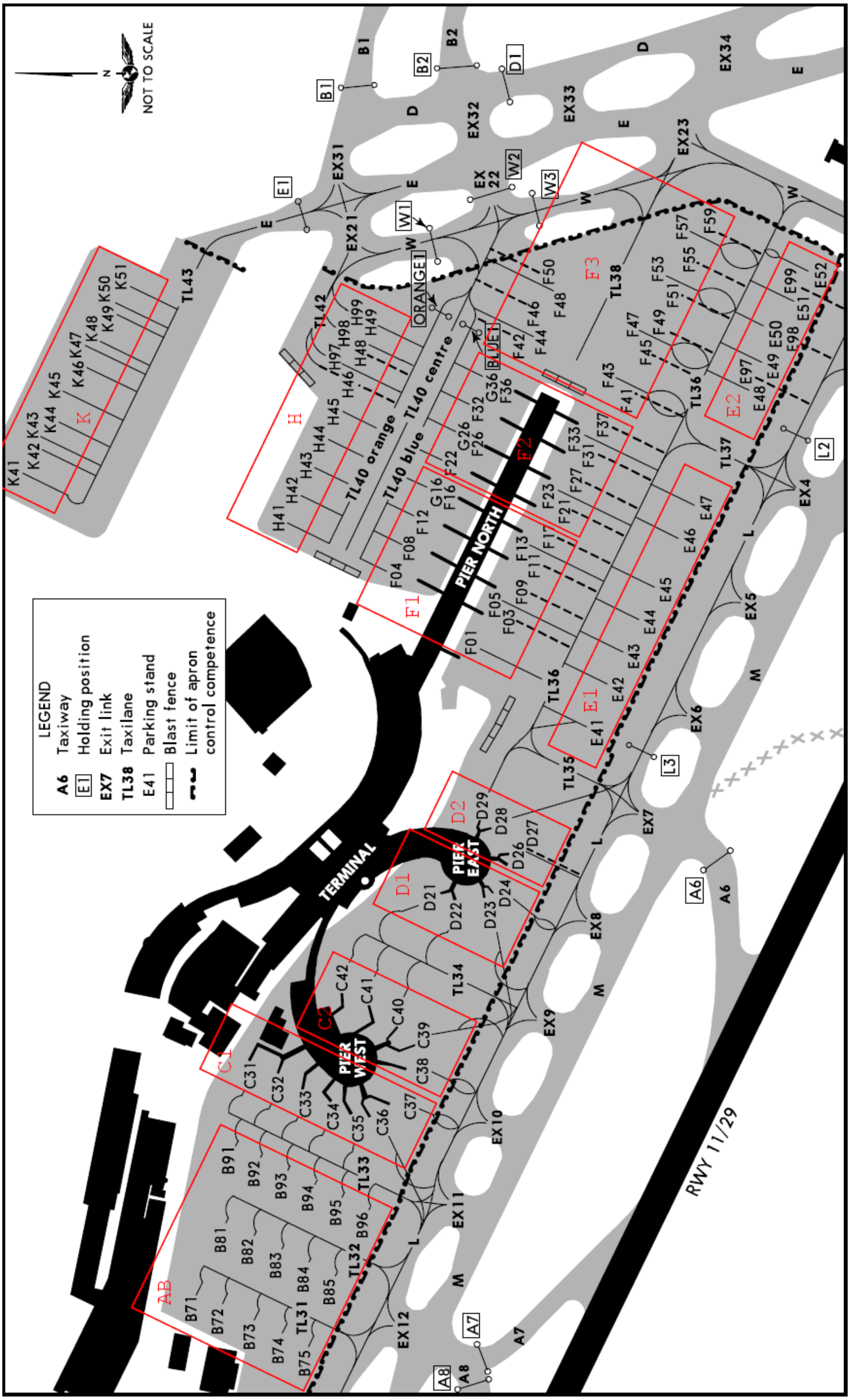

Figure B.1: Map of Vienna Airport - part 1. Adjusted from http://vau.aero/navdb/chart/LOWW.pdf

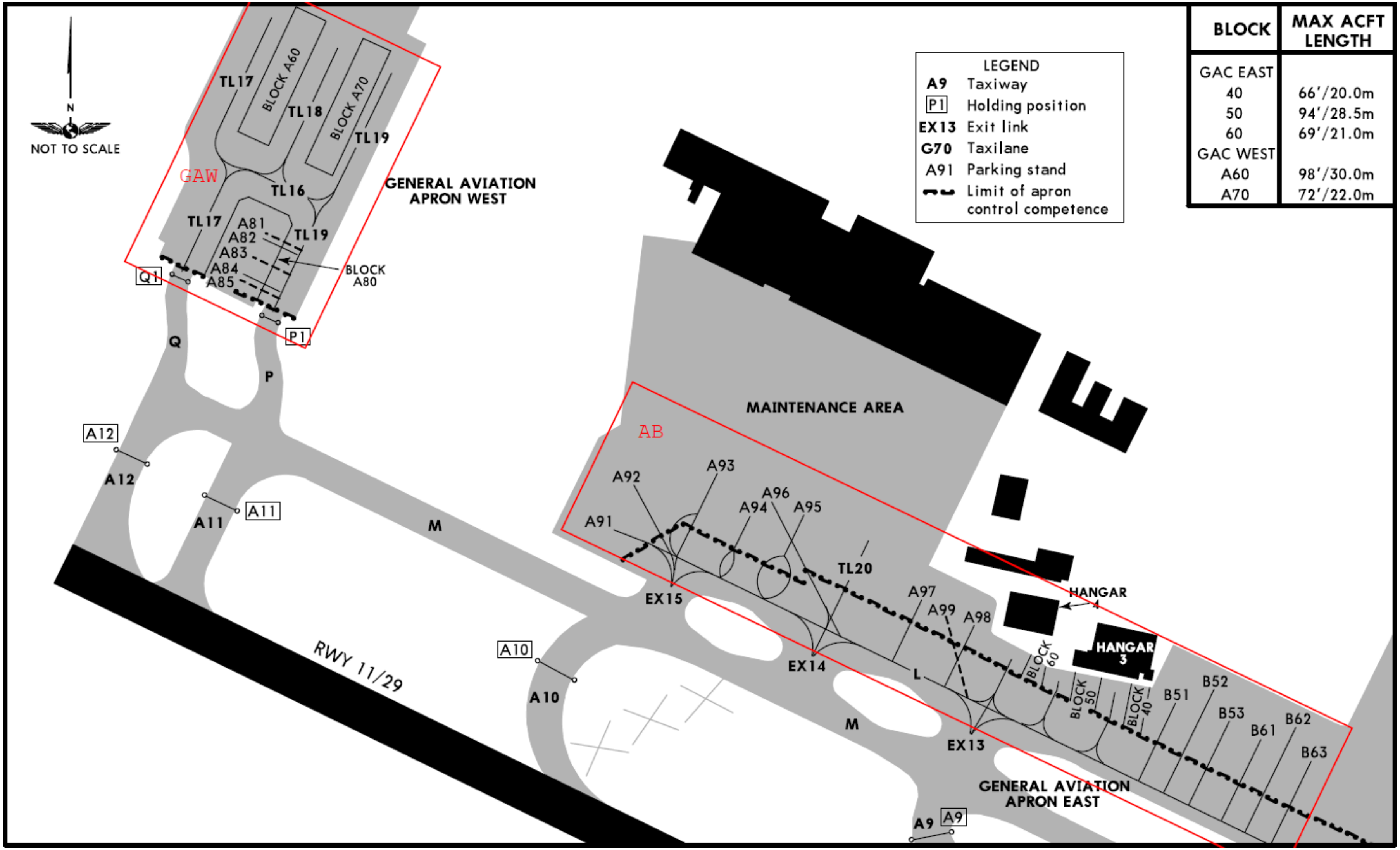

Figure B.2: Map of Vienna Airport - part 2. Adjusted from `http://vau.aero/navdb/chart/LOWW.pdf`

