Operational Analysis of Dutch Air Traffic using ADS-B Data Statistics

By group CD10:
Amant, B. (4672291) - van Amstel, N. (4666895) - Goetzee, T. (4539907) - Hoyng, J. (4664299)
Marquez, S. (4678974) - Middelhoek, C. (4672364) - Ramirez, M. (4682254)
Thu Tun, A. (4650395) - Vassen, F. (4667557) - Vermani, S. (4657764)
June 14, 2019

Abstract

Air Traffic Management (ATM) research studies the behaviour of aircraft in a certain airspace. This process involves simulation which works with data that is proprietary and/or restricted, which often makes sharing and comparing results between different investigations difficult. An open-source ATM simulator, such as the BlueSky project of the Delft University of Technology, is an ideal solution to this problem. For such a project, however, large amounts of freely available data regarding aircraft, airspace and airport usage are needed. This research paper aims to take advantage of Automatic Dependent Surveillance Broadcast (ADS-B) data to produce three statistics that represent the Dutch airspace and airports. This representation can then be used in open-source ATM simulation projects such as BlueSky. In this research, only data from January 2018 has been analysed, which has been collected from an antenna at the Delft University of Technology. The antenna range is limited to the majority of the Dutch airspace, so the analysis will also be limited to the Dutch airspace and airports. Nonetheless, the underlying code can be used by others as a basis to represent other airspaces and airports. This research project therefore is not only useful as a representation of the Dutch airspace, it is also a useful contribution to any worldwide open-source air traffic simulator.

I. Introduction

Automatic Dependent Surveillance - Broadcast (ADS-B) is a technology that allows aircraft to determine their own position and velocity, and then broadcast this information along with identification [1]. ADS-B is now equipped in the majority of commercial aircraft in Europe, and by 2020 it will be a requirement for virtually all aircraft in Europe [2]. The broadcasted messages are not encrypted and can be received by anyone who sets up their own monitoring station. When processed and analysed, this large amount of publicly available flight data can yield useful results. For example, research by Sun et al. [3] used machine learning methods to filter a large and noisy set of ADS-B data into separate flights and their flight phases. In another research by Sun et al. [4], ADS-B data has been used to estimate the takeoff mass of different aircraft which is then useful for aircraft performance models.

Specific and high accuracy data on aircraft performance tends to be restricted due to licensing, since aircraft manufacturers want to keep this data confidential. The Base of Aircraft Data (BADA), provided by the European Organisation for the Safety of Air Navigation (EUROCONTROL), for example, is partially restricted [5]. This has had the consequence that research by different people involving air traffic simulation is hard to compare, since openly sharing their simulator and/or data is difficult due to the restrictions mentioned above. The BlueSky Air Traffic Management (ATM) simulator project by the Control & Simulation department of the Aerospace Engineering Faculty at the Delft University of Technology aims to address exactly this issue by developing an open-source simulator using publicly available data [5]. Since ADS-B data is public and easily attainable, it is an ideal source for such a project.

In this research paper, the following research question will be explored: How can the Dutch airspace and airports be represented through statistical relations regarding airport traffic mix, landings and takeoffs per hour, and the average shortest separation distance of aircraft? The produced statistics will then be useful to represent the Dutch airspace, whereas the used code [6] can serve as a basis for representing another airspace than the Netherlands.

To see how statistics can be made and why they can be useful, landings and take offs per hour will be used as an example. Using the ADS-B data, the mean and variance of the number of take-offs and/or landings per hour can be found, which can then be used to create distributions. Simulators like the BlueSky ATM simulator can use these distributions to generate realistic flight schedule for a given day. Moreover, simulations based on statistics are favoured instead of historical data, since the statistics can be manipulated with the researched variables of influence. With the expected grow of air traffic in the future, for example, the statistical relations can still be used to simulate increases or decreases in flight frequency, which is not possible with historical data.

After consulting Dr. ir. J. Ellerbroek, the tutor of this research project, these three statistics were chosen to research since they originate from a flight cycle. To simulate this cycle, the simulator must know when and where a certain type of aircraft takes off or lands. Once airborne, the simulator must separate the aircraft in a realistic way. The shortest separation distance can then be used for this.

The core of this article will only focus on the three described statistics. However, other relations or parameters can be obtained from the ADS-B data. Since these 'extra' statistics provide useful information to run a more detailed simulation, five other statistics have been included in Appendices D - H.

II. Data Description

The provided ADS-B data has been obtained from an antenna located at the faculty of Aerospace Engineering of the TU Delft (lat: 51.989884, lon: 4.375374). The raw ADS-B data received by the antenna was provided to us already decoded with methods described in [7] by Sun.

The decoded data (provided as CSV file) consists of the following set of data: time stamp, icao, latitude, longitude, altitude, ground speed, track/heading, rate of climb (ROC), call sign, and flight ID. The 'icao' data consists of the 24-bit Aircraft Address. This is a unique verification code for every aircraft coordinated by the International Civil Aviation Organization (ICAO) [8]. For simplicity this unique code is referred to as 'icao' from now on. Furthermore, the call sign and flight ID data represent unique flight identification. Each flying aircraft transmits its data continuously, therefore multiple lines of data exist for a unique flight.

For the airport traffic mix statistic, information regarding the type of aircraft of each flight is required. Since this is not present in the provided ADS-B data, another database must be used. The 'World Aircraft Database' [9] has been used since this is currently the most accessible available open-source database. It contains the following set of data: icao, registration ID, aircraft model, aircraft type and operator. Again the 'icao' data consists of the unique aircraft codes.

Before starting the data analysis, it is necessary to combine these two databases. In this research, Python (v3.7) has been used for this as well as for further statistical analysis. Specific elements of the package 'pandas' were utilised to analyse and process data.

First, both databases need to be read into a pandas dataframe. For a faster processing, the type of each column inputs should be specified. Then, the two dataframes were merged by the 'icao' inputs, which is present in both data sets. The resulting dataframe now consists of columns which represent all the data that is present in both the ADS-B dataframe as well as the aircraft database. Lastly, the package 'datetime' has been used to convert the time stamp into the correct date and time(zone). For a visual representation of the steps taken, see Figure 1. This obtained main ADS-B dataframe now forms the basis for further analysis in section III.

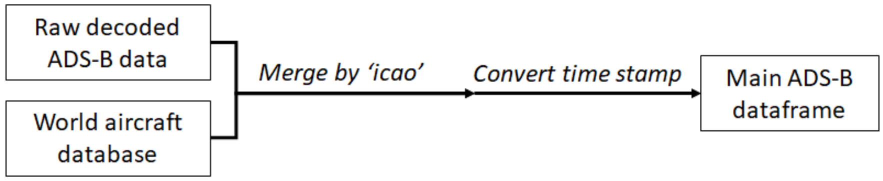

Figure 1. Flow chart to generate the 'main ADS-B dataframe'.

III. Data Analysis Method

Now that the main ADS-B dataframe has been obtained, a division between airport and airspace can be made. For the airport statistics, first in subsection A, the main dataframe is used to determine which runway is used by landing and departing flights. Additionally, take-off or landing is specified. Obtaining the actual airport statistics will be elaborated upon in subsection B. The method for generating the statistics related to the average minimum separation distance will be discussed in subsection C.

A. Airport Runway Detection Dataframe

The statistics related to airports require an extra set of data regarding the runways being considered. In this research only commercial Dutch airports (Schiphol, Eindhoven, Rotterdam, Maastricht and Groningen) were considered. The following data is needed: exact runway headings, location (longitude and latitude) and altitude of the specific runways. For the considered runways, information can be found through 'AIS The Netherlands' [10].

A certain area around the runway, based on its real location, must now be set up by defining the coordinates of the area's vertices. Along with the heading, this area will be used to assign a runway to an aircraft landing on or taking off from it. It is important to make the area large enough so that all data points from landing and departing aircraft from the ADS-B data are inside this defined area. However, note that the defined areas of runways with a similar heading should not interfere with each other since this can cause an erroneous runway assignment. To visualise the areas' coordinates, 'Google Maps' [11] was used. Additionally, 'Flightradar24' [12] was utilised to check altitude and position from real aircraft. In this way, a more realistic area can be defined. Next, the headings and the created areas' coordinates were saved in a separate 'runway' csv file.