C
Distributions of unimpeded taxi-out time per gate group

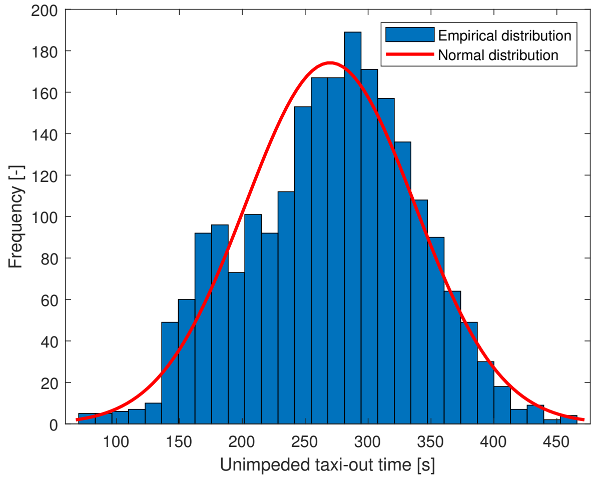

Figure C.1: Histogram of unimpeded taxi-out time - Group AB

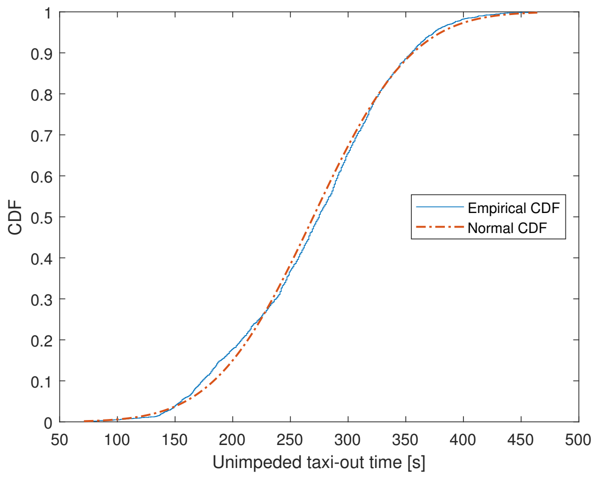

Figure C.2: CDF of unimpeded taxi-out time - Group AB

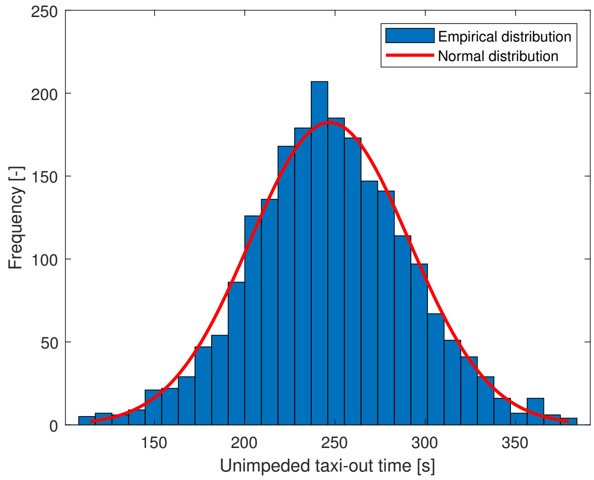

Figure C.3: Histogram of unimpeded taxi-out time - Group C1

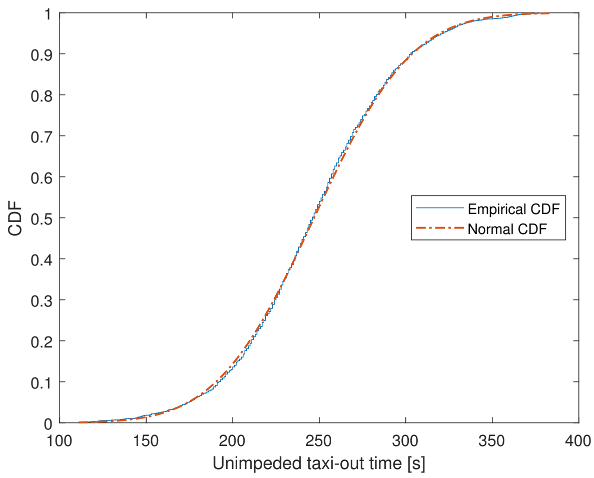

Figure C.4: CDF of unimpeded taxi-out time - Group C1

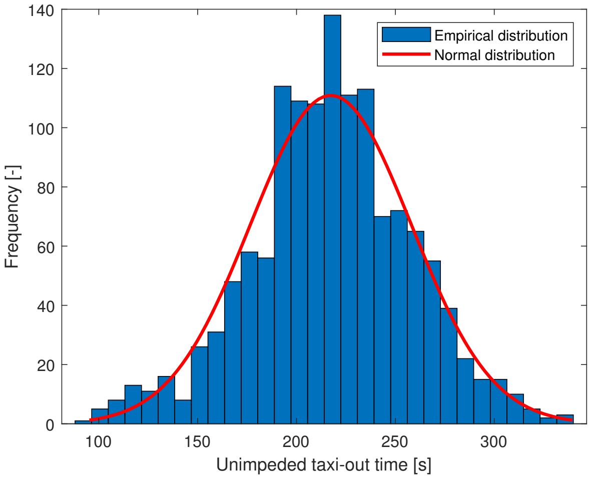

Figure C.5: Histogram of unimpeded taxi-out time - Group C2

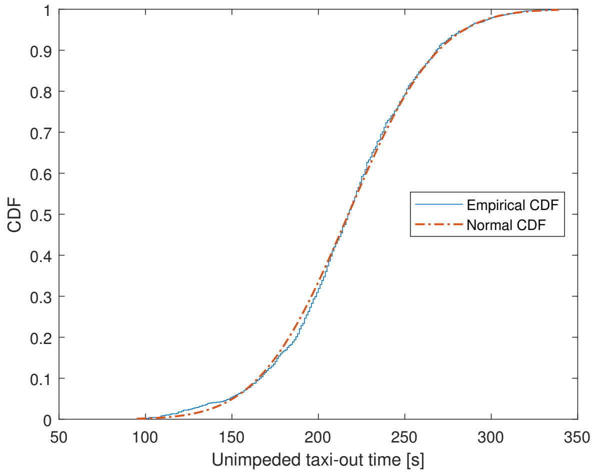

Figure C.6: CDF of unimpeded taxi-out time - Group C2

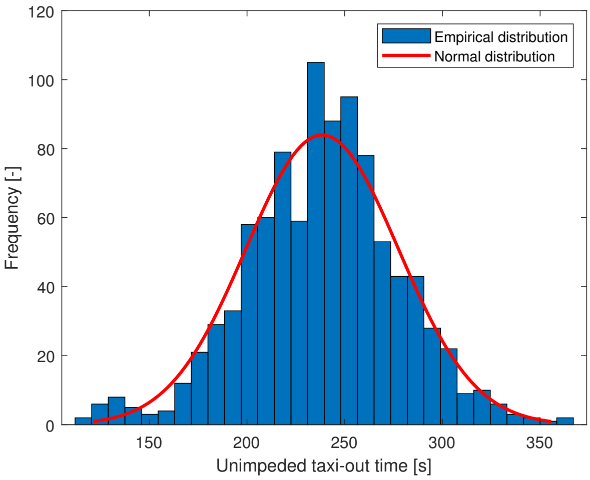

Figure C.7: Histogram of unimpeded taxi-out time - Group D1

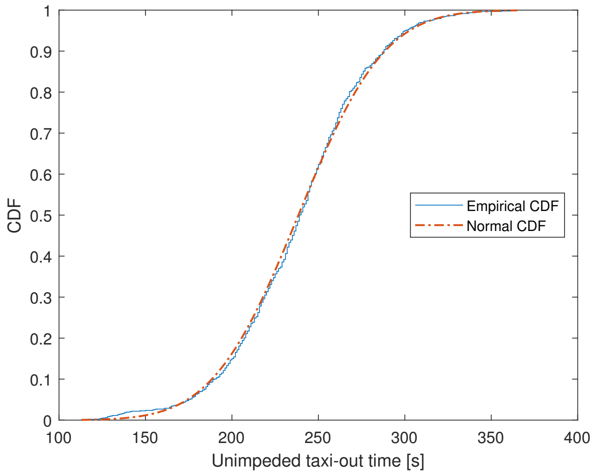

Figure C.8: CDF of unimpeded taxi-out time - Group D1

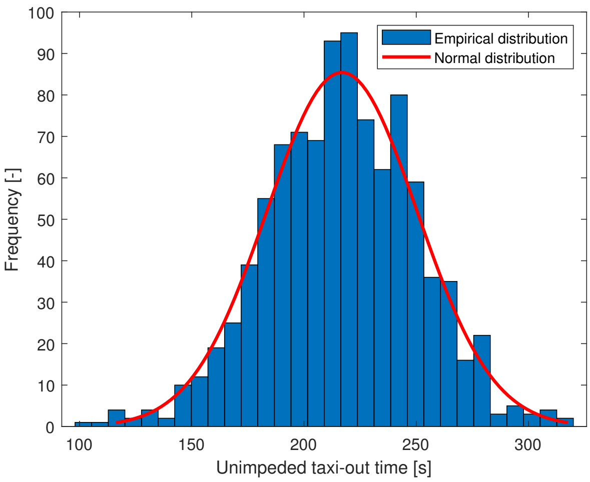

Figure C.9: Histogram of unimpeded taxi-out time - Group D2

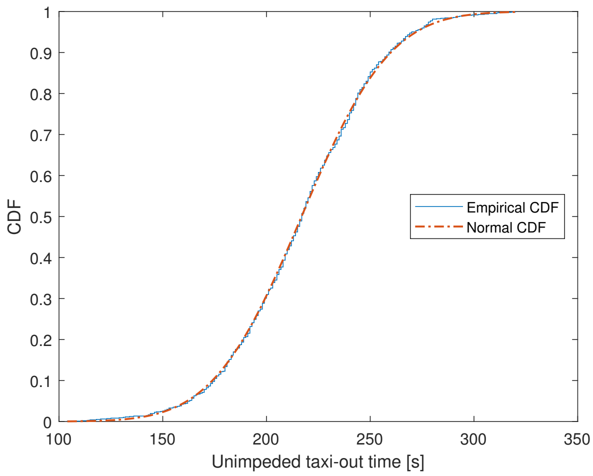

Figure C.10: CDF of unimpeded taxi-out time - Group D2

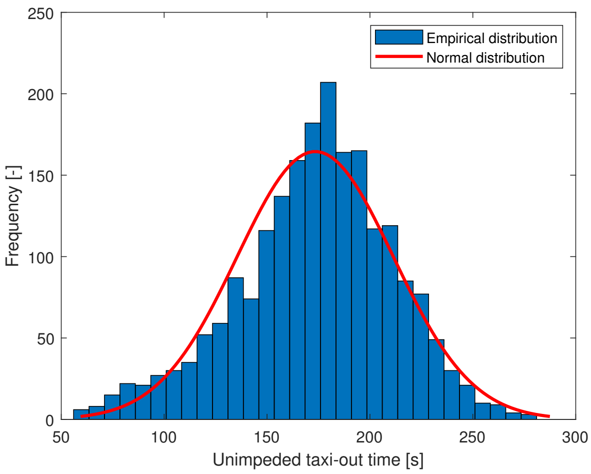

Figure C.11: Histogram of unimpeded taxi-out time - Group E1

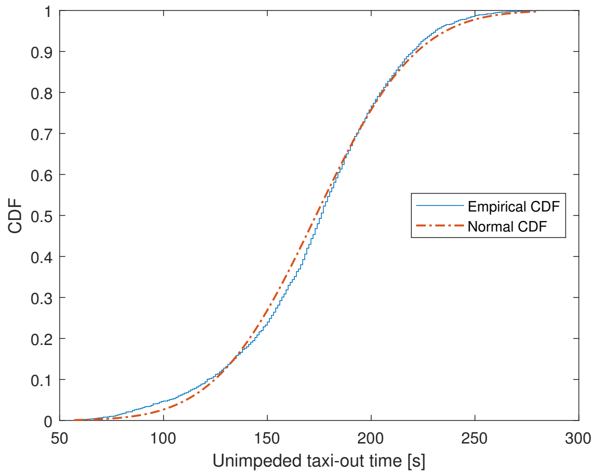

Figure C.12: CDF of unimpeded taxi-out time - Group E1

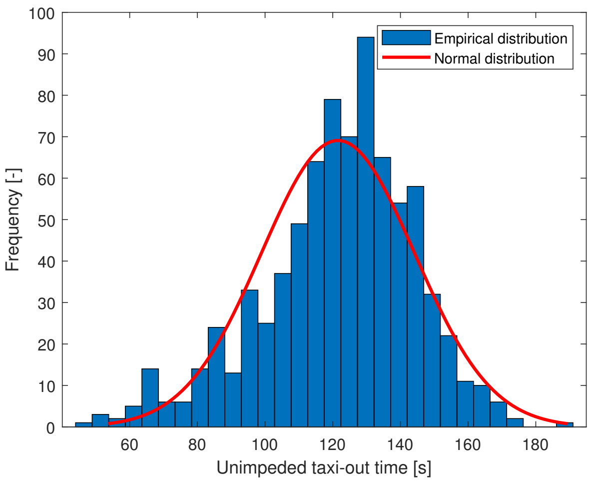

Figure C.13: Histogram of unimpeded taxi-out time - Group E2

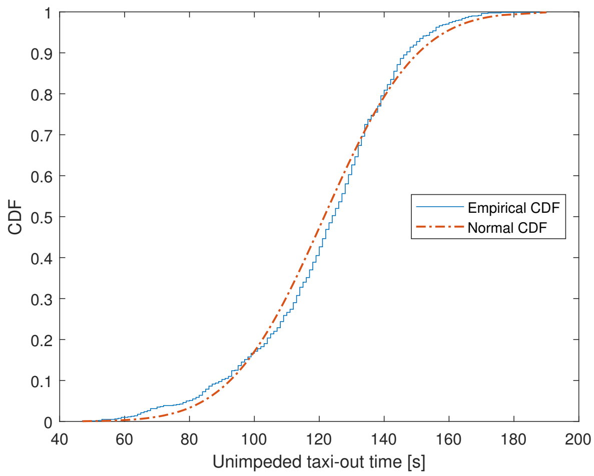

Figure C.14: CDF of unimpeded taxi-out time - Group E2

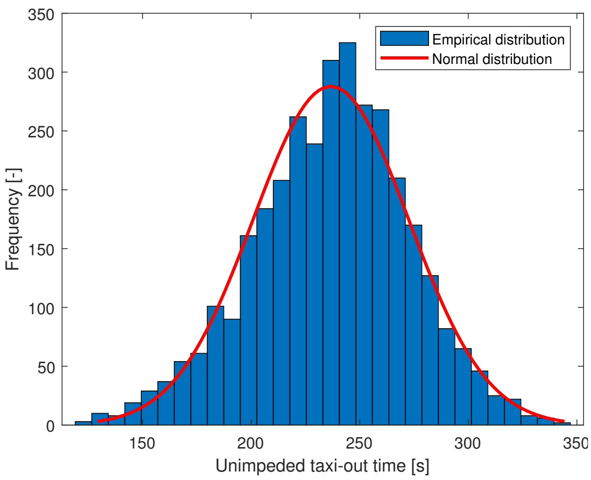

Figure C.15: Histogram of unimpeded taxi-out time - Group F1

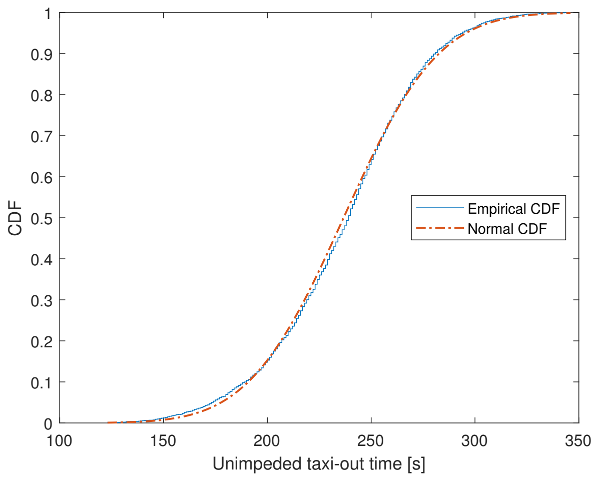

Figure C.16: CDF of unimpeded taxi-out time - Group F1

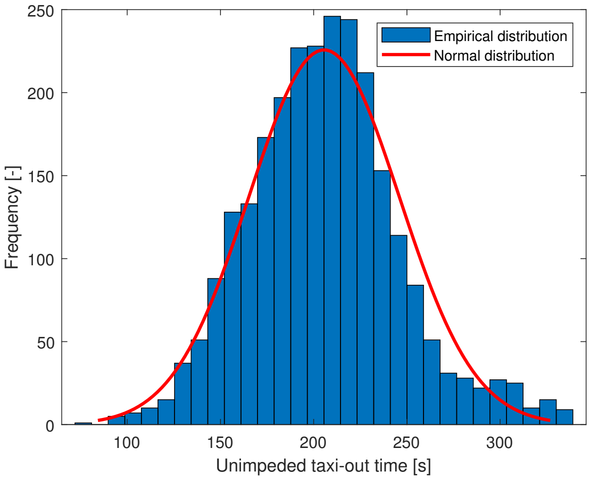

Figure C.17: Histogram of unimpeded taxi-out time - Group F2

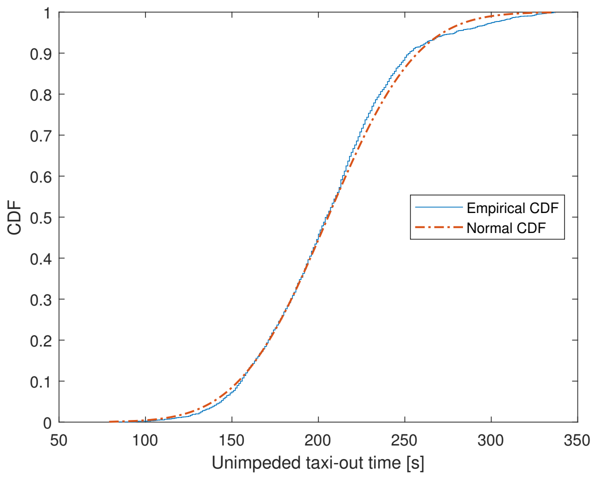

Figure C.18: CDF of unimpeded taxi-out time - Group F2

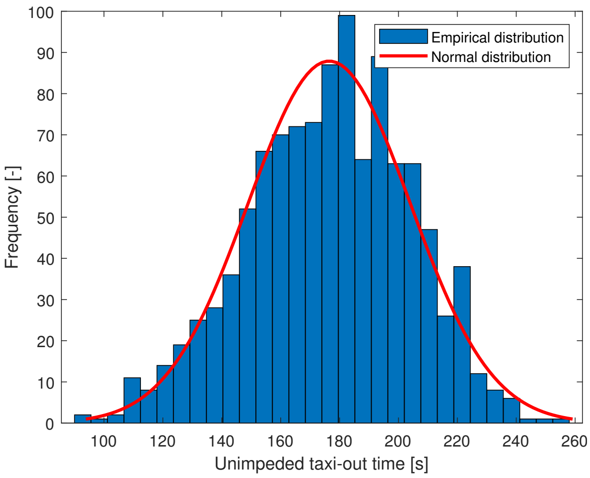