Now, a specific runway will be assigned to a certain aircraft/flight. To do this, first the main ADS-B dataframe and the 'runway' file must be read into a python script. Then, when an aircraft flies below a certain altitude (in this analysis $< 5000ft$), within one of the specified areas of the runways, and with a heading that matches the given runway, this specific runway is assigned to that aircraft. A margin of five degrees in heading is taken to factor out certain errors/uncertainties.

Besides runway detection, landing or take-off should also be determined. This is based on the value of the rate of climb (ROC). For a positive rate of climb ($ROC > 0$), the aircraft is specified as taking off, while for a negative rate of climb ($ROC < 0$) the aircraft is specified as landing. By inspection of the results, another limit value than $ROC = 0$ may be chosen for specific runways. This originates from the fact that double landings could erroneously be determined by the program, since an approach path is not always flown with $ROC < 0$ at every point.

Finally, since the ADS-B data has multiple data lines for each aircraft, landing and take-off are now specified for every data line. Therefore, duplicate flight IDs will need to be deleted to obtain only one landing and/or take-off per flight. For take-off, only the first detectable data line was kept. For landing, only the last detectable data line was kept. This is done to estimate the departure or arrival time as accurately as possible.

Every line of data in this 'runway detection dataframe' now represents a landing or departing aircraft of which its used runway is specified. A flowchart of the overall process is given in Figure 2.

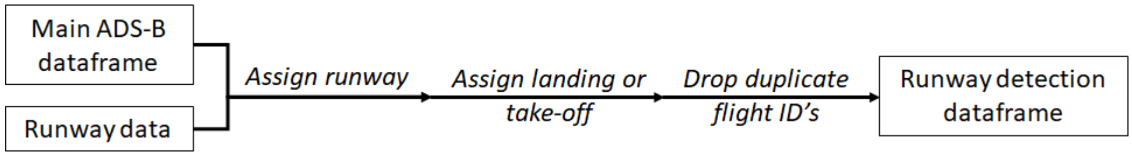

Figure 2. Flow chart to generate the 'runway determination dataframe'.

B. Airport & Runway Statistics

1. *Airport Traffic Mix*

One of the main statistics to be analysed is the airport traffic mix. The distribution of aircraft types in the Dutch airports can be represented through percentages. First the total number of movements (landings and take-offs) of the month January 2018 is counted for each detected aircraft type in the 'runway detection dataframe'. If the counted number per type is then divided by the overall number of detected movements, a monthly average percentage can be obtained. Note that this statistic can be generated for the total traffic or only for a specific airport or a specified runway.

2. *Landing and Take-off Distribution*

The second statistic regarding the Dutch airports is the landing and take-off distributions per hour. This can again be specified for the total traffic or for a specified airport and/or runway. With the dataframe created in subsection A, the number of landings and take-offs can be counted for every hour.

Now the mean and variance can be calculated. The mean and variance can be used for simple and accurate representation of the landing and take-off distributions for airspace simulation programs. The mean values are calculated by applying a for-loop. In this loop the total amount of flights for every hour is counted for each day and added with previously counted flights at that hour. This sum will then be divided by the total amount of days, which results in the mean for that hour.

The variance is calculated using Equation 1. In this equation x_i are the counted flights for one specific day and hour, while x_{mean} is the mean for the same hour as x_i. The result of this equation is added to the previous value. When the for-loop is over, the sum of these values is divided by the total amount of days minus one.

$$(x_i - x_{mean})^2 \tag{1}$$

C. Average Shortest Separation Distance

As mentioned in section I, the average shortest separation between aircraft (**d**) is one of the important parameters for ATM simulators. In order to compute this shortest distance, the Haversine distance formula was used, described by Equation 2. Here, r is the radius of the Earth (6371 km), Φ_1 and Φ_2 represent the latitude position of point 1 and 2 respectively. λ_1 and λ_2 represent the longitude position of point 1 and 2 respectively. This Haversine formula gives the great-circle distance or the shortest distance between two given latitude and longitude positions and thus was used for the average shortest separation computations.

$$d = 2 \cdot r \cdot arcsin(\sqrt{sin^2(\frac{\Phi_2 - \Phi_1}{2}) + cos(\Phi_1) \cdot cos(\Phi_2) \cdot sin^2(\frac{\lambda_2 - \lambda_1}{2})}) \tag{2}$$

In order to compute the average shortest separation distance in the Dutch airspace, the following methodology was adopted. Initially, the data set was modified to restrict the computational domain to the Dutch airspace only. This was done by introducing the two constraints: $50.5 < \Phi < 53.5$ and $3.5 < \lambda < 7.0$. These constraints were applied to the main ADS-B database obtained in section II and a new sub-database was obtained. This sub-database contained the different aircraft data at different time stamps. Therefore in order to compute the shortest separation distance, a certain initial sampling time step (t_s) was chosen, which was later iterated over different values, as explained later. The mean positions of all the aircraft over that time step were calculated. By using these new mean positions, for every aircraft, the nearest aircraft using the Haversine formula was found and the corresponding shortest distance was calculated. A similar computation was further iterated over one whole day and results were stored for every hour of the day. This resulted in the average shortest separation for every hour of the day. A similar calculation has been executed for each day of the month.

After performing the mentioned procedure for different sampling time steps (t_s) such as 60s, 30s, 15s and 10s, the obtained results were compared. It was found that for $t_s <= 15s$, the deviations in the trends resulting curves were minimum whereas for higher t_s ,there was a significant difference. Therefore, the time step of 15s was used and the obtained results are presented in section IV.

IV. Results

A. Airport Statistics

1. Landing and Take-off per hour

The airport movements were counted for all commercial runways in the Netherlands. The mean and variance for the number of landings and take-offs were found for every hour of the day. The full results of this can be found in Table 5 in Appendix A. An interesting sample of the data can be found below in Table 1, which shows 6 hours of the day. The highest total mean occurs at 10:00. For landings, the highest value occurs at 8:00, but there is also a similarly high value at 19:00. For take-off, the highest value is at 21:00, and, similarly to the landings, there is also a second value of similar magnitude at 10:00. It can be seen that at 3:00 there are almost no flights. In Figure 7 and Figure 8 in Appendix B, all the mean values of Table 5 can be found in the form of a bar chart.

Table 1. The variance and mean for landing and take-off for all of the runways combined, for every hour of the day. Hour 0 means from 24:00 to 00:59, hour 1 means 1:00 to 1:59, etc.

Hour	Mean Landing	Variance Landing	Mean Take-off	Variance Take-off	Mean Total	Variance Total
3	0.84	0.87	0.00	0.00	0.87	0.85
8	48.16	80.74	24.10	28.69	72.26	152.33
9	28.94	21.80	33.48	70.79	62.42	103.65
10	30.26	21.06	51.74	93.13	82.00	172.53
19	44.06	43.20	20.03	20.63	64.10	98.22
21	21.48	25.99	52.65	67.57	74.13	150.78

The mean and variance are calculated for every runway, for landing/take-off separately. The mean can be found in Table 6 and Table 7. The variance can be found in Table 8 and Table 9. Table 2 is a small sample of the results that can be found in Appendix A. This table gives information about the mean number of aircraft that land on the Zwanenburgbaan. The tables in the Appendix show that Groningen and Maastricht are not in the list of Runways. This is because landing and taking off can not be determined accurately for these airports, since they are too far away from the antenna. Next to that, the amount of fights on these airports are negligible compared to Schiphol, so they were excluded from the list. It can be seen that for landing, the most used runways are the Polderbaan and the Zwanenburgbaan. For both of these the highest values occur at 8:00 and at 19:00. For take-off, the Kaagbaan and the Aalsmeerbaan were used the most.

Table 2. The mean of the number of aircraft that land at the Zwanenburgbaan for every hour.