Figure C.19: Histogram of unimpeded taxi-out time - Group F3

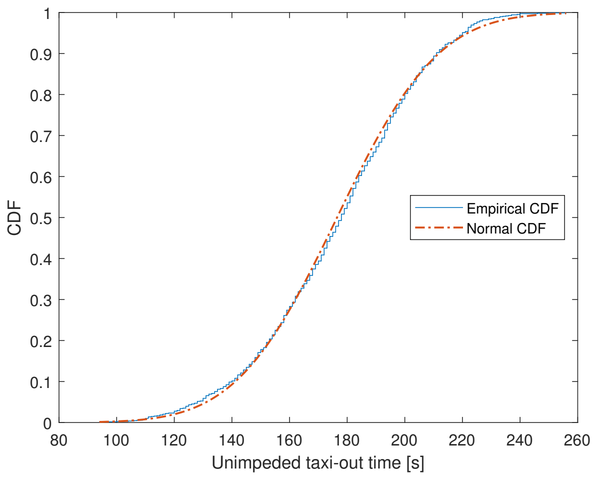

Figure C.20: CDF of unimpeded taxi-out time - Group F3

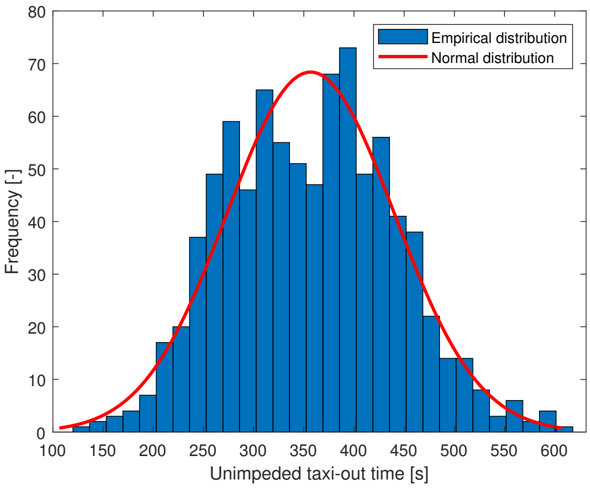

Figure C.21: Histogram of unimpeded taxi-out time - Group GAW

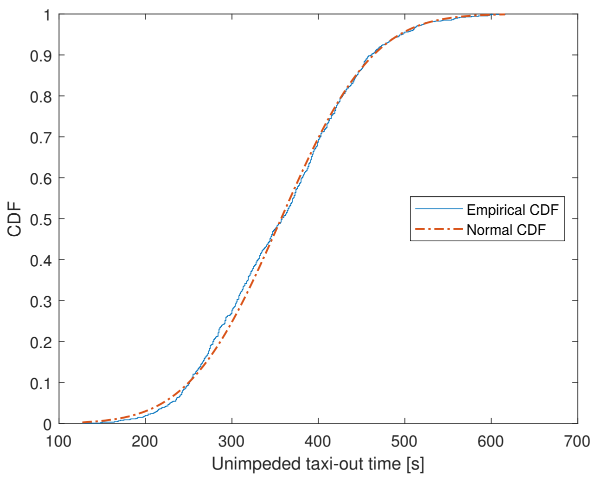

Figure C.22: CDF of unimpeded taxi-out time - Group GAW

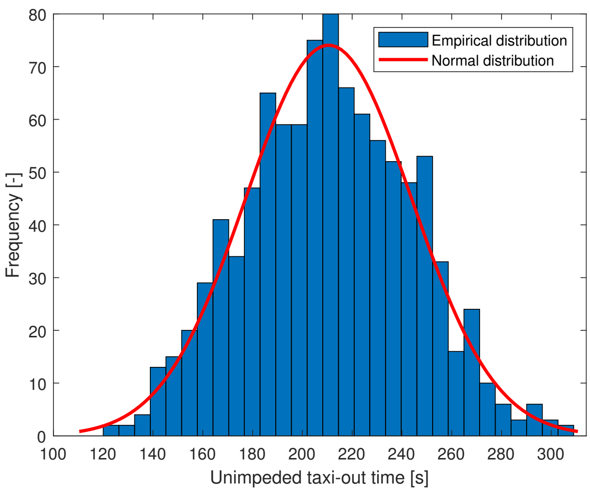

Figure C.23: Histogram of unimpeded taxi-out time - Group H

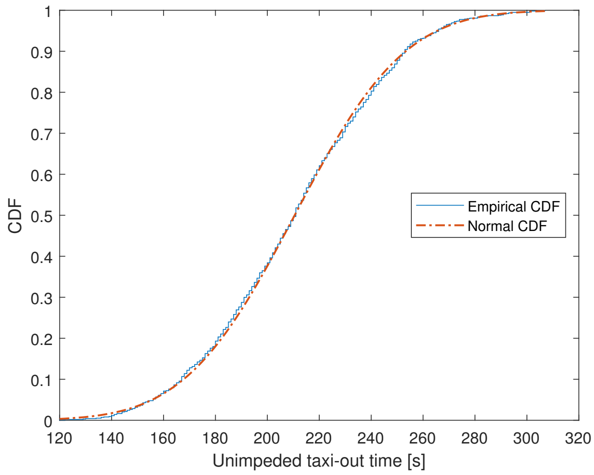

Figure C.24: CDF of unimpeded taxi-out time - Group H

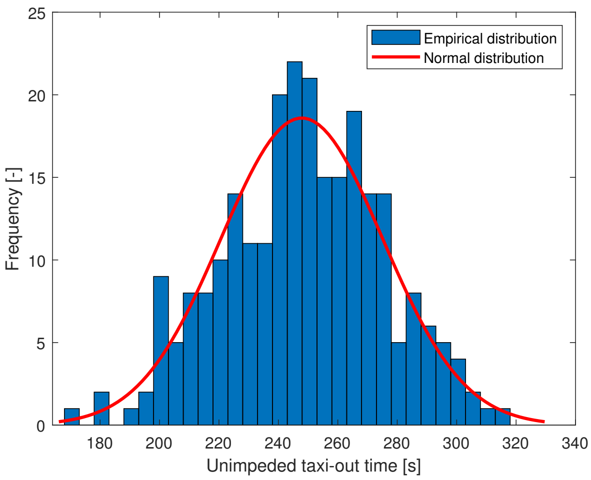

Figure C.25: Histogram of unimpeded taxi-out time - Group K

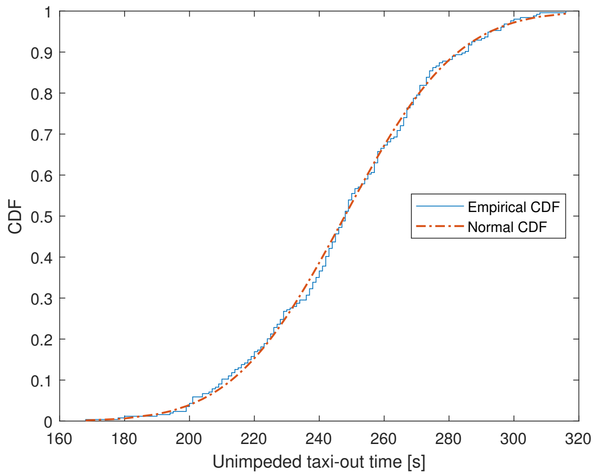

Figure C.26: CDF of unimpeded taxi-out time - Group K

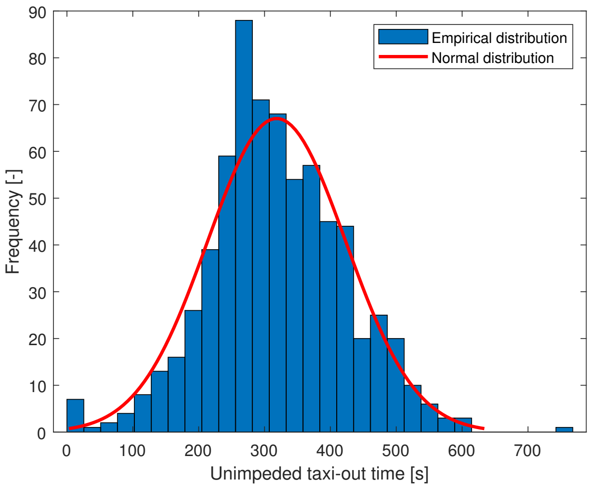

Figure C.27: Histogram of unimpeded taxi-out time - Group none

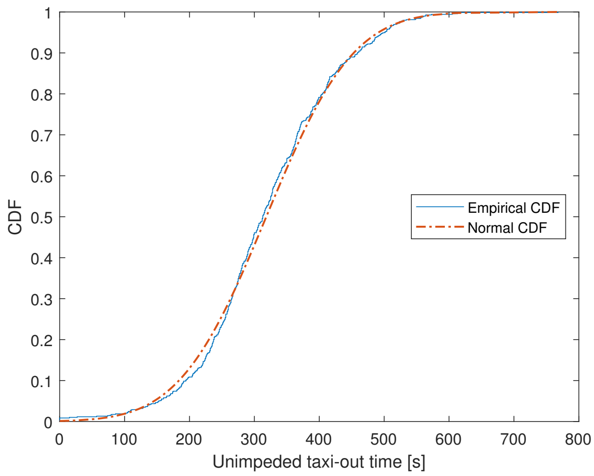

Figure C.28: CDF of unimpeded taxi-out time - Group none

D
Distributions of departure runway occupancy time per ICAO weight category

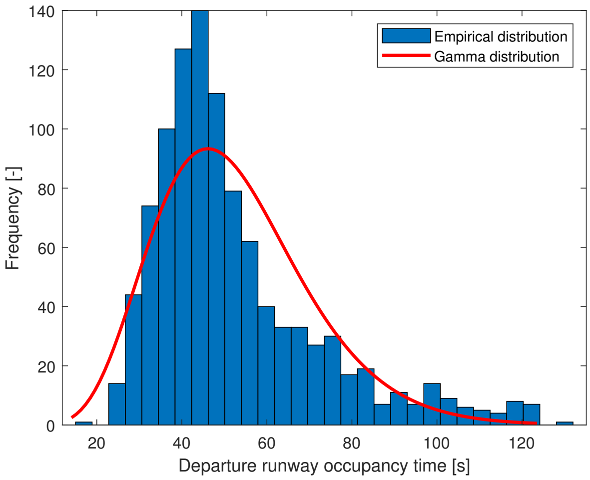

Figure D.1: Histogram of departure runway occupancy time for heavy aircraft

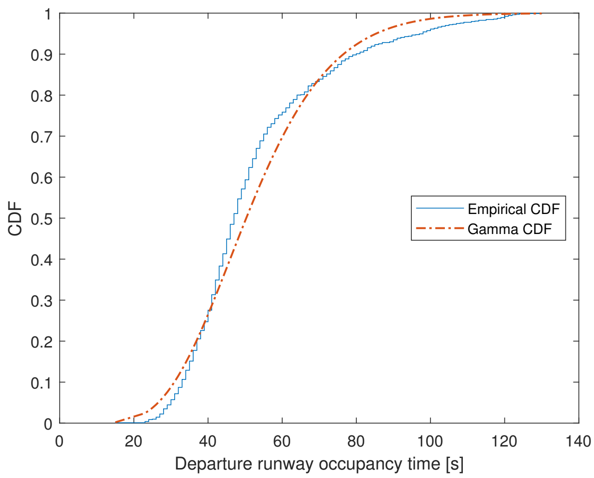

Figure D.2: CDF of departure runway occupancy time for heavy aircraft

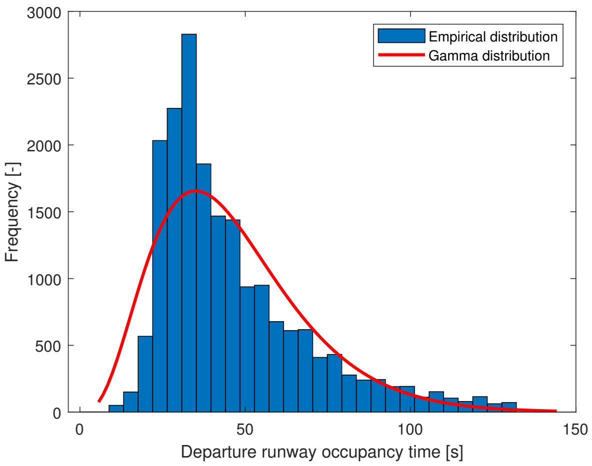

Figure D.3: Histogram of departure runway occupancy time for medium aircraft

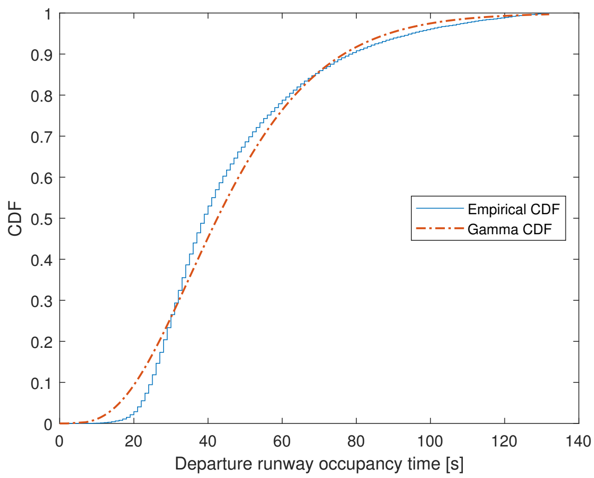

Figure D.4: CDF of departure runway occupancy time for medium aircraft

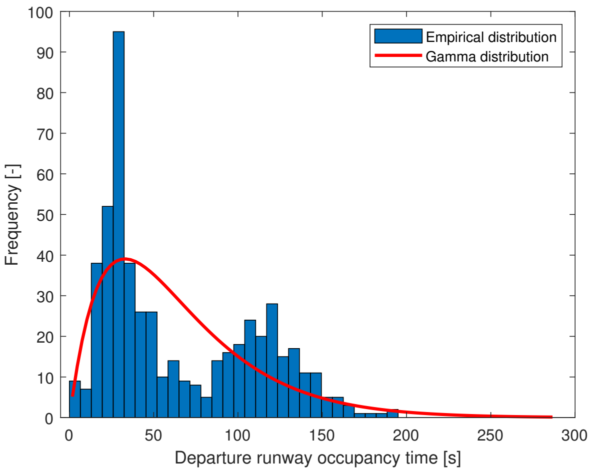

Figure D.5: Histogram of departure runway occupancy time for light aircraft

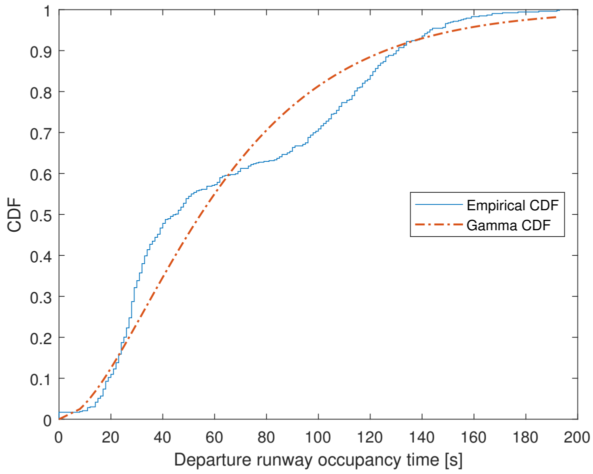

Figure D.6: CDF of departure runway occupancy time for light aircraft

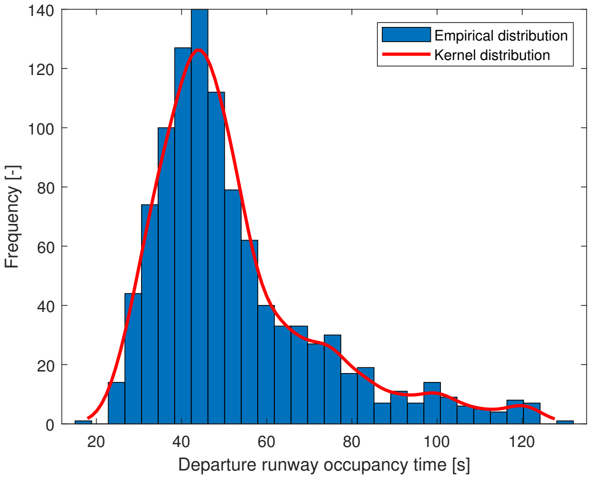

Figure D.7: Histogram of departure runway occupancy time for heavy aircraft. Empirical distribution with a kernel fit.