Hour	Mean	Hour	Mean	Hour	Mean	Hour	Mean
0	0.26	6	0.55	12	3.58	18	7.71
1	0.10	7	10.84	13	9.29	19	14.68
2	0.13	8	14.42	14	0.84	20	2.61
3	0.06	9	4.81	15	9.90	21	0.65
4	0.13	10	2.90	16	1.71	22	1.06
5	0.16	11	8.03	17	0.94	23	1.10

The mean and variance for every runway for a day are also calculated. The results from this are in

Table 3. The mean values can also be represented in a bar graph. This bar graph can be found in Figure 19 in Appendix B. Groningen is exempted from these graphs for the same reason as in subsubsection 1. As can be seen in Table 3, there is an average of 1 flight a day measured on Maastricht (looks like zero compared to other runways), this is also why it was omitted from other statistics.

Table 3. The mean and variance for the amount of flights per day of each runway.

Runway	Mean number of flights	Variance number of flights
Aalsmeerbaan	181.10	4010.64
Buitenveldertbaan	124.17	14404.58
Eindhoven	80.42	125.45
Kaagbaan	261.32	6571.96
Oostbaan	14.65	197.04
Polderbaan	293.68	6985.83
Rotterdam	24.94	29.20
Zwanenburgbaan	120.76	3828.62
Maastricht	1.33	0.25

2. Airport Traffic Mix

For the arriving and departing flights, the traffic mix has also been determined. A percentage for every type of aircraft that lands at or takes off from a Dutch airport is obtained. This statistic has been generated for the overall movements as well as for movements on each individual runway. Part of the result of the overall traffic mix can be found in Table 4.

Table 4. The overall traffic mix for dutch airports extracted from ADS-B data of January 2018 is given per aircraft type. Here, 'Other' is defined as the sum of percentages below 1.4%.

Type	Percentage	Type	Percentage	Type	Percentage
a319	8.0	b738	27.2	b77w	2.8
a320	13.4	b739	2.5	b789	1.8
a321	3.6	b744	3.1	e190	1.5
a332	1.6	b763	1.4	e75l	7.4
a333	3.0	b772	2.9	Other	5.6
b737	12.8	b77l	1.4		

As can be seen in Table 4, the most common aircraft in the Netherlands is the Boeing 737-800 with 27.2%. For a more complete result of the overall traffic mix of, including further specification of 'Other', please refer to Table 11 and Table 12 in Appendix C. In the same tables, also the results for the traffic mix per runway can be found.

B. Average Shortest Separation Distance

Using the method in section III, the analysis was done for the month January 2018 using the ADS-B data. The obtained result was the mean value of the shortest separation distance (**d**) for each hour of every day. This data was further sorted and analysed to obtain more insightful trends and the results obtained are shown below. Figure 3 provides an overview of the variation of the **d** over the whole month. As can be clearly observed, there are three main observations in the graph. Firstly, at the start of the graph, high peaks are observed. These peaks represent the high value of **d** during night hours (00:00 - 7:00).

Secondly, over the peak/day hours (8:00-20:00), there are no peaks, and the variation of **d** is not visible and it looks like a constant curve at about **d**=20 km. However, that is not the case as there are obvious variations for the different days of the month. Thus, these variations were studied using different representations as explained later. Finally, as the graph approaches night hours (21:00), the curve shows an uplift, which means that the **d** value starts rising again. Therefore, this graph clearly provided a general overview of different trends of variation of **d** over different hours of day for whole month. However, it is unable to provide a clear overview of the variations during peaks or during constant curves as mentioned. Thus, in order to study this, box plots were constructed. Figure 4 represent the box plots of **d** for different days during the peak hours (8:00-20:00). As can be clearly seen, the box plots for most of the days are comparatively short except the ones for Tuesday, Friday and Saturday. This represents that the variation of **d** compared to the median value is small for most of the days. The median values for all of the days are close to each other except the one for Saturday (which shows a higher value for median **d**). However, the distributions for each day are different as clearly visible from the box plot.