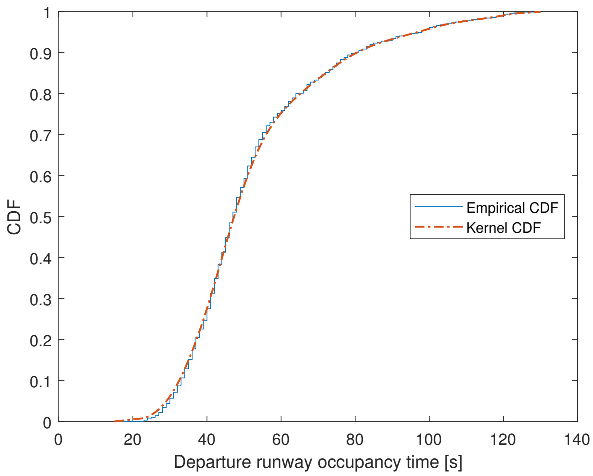

Figure D.8: CDF of departure runway occupancy time for heavy aircraft. Empirical data and kernel distribution.

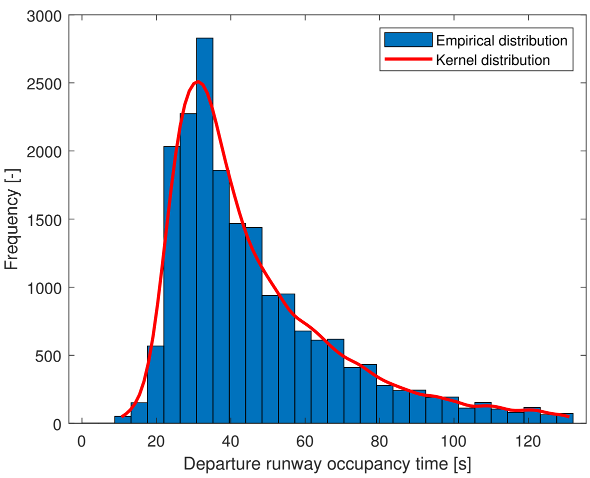

Figure D.9: Histogram of departure runway occupancy time for medium aircraft. Empirical distribution with a kernel fit.

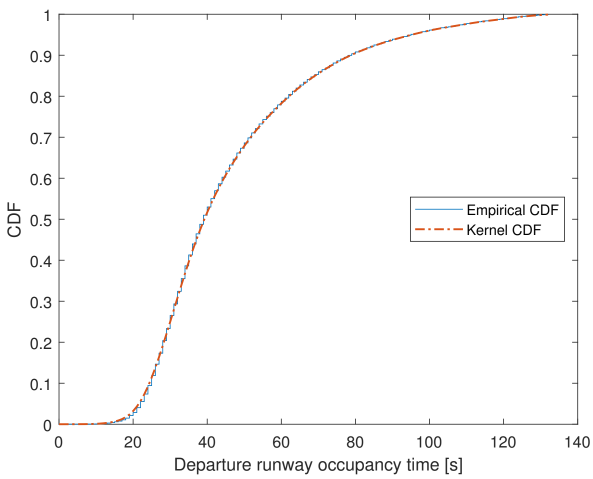

Figure D.10: CDF of departure runway occupancy time for medium aircraft. Empirical data and kernel distribution.

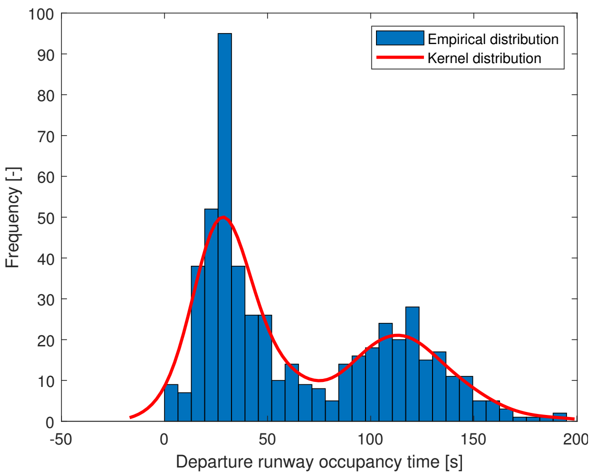

Figure D.11: Histogram of departure runway occupancy time for light aircraft. Empirical distribution with a kernel fit.

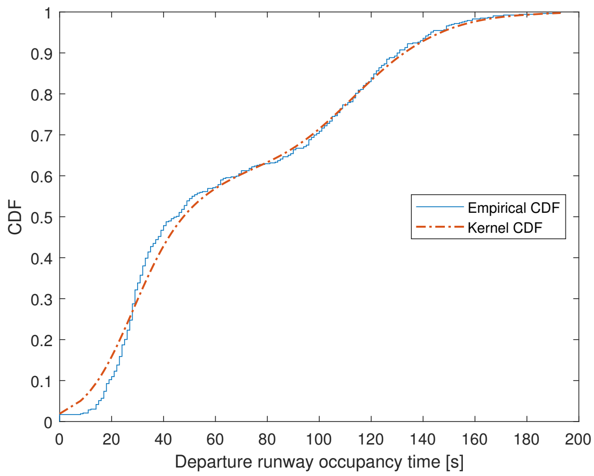

Figure D.12: CDF of departure runway occupancy time for light aircraft. Empirical data and kernel distribution.

E

Distributions required for modelling multiple runways

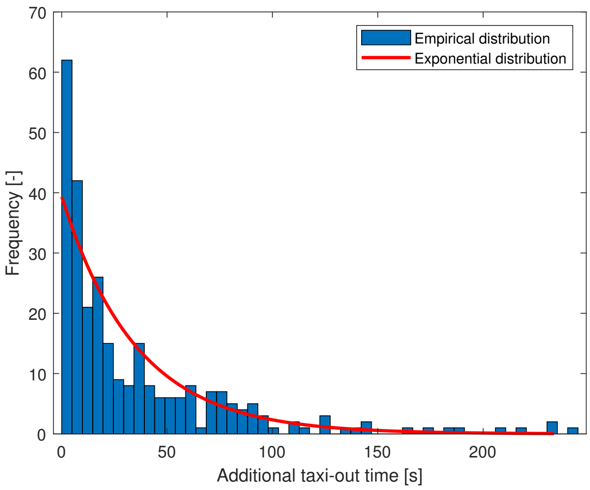

Figure E.1: Histogram of additional taxi-out time when 0-4 aircraft are in the system. Flights departing from R29.

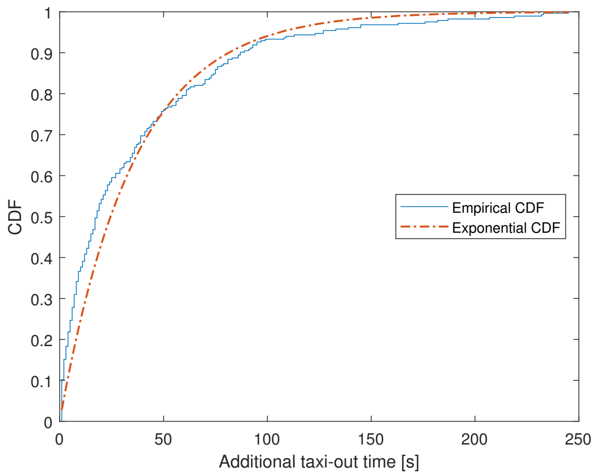

Figure E.2: CDF of additional taxi-out time when 0-4 aircraft are in the system. Flights departing from R29.

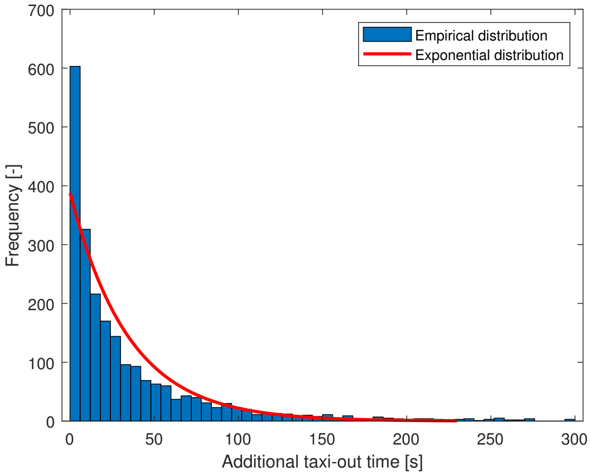

Figure E.3: Histogram of additional taxi-out time when 5-8 aircraft are in the system. Flights departing from R29.

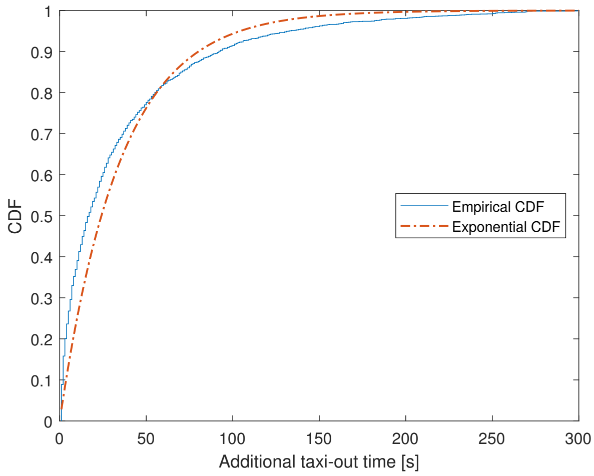

Figure E.4: CDF of additional taxi-out time when 5-8 aircraft are in the system. Flights departing from R29.

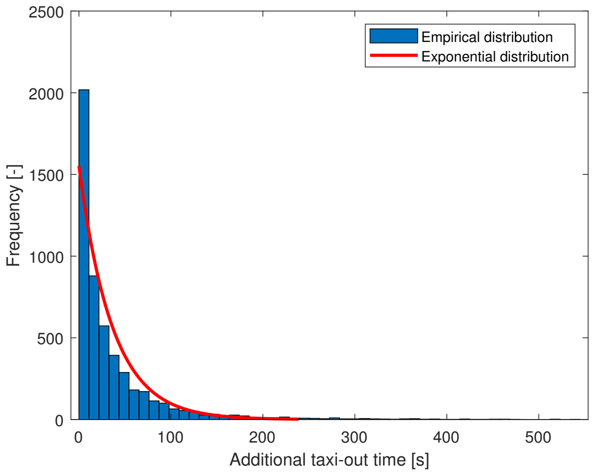

Figure E.5: Histogram of additional taxi-out time when 9-12 aircraft are in the system. Flights departing from R29.

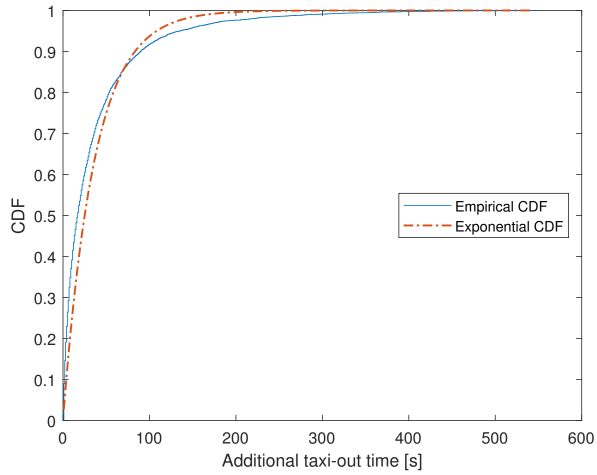

Figure E.6: CDF of additional taxi-out time when 9-12 aircraft are in the system. Flights departing from R29.

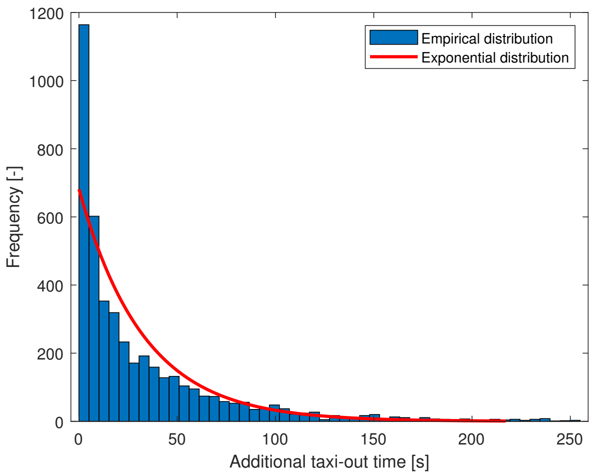

Figure E.7: Histogram of additional taxi-out time when 13-16 aircraft are in the system. Flights departing from R29.

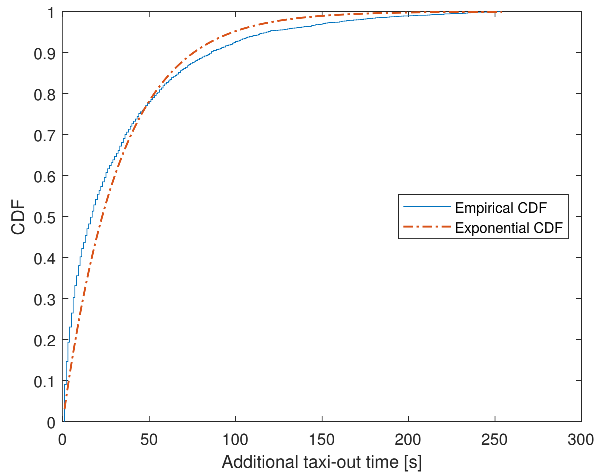

Figure E.8: CDF of additional taxi-out time when 13-16 aircraft are in the system. Flights departing from R29.

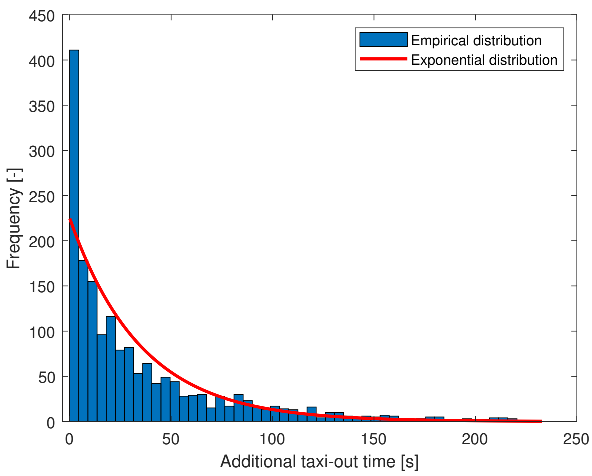

Figure E.9: Histogram of additional taxi-out time when 17-20 aircraft are in the system. Flights departing from R29.

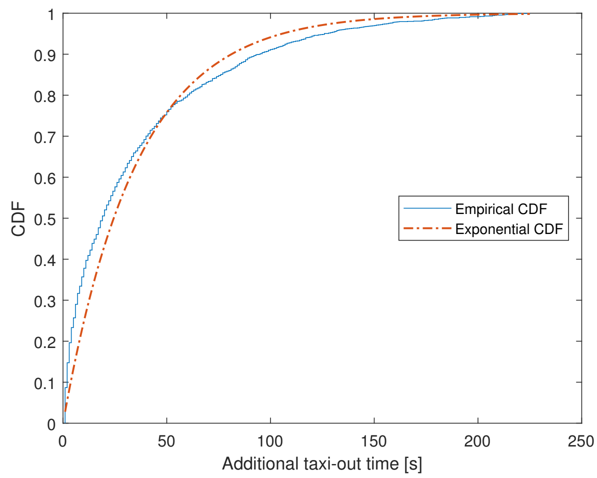

Figure E.10: CDF of additional taxi-out time when 17-20 aircraft are in the system. Flights departing from R29.

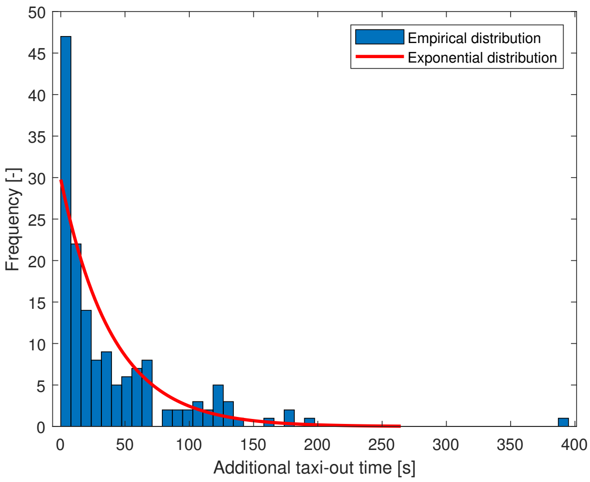

Figure E.11: Histogram of additional taxi-out time when 21-24 aircraft are in the system. Flights departing from R29.

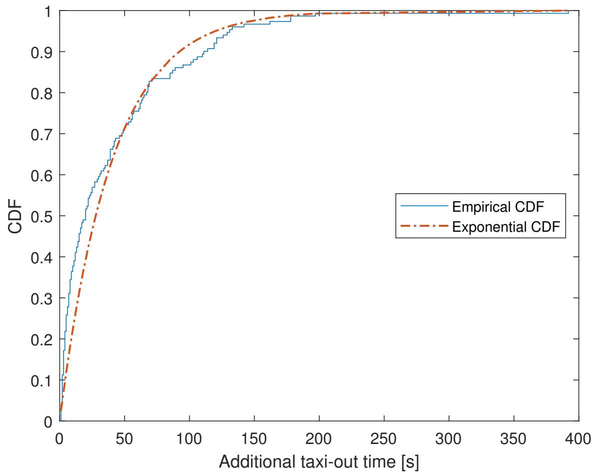

Figure E.12: CDF of additional taxi-out time when 21-24 aircraft are in the system. Flights departing from R29.

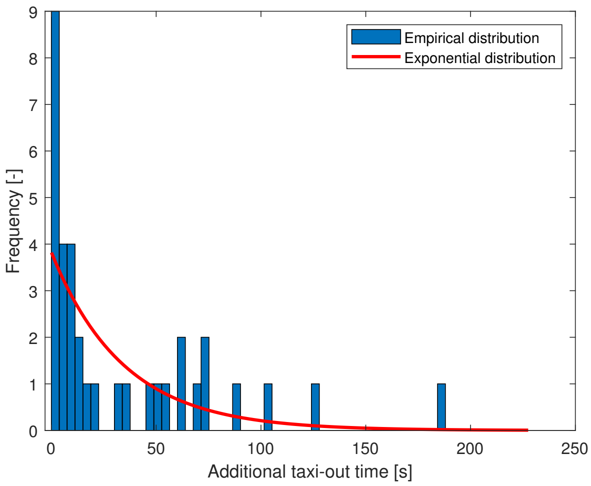

Figure E.13: Histogram of additional taxi-out time when 0-4 aircraft are in the system. Flights departing from R34.

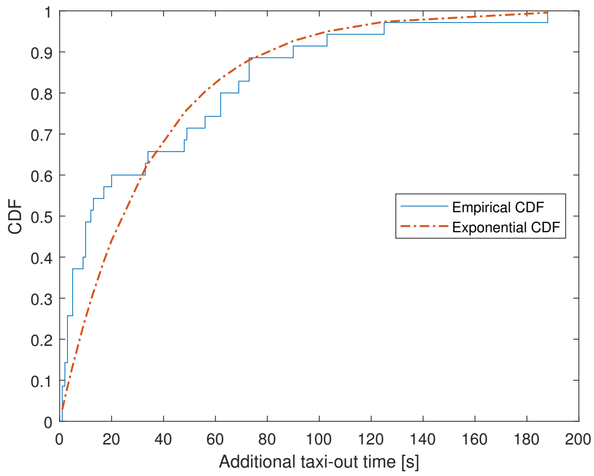

Figure E.14: CDF of additional taxi-out time when 0-4 aircraft are in the system. Flights departing from R34.

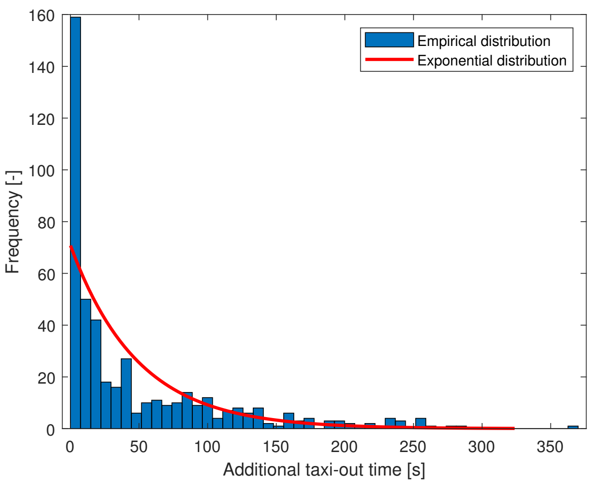

Figure E.15: Histogram of additional taxi-out time when 5-8 aircraft are in the system. Flights departing from R34.

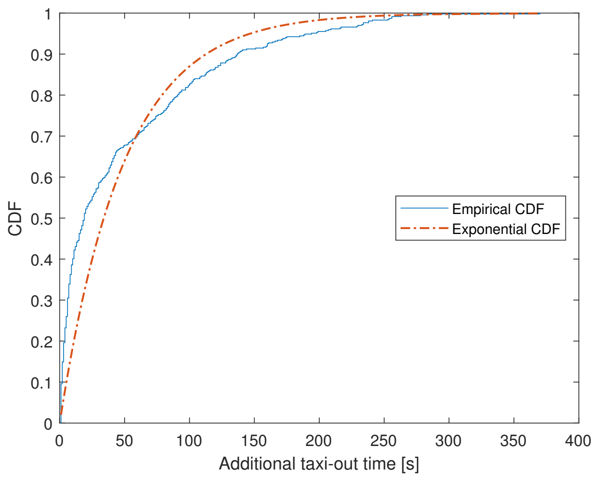

Figure E.16: CDF of additional taxi-out time when 5-8 aircraft are in the system. Flights departing from R34.

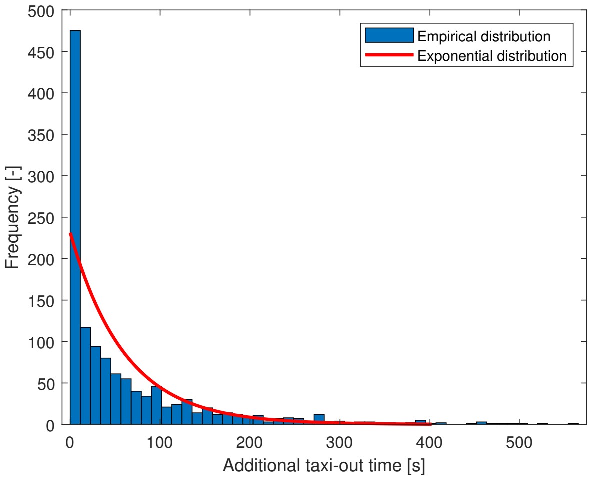

Figure E.17: Histogram of additional taxi-out time when 9-12 aircraft are in the system. Flights departing from R34.

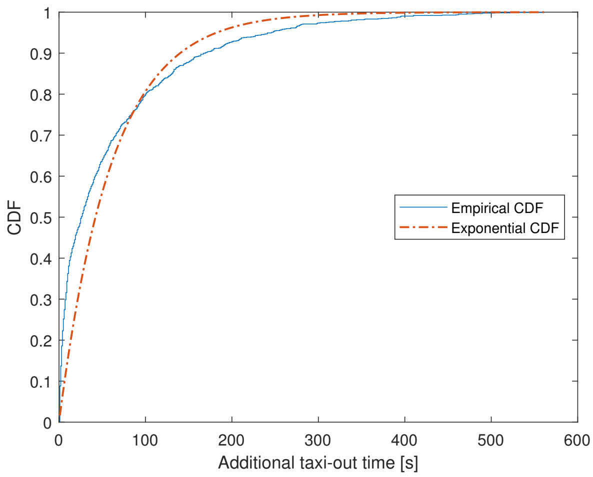

Figure E.18: CDF of additional taxi-out time when 9-12 aircraft are in the system. Flights departing from R34.

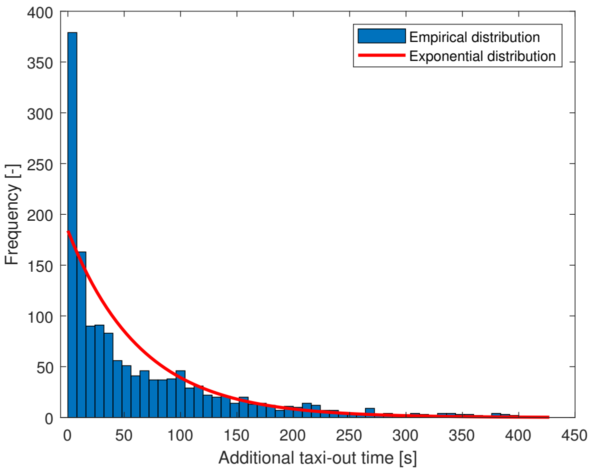

Figure E.19: Histogram of additional taxi-out time when 13-16 aircraft are in the system. Flights departing from R34.

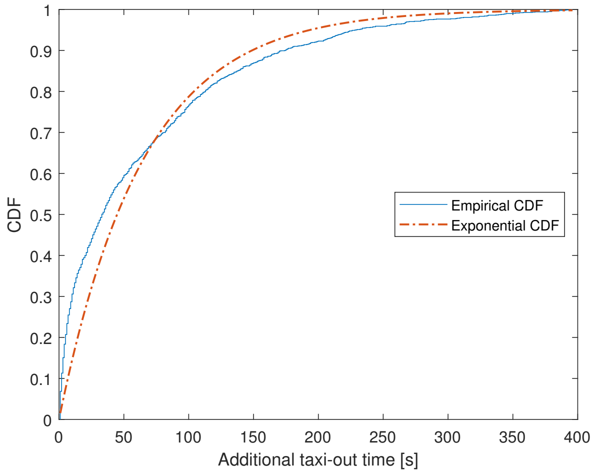

Figure E.20: CDF of additional taxi-out time when 13-16 aircraft are in the system. Flights departing from R34.

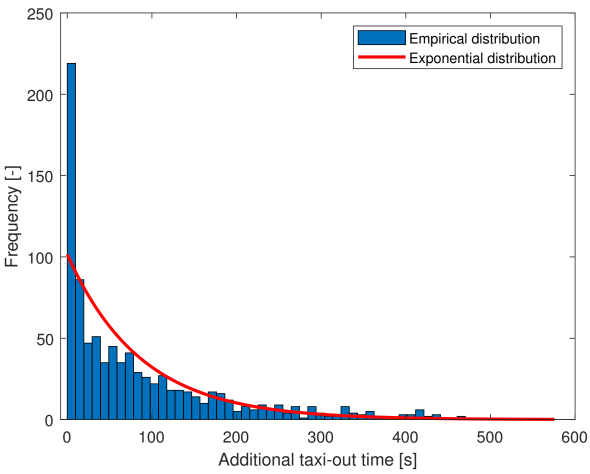

Figure E.21: Histogram of additional taxi-out time when 17-20 aircraft are in the system. Flights departing from R34.