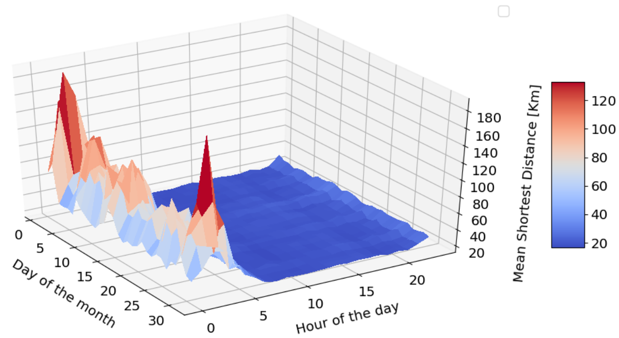

Figure 3. Overview of average shortest separation distance for different days of January month on hourly basis

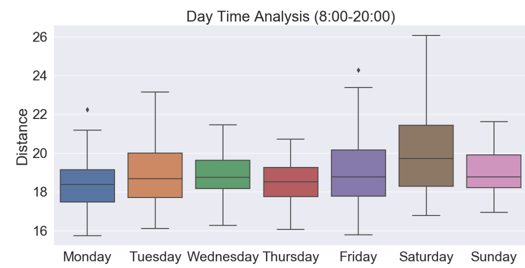

Figure 4. Box plot of average shortest separation distance during peak time hours(8:00-20:00) averaged for each day of the week over the whole month

Thus, these results provide a good insight into the variation trends of **d** over different hours of the day as well as different days of the week.

V. Discussion

In order to verify the validity of the obtained results, some of the results were compared to publicly available data provided by airports. Firstly, the obtained distribution of hourly take-offs can be compared to the data given in the Schiphol Traffic Review of 2018 [13]. The former can be seen in the histogram in Figure 5, and the latter in Figure 6. Even though the data from the traffic review is for the entire year, and the ADS-B data is only from January 2018, the similarity in the two distributions is still very clear. This high similarity implies that the detection of take-off is reliable.

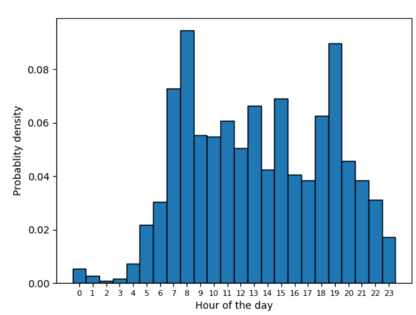

Figure 5. Histogram of hourly take-offs in Schiphol

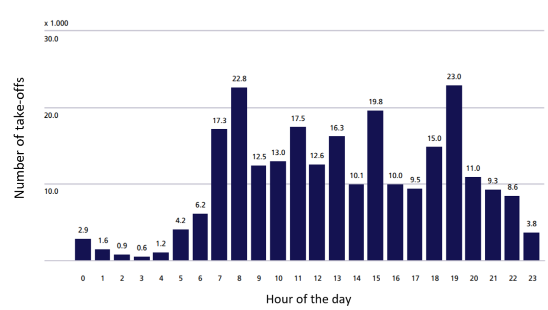

Figure 6. Data on hourly take-offs from the Schiphol Traffic Review 2018 [13]

Additionally, Schiphol gives some qualitative information about when specific runways are in use. During night hours, between 22:30-6:00, the Polderbaan and Kaagbaan are mostly used [14]. In the results, this trend is also visible. Between 23:00 and 6:00, it can be seen that the Kaagbaan and Polderbaan have a higher mean compared to the rest of the runways. The Oostbaan is mostly used for general aviation, helicopters and private jets [14]. These aircraft often do not use ADS-B data, so they will not be detected by the receiver and thus will not be incorporated in the resulting data. This then explains why in Table 6 the mean of the Oostbaan is significantly lower than that of the other Schiphol runways.

Regarding the traffic mix, Schiphol has only specified the types of aircraft that arrive or depart for the whole year of 2018 [13]. Thus, an exact comparison cannot be made. However, the results are expected to be in the same range.