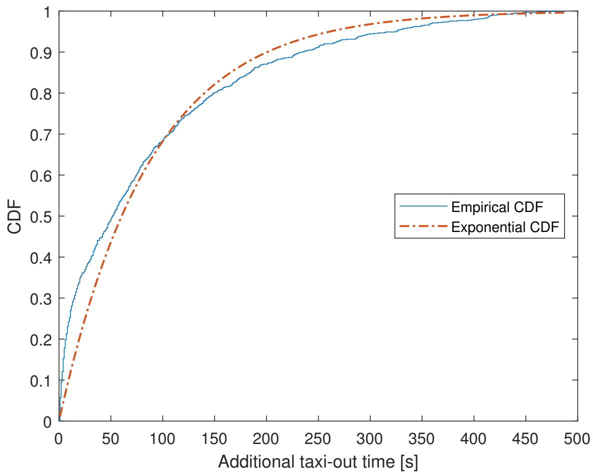

Figure E.22: CDF of additional taxi-out time when 14-20 aircraft are in the system. Flights departing from R34.

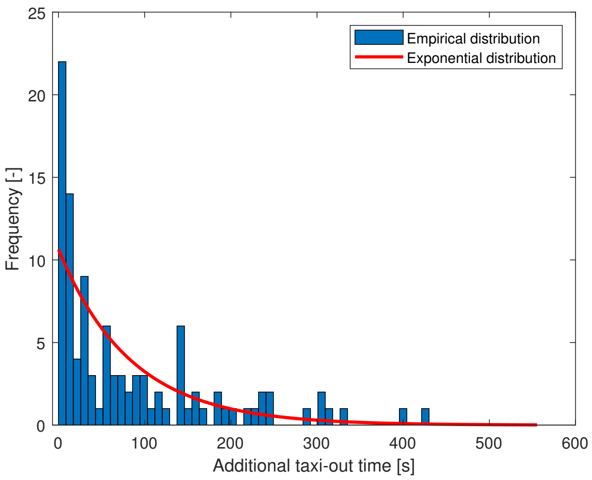

Figure E.23: Histogram of additional taxi-out time when 21-24 aircraft are in the system. Flights departing from R34.

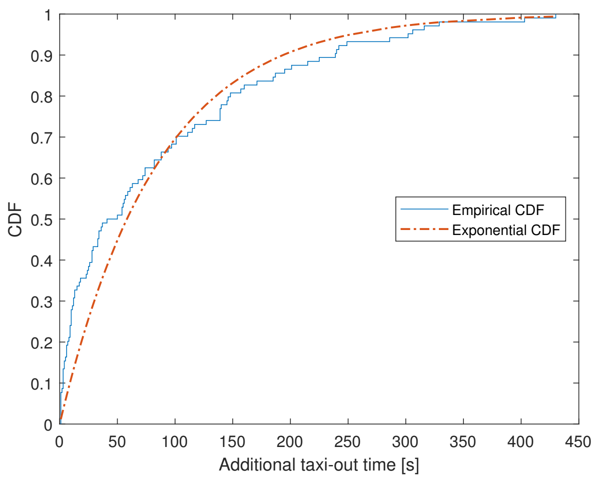

Figure E.24: CDF of additional taxi-out time when 21-24 aircraft are in the system. Flights departing from R34.

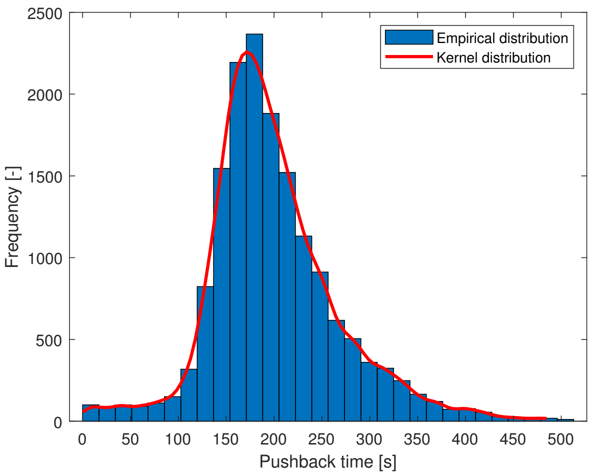

Figure E.25: Histogram of push-back duration with a kernel fit. Combined data from multiple runways.

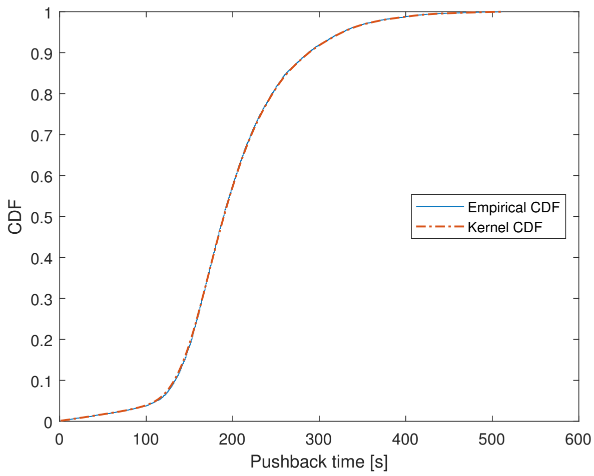

Figure E.26: CDF of push-back duration with a kernel fit. Combined data from multiple runways.

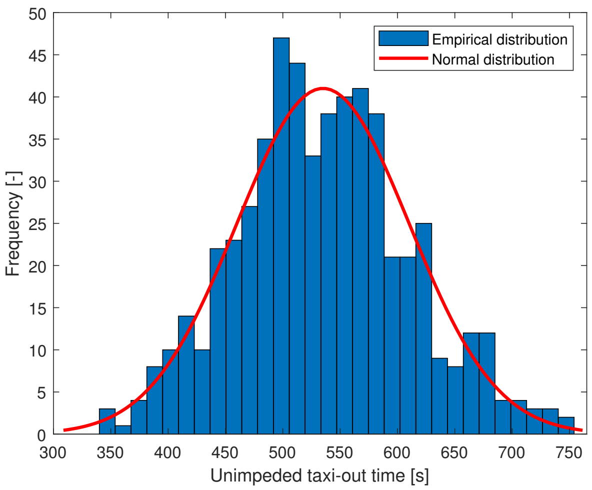

Figure E.27: Histogram of unimpeded taxi-out time for flights departing at R34 - Group AB

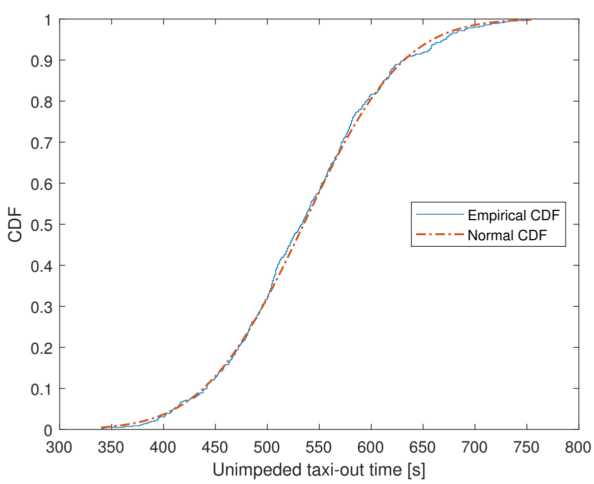

Figure E.28: CDF of unimpeded taxi-out time for flights departing at R34 - Group AB

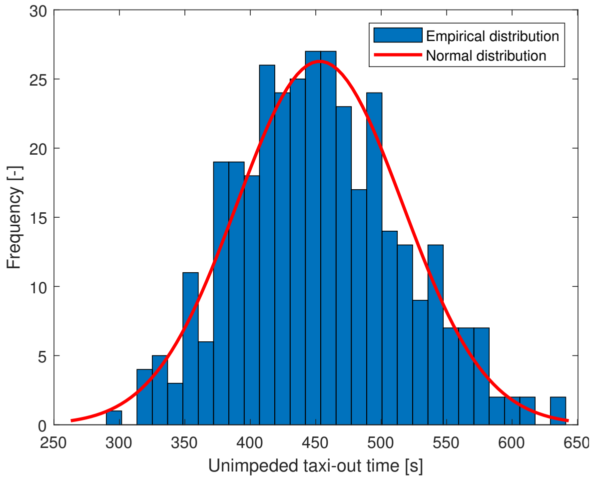

Figure E.29: Histogram of unimpeded taxi-out time for flights departing at R34 - Group C1

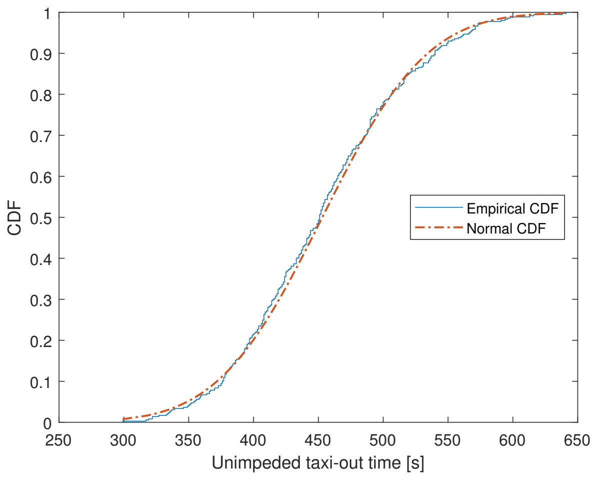

Figure E.30: CDF of unimpeded taxi-out time for flights departing at R34 - Group C1

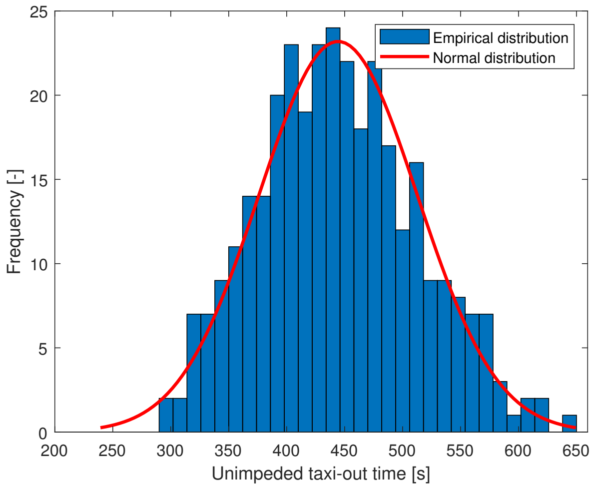

Figure E.31: Histogram of unimpeded taxi-out time for flights departing at R34 - Group C2

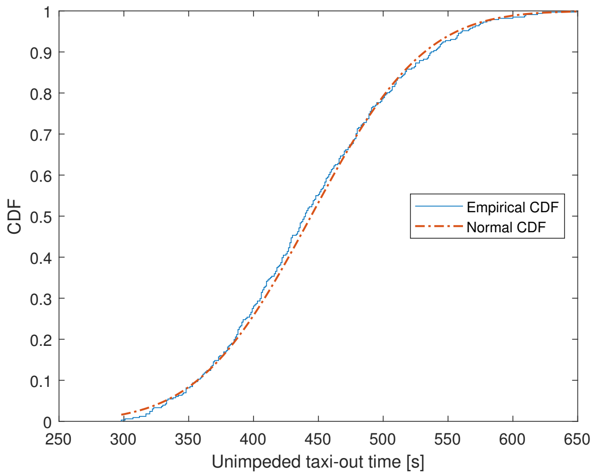

Figure E.32: CDF of unimpeded taxi-out time for flights departing at R34 - Group C2

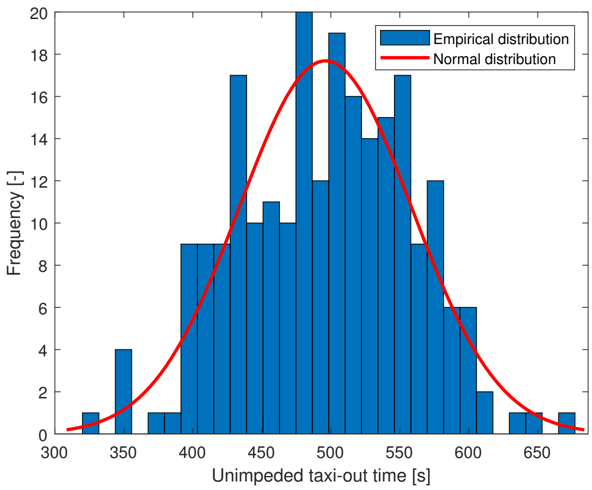

Figure E.33: Histogram of unimpeded taxi-out time for flights departing at R34 - Group D1

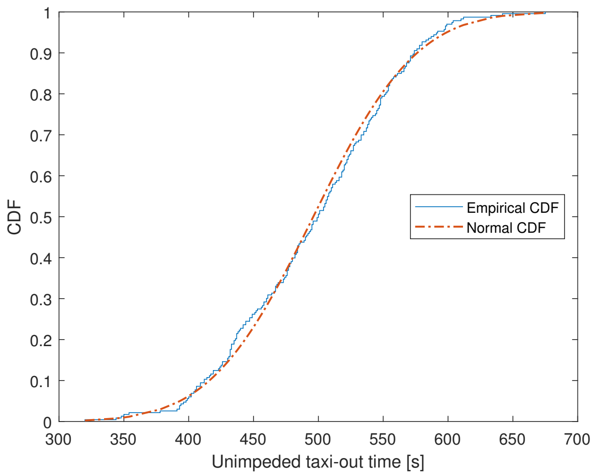

Figure E.34: CDF of unimpeded taxi-out time for flights departing at R34 - Group D1

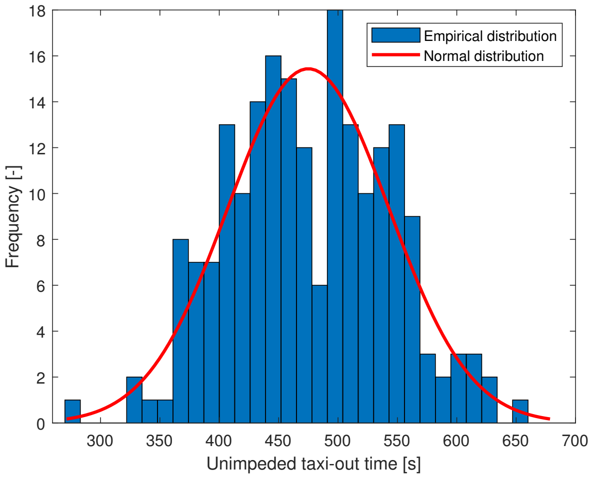

Figure E.35: Histogram of unimpeded taxi-out time for flights departing at R34 - Group D2

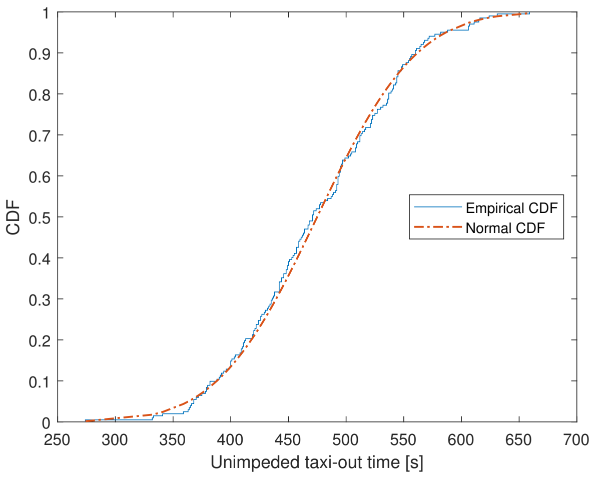

Figure E.36: CDF of unimpeded taxi-out time for flights departing at R34 - Group D2

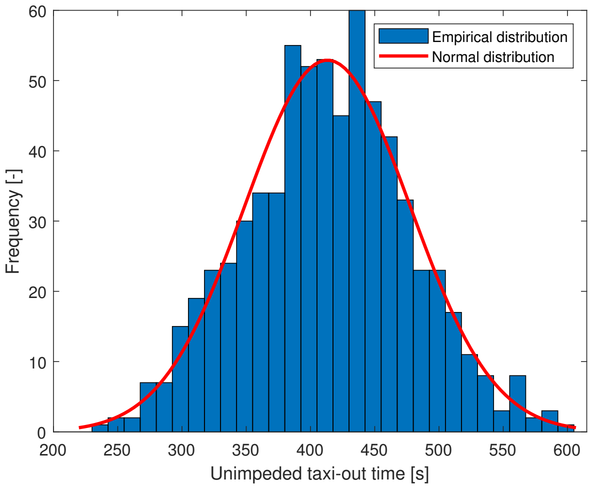

Figure E.37: Histogram of unimpeded taxi-out time for flights departing at R34 - Group E1

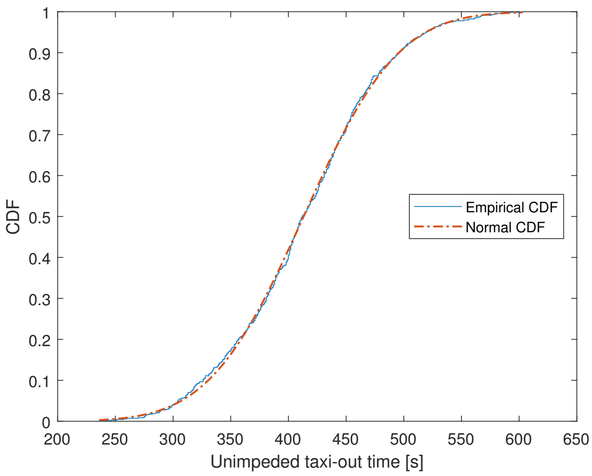

Figure E.38: CDF of unimpeded taxi-out time for flights departing at R34 - Group E1

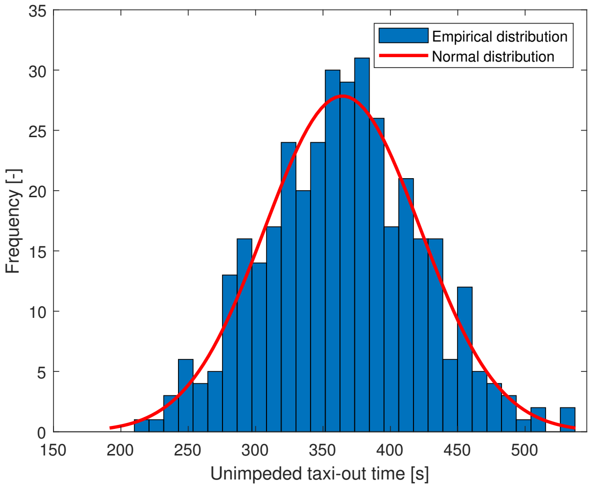

Figure E.39: Histogram of unimpeded taxi-out time for flights departing at R34 - Group E2

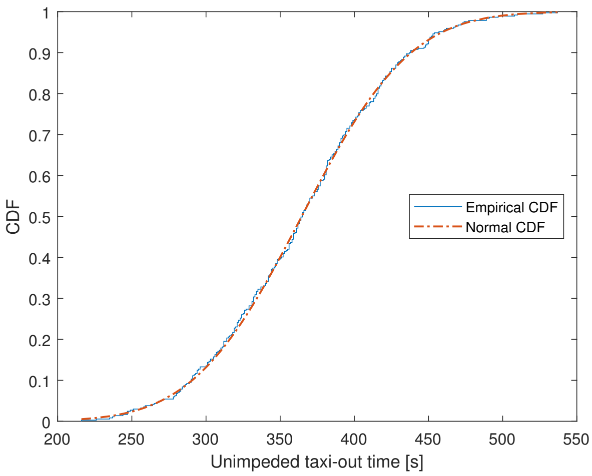

Figure E.40: CDF of unimpeded taxi-out time for flights departing at R34 - Group E2

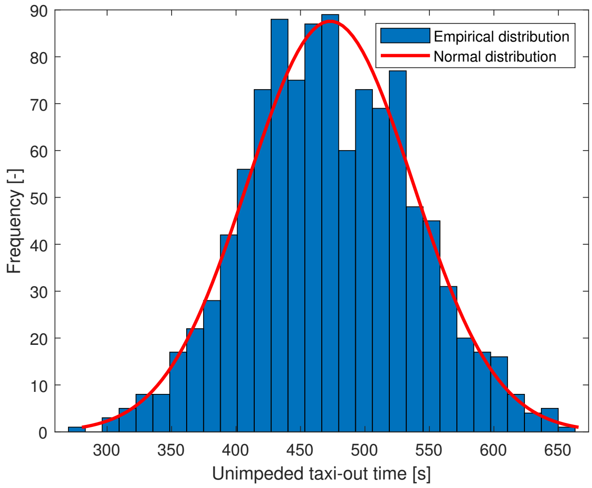

Figure E.41: Histogram of unimpeded taxi-out time for flights departing at R34 - Group F1

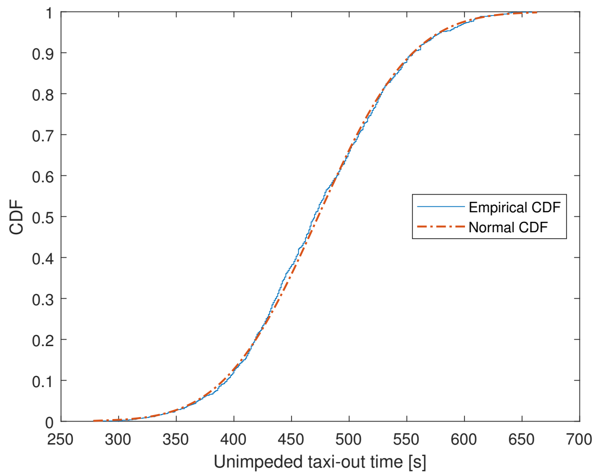

Figure E.42: CDF of unimpeded taxi-out time for flights departing at R34 - Group F1

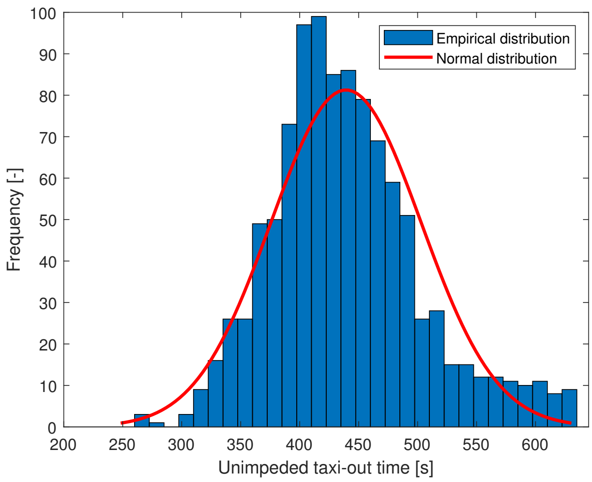

Figure E.43: Histogram of unimpeded taxi-out time for flights departing at R34 - Group F2

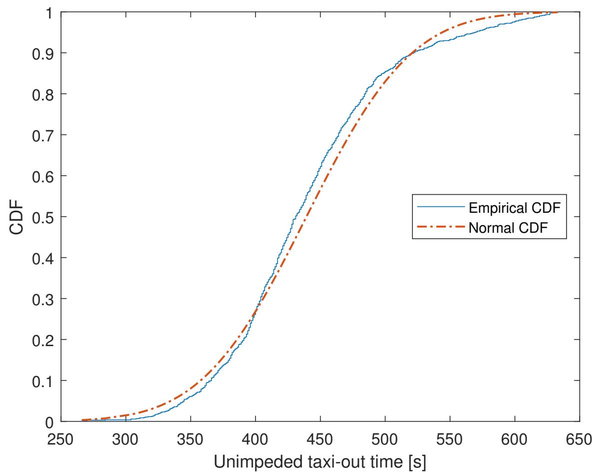

Figure E.44: CDF of unimpeded taxi-out time for flights departing at R34 - Group F2

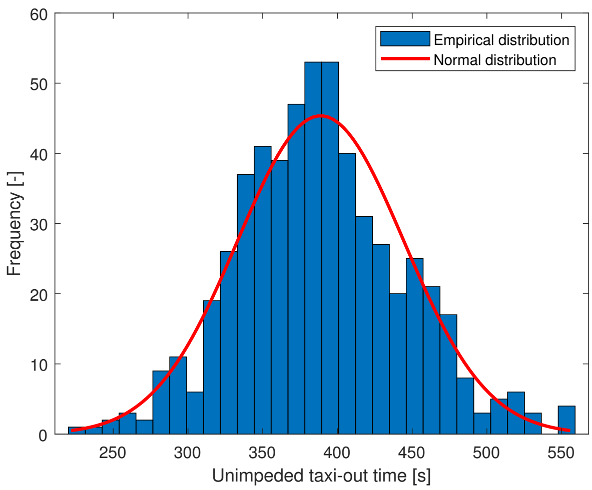

Figure E.45: Histogram of unimpeded taxi-out time for flights departing at R34 - Group F3

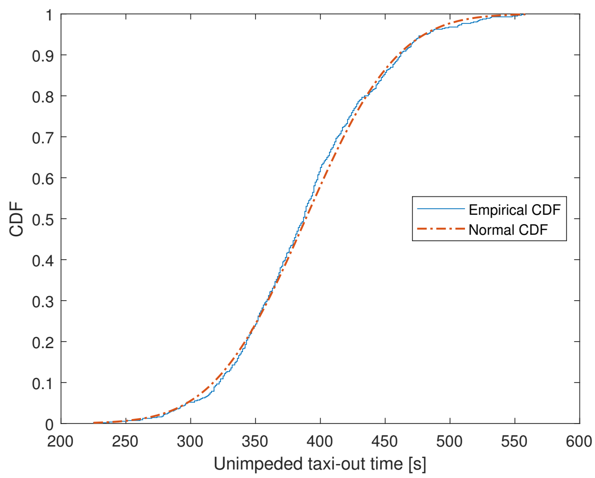

Figure E.46: CDF of unimpeded taxi-out time for flights departing at R34 - Group F3

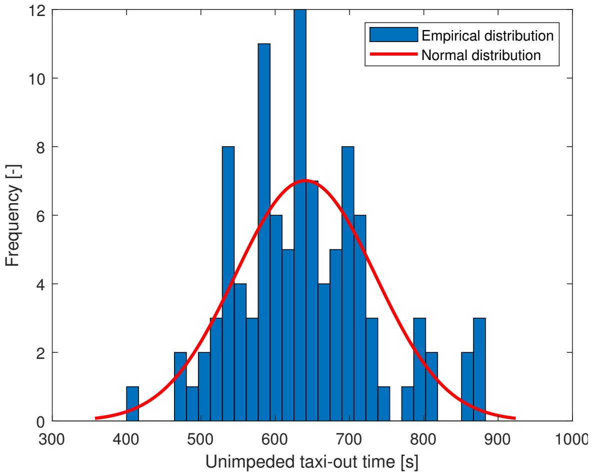

Figure E.47: Histogram of unimpeded taxi-out time for flights departing at R34 - Group GAW

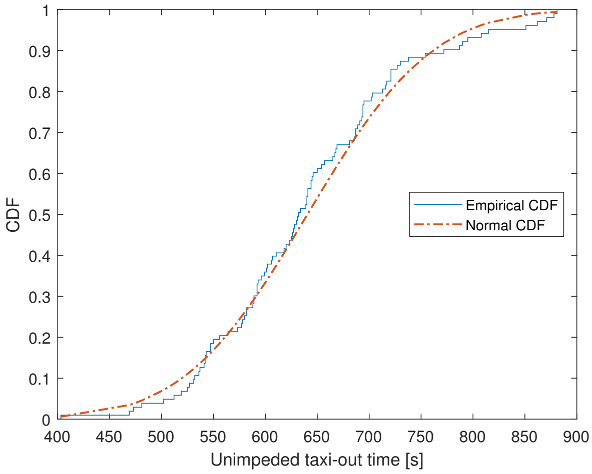

Figure E.48: CDF of unimpeded taxi-out time for flights departing at R34 - Group GAW