For the most used aircraft at Schiphol, the Boeing 737-800, the actual percentage over a full year equals 21.8%. From the results in Table 11, a value of 24.8% has been found. These values do not differ that much, and hence the ADS-B approximates the real movements quite well for this type of aircraft. For other aircraft types, the analysis of ADS-B data approximates the real values also without too much difference (within 3%). However, there is one widely used aircraft type at Schiphol that is not accurately approximated: the Embraer 190/195. According to the data from Schiphol, 14.5% of the movements in 2018 have been operated by this aircraft type. From the results in Table 11, only 2% was found. This significant difference is most likely caused by the absence of ADS-B transmitters in most of those aircraft. If all E190 aircraft from KLM Cityhopper are analysed using Flightradar24 [12], it can be concluded that only a few out of the 32 [15] aircraft are visualised on the website by means of ADS-B data. The rest of the E190 KLM Cityhopper fleet is represented by the 'MLAT' system.

The higher shortest separation during night hours shows similar flight trends as the take-off and landing statistics. Early in the morning, the separation has a peak due to the lack of aircraft. On the other hand, during most of the day hours, the separation decreases to about 20 km and remains constant, since the airspace becomes more crowded then. Since for the analysis the average values were taken over the sampling time step, the method has some limitations. Taking the average provides advantage in terms of computations but at the cost of potentially losing some important insights of underlying variations.

In the past, other studies, for instance by Sun et. al. [3, 4] have already used ADS-B data to obtain useful results for open-source simulators. In [3], for example, machine learning is used to efficiently separate individual flights into their flight phases. The conclusion of [3] also mentions an important limitation, however. Namely, that more specific phases such as landing or take-off cannot be identified, since they would require "...a more deterministic approach and possibly aggregating more data sources, which is beyond the scope of this paper" (pp. 8). One of the sections of this project addresses this gap, since a deterministic approach was used to detect take-off and landing.

Regarding the usage of these statistics for open-source airspace simulation, it is important to remember that the data used was only for January, 2018, and collected only from the ground station at the Delft University of Technology. Ideally, data from a longer time period as well as from more ground stations in the Netherlands would be used to create more representative statistics. Detecting landing and take-off at Groningen, for example, proved impossible due to the large distance restricting the altitude at which the antenna could detect aircraft. For Maastricht, only a few flights were detected. However, it is known that more flights landed at Maastricht than were detected from sources like Flightradar24 [12]. Thus, Maastricht was ignored for most of the results since these were not accurate.

VI. Conclusions & Recommendations

The objective of this paper was to explore how the Dutch airspace and airports can be represented through statistical relations regarding airport traffic mix, landings and takeoffs per hour and average shortest separation distance of aircraft. The produced statistics which aim to achieve this have been shown in section IV. As mentioned before, these statistics can then be used in open-source air traffic simulation projects, which aspire to make sharing and comparing research easier through the use of openly available, non-restricted data. The take-off and landing statistics, for example, can be used to generate a "schedule" for a given day of a simulation. This is better than simply using historical data since the statistics can be used to also create and test new scenarios, such as an increase or a decrease in the traffic.

Regarding traffic mix, the most frequent aircraft was the B737-800, with a percentage of 27.2%. The percentage for the B737-800 related to Schiphol has been determined as 24.8%, which agrees with data provided by Schiphol as explained above. Also other aircraft types are approximated really good by the ADS-B data, the only exception is the Embraer 190/195 type.

The obtained statistics regarding take-off and landing showed two main peaks in the morning (7:00-8:00) and early evening (18:00-19:00) hours, and a large decrease in movements during the late evening and early morning (about 21:00-6:00). This general result agrees with the way Schiphol (and the other Dutch airports to a lesser extent) operate. Lastly, regarding the average shortest separation distance, a peak of 90 km was found around 2:00, and following that the separation decreases until it reaches a value of about 20 km which remains constant from 6:00 to 20:00. The large separation peak is explained by the reduced amount of flights at that time, while the lower constant value of 20 km makes sense during the hours where most flights are scheduled. However, for future work it is possible to extend the analysis to even smaller time steps. Also, instead of averaging over the whole time step, use of more robust separation techniques could help to get more in depth understanding of different trends.