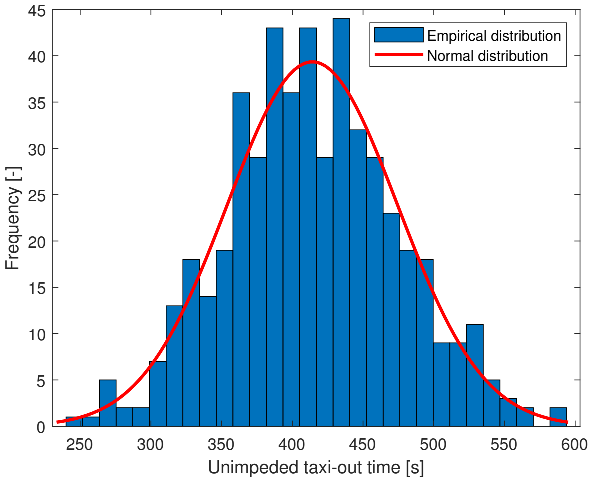

Figure E.49: Histogram of unimpeded taxi-out time for flights departing at R34 - Group H

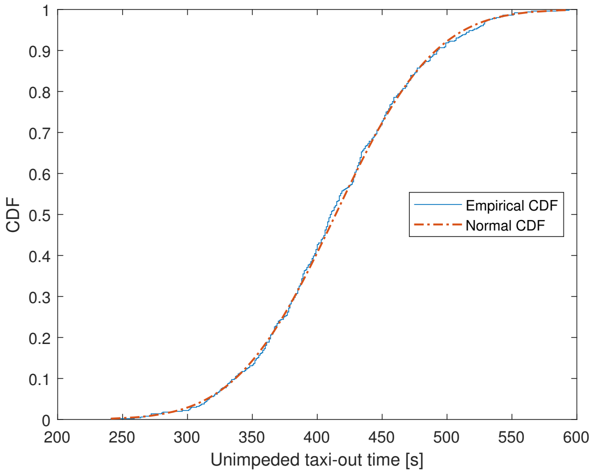

Figure E.50: CDF of unimpeded taxi-out time for flights departing at R34 - Group H

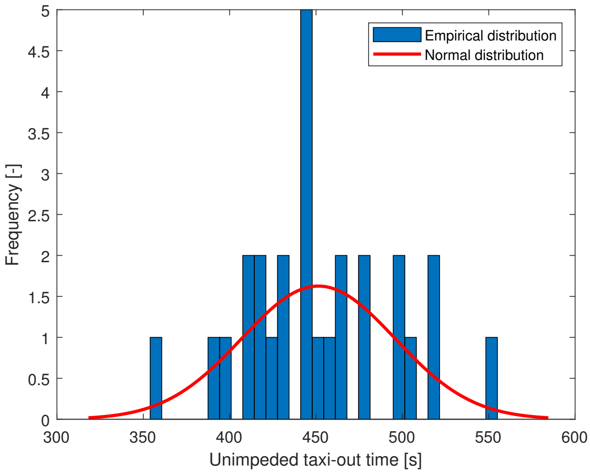

Figure E.51: Histogram of unimpeded taxi-out time for flights departing at R34 - Group K

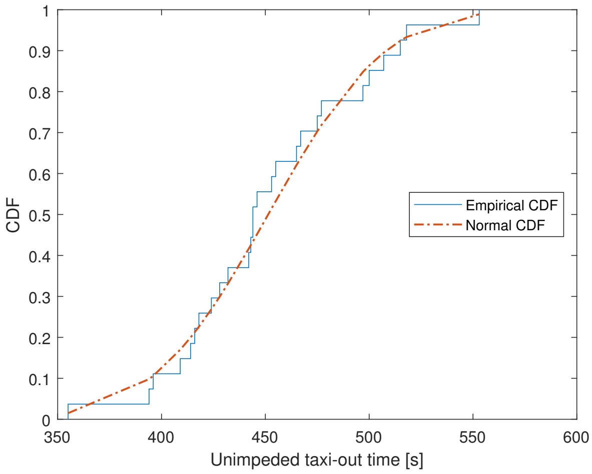

Figure E.52: CDF of unimpeded taxi-out time for flights departing at R34 - Group K

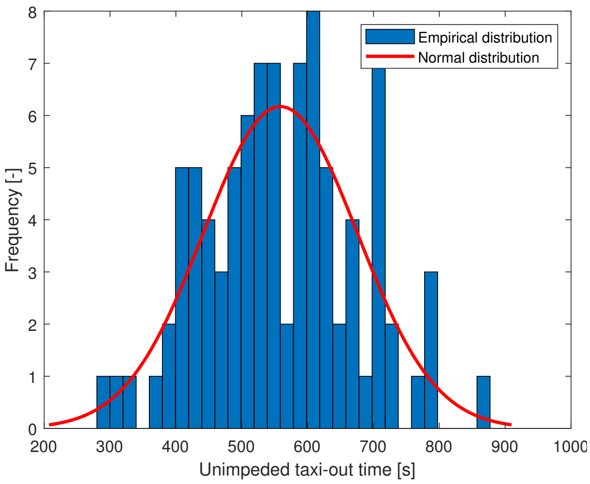

Figure E.53: Histogram of unimpeded taxi-out time for flights departing at R34 - Group none

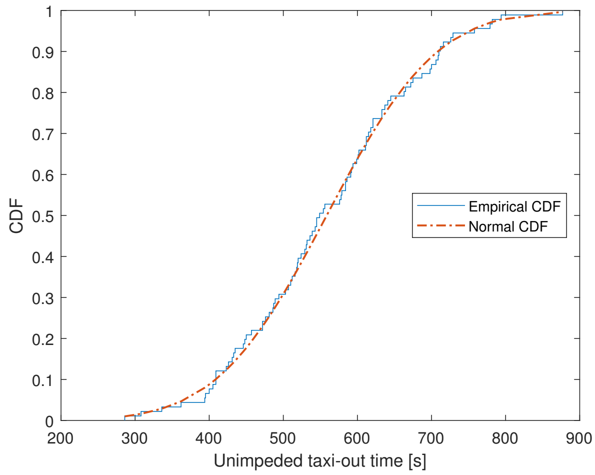

Figure E.54: CDF of unimpeded taxi-out time for flights departing at R34 - Group none

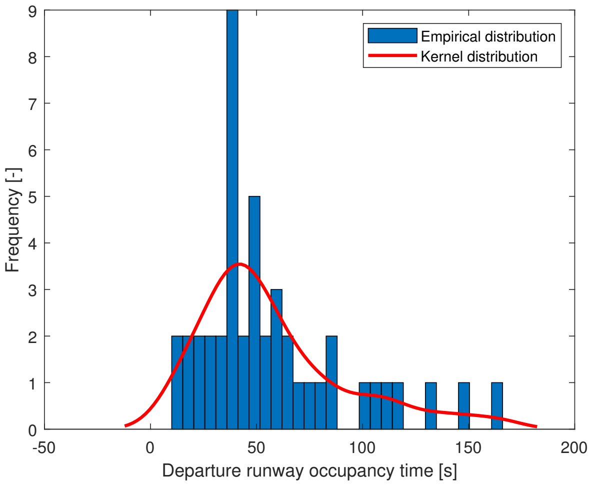

Figure E.55: Histogram of departure runway occupancy time for flights departing at R34 - Light aircraft

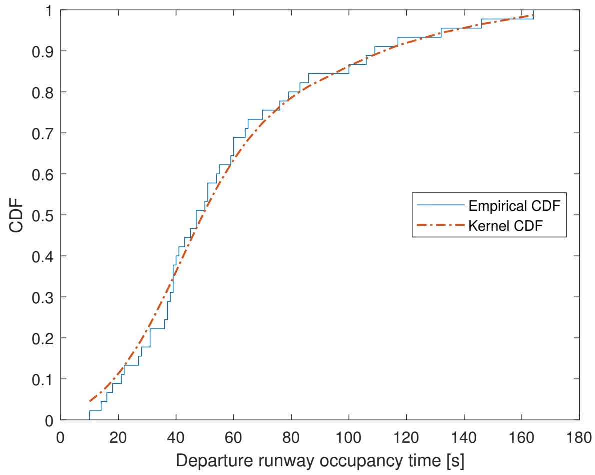

Figure E.56: CDF of departure runway occupancy time for flights departing at R34 - Light aircraft

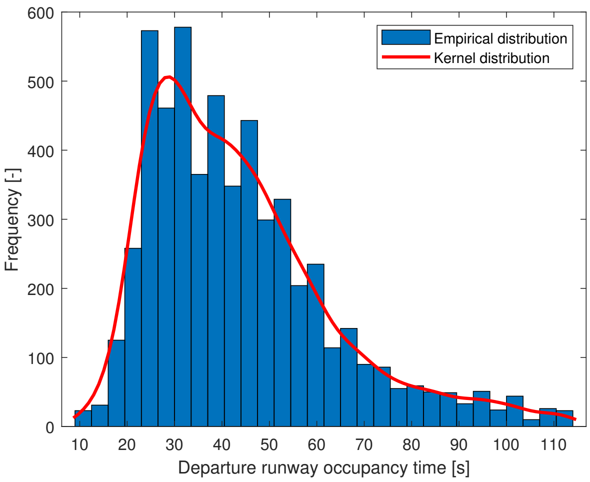

Figure E.57: Histogram of departure runway occupancy time for flights departing at R34 - Medium aircraft

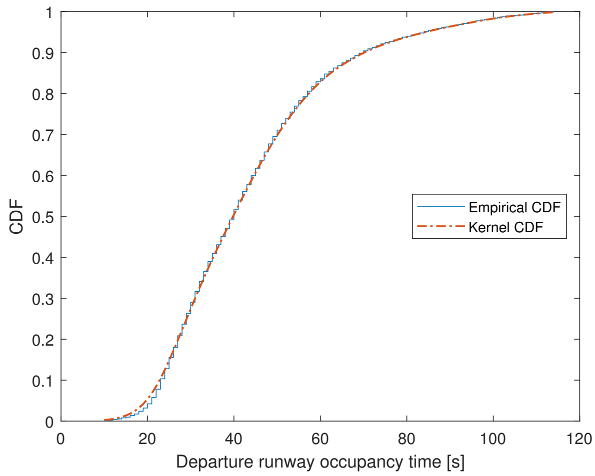

Figure E.58: CDF of departure runway occupancy time for flights departing at R34 - Medium aircraft

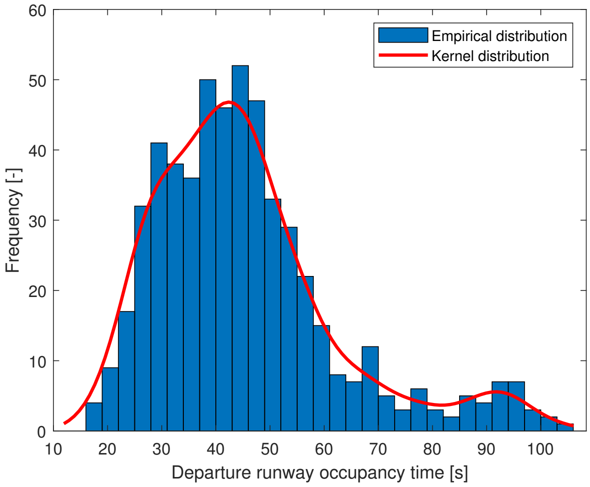

Figure E.59: Histogram of departure runway occupancy time for flights departing at R34 - Heavy aircraft

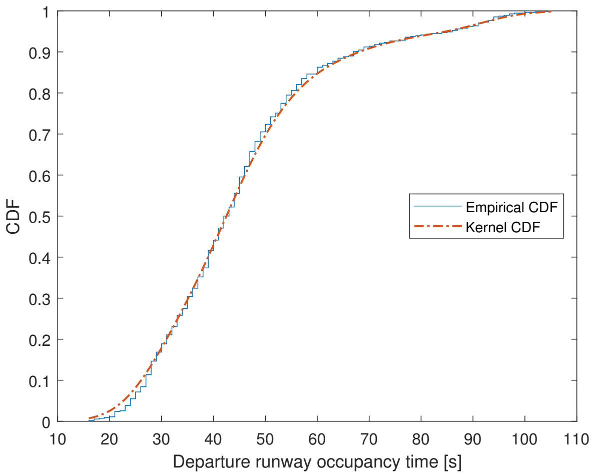

Figure E.60: CDF of departure runway occupancy time for flights departing at R34 - Heavy aircraft

F
Outlier removal

Table F.1: Outlier removal for segregated operations model

Distribution	Specification	Flights	Outliers	Percentage
Push-back		12435	78	0.63%
Unimpeded taxi-out time	AB	2234	5	0.22%
	C1	2207	11	0.50%
	C2	1351	4	0.30%
	D1	980	13	1.33%
	D2	988	17	1.72%
	E1	2100	10	0.48%
	E2	810	10	1.23%
	F1	3431	27	0.79%
	F2	2602	31	1.19%
	F3	1090	6	0.55%
	GAW	867	5	0.58%
	H	988	4	0.40%
	K	255	1	0.39%
	none	694	4	0.58%
Additional taxi-out time		21139	112	0.53%
Departure runway occupancy time	H	1052	21	2.00%
	M	19536	377	1.93%
	L	531	2	0.38%
Service time		7783	8	0.10%

Table F.2: Outlier removal for mixed-mode operations model

Distribution	Specification	Flights	Outliers	Percentage
Push-back		16075	104	0.65%
Unimpeded taxi-out time R34	AB	563	1	0.18%
	C1	360	3	0.83%
	C2	331	0	0.00%
	D1	233	0	0.00%
	D2	203	1	0.49%
	E1	687	3	0.44%
	E2	371	2	0.54%
	F1	1079	3	0.28%
	F2	1043	5	0.48%
	F3	563	3	0.53%
	GAW	104	1	0.96%
	H	506	2	0.40%
	K	27	0	0.00%
	none	92	1	1.09%
Additional taxi-out time R29	0-4	456	11	2.41%
	5-8	3487	43	1.23%
	9-12	7788	25	0.32%
	13-16	6676	59	0.88%
	17-20	2542	40	1.57%
	21-24	190	1	0.53%
Additional taxi-out time R34	0-4	78	1	1.28%
	5-8	833	9	1.08%
	9-12	1962	13	0.66%
	13-16	2172	21	0.97%
	17-20	1144	21	1.84%
	21-24	126	4	3.17%
Departure runway occupancy time R34	H	555	9	1.62%
	M	5711	104	1.82%
	L	46	1	2.17%
Runway waiting time R34		6315	186	2.95%