While only one month of data has been used for this research, more ADS-B data can be input by other researchers into the code [6] to produce more statistics. An important limitation is that due to the deterministic nature of our code, processing time will grow significantly as more and more data is inputted into it. This can be addressed by others using our code by pre-processing their data in ”chunks” (for example, dividing it by days, or removing unnecessary columns).

Acknowledgment

We would particularly like to thank Dr. ir. Joost Ellerbroek from the department of Control and Simulation of the Faculty of Aerospace Engineering at the Delft University of Technology, for providing us with the decoded ADS-B data set and for the support during our research.

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Appendix A - Landing/Take-off per Hour (Normal Distributions)

The variance and mean for all the runways combined are shown in 5. It is separated by landing, take-off and hour of the day.

Table 5. The variance and mean for landing and take-off for all of the runways combined, for every hour of the day. Hour 0 means from 00:00 to 00:59, hour 1 means 1:00 to 1:59, etc.

Hour	Mean Landing	Variance Landing	Mean Take-off	Variance Take-off	Mean Total	Variance Total
0	2.81	3.89	0.61	0.58	3.42	3.58
1	1.32	1.63	0.35	0.24	1.97	1.77
2	0.39	0.45	0.00	0.00	0.52	0.52
3	0.84	0.87	0.00	0.00	0.87	0.85
4	3.52	2.59	0.03	0.03	3.55	2.72
5	10.55	5.19	1.65	0.97	12.19	7.03
6	14.81	4.83	7.29	7.81	22.10	10.89
7	35.71	32.41	37.65	27.64	73.35	48.84
8	48.16	80.74	24.10	28.69	72.26	152.33
9	28.94	21.80	33.48	70.79	62.42	103.65
10	30.26	21.06	51.74	93.13	82.00	172.53
11	32.77	48.58	34.84	41.14	67.61	138.18
12	28.68	35.49	40.77	38.45	69.45	93.79
13	36.19	31.76	36.45	19.72	72.65	52.77
14	24.71	28.88	37.19	19.49	61.90	65.62
15	37.68	23.56	32.32	52.03	70.00	83.07
16	23.35	19.30	30.06	19.53	53.42	45.65
17	21.71	14.95	38.35	39.17	60.06	79.73
18	32.71	21.68	21.16	32.94	53.87	53.52
19	44.06	43.20	20.03	20.63	64.10	98.22
20	23.10	44.02	24.77	17.38	47.87	57.72
21	21.48	25.99	52.65	67.57	74.13	150.78
22	22.32	38.49	15.45	37.26	37.77	117.78
23	9.19	18.69	3.10	7.42	12.29	38.21

In Table 6 and Table 7 the mean of the number of landings and take-offs for each runway and each hour of the day can be found.

Table 6. The mean for every hour of the day for every runway, landing and take-off. On the left are the hours. Hour 0 means from 24:00 to 00:59, hour 1 means 1:00 to 1:59, etc.

Hour	Oostbaan Landing	Oostbaan Take-off	Kaagbaan Landing	Kaagbaan Take-off	Polderbaan Landing	Polderbaan Take-off	Buitenveldertbaan Landing	Buitenveldertbaan Take-off
0	0.00	0.00	0.48	0.45	1.68	0.03	0.23	0.00
1	0.00	0.00	0.26	0.42	0.74	0.13	0.23	0.00
2	0.00	0.00	0.06	0.03	0.16	0.03	0.03	0.00
3	0.00	0.00	0.19	0.03	0.52	0.00	0.03	0.00
4	0.00	0.00	0.48	0.03	2.48	0.00	0.39	0.00
5	0.00	0.00	1.58	1.39	7.10	0.26	1.71	0.00
6	0.06	0.03	2.87	4.84	8.61	1.87	2.52	0.00
7	0.71	0.10	3.19	9.61	12.77	5.03	4.84	2.81
8	0.94	0.42	4.13	5.13	17.55	4.03	5.16	2.39
9	0.45	0.35	2.97	11.90	12.52	3.26	5.42	2.65
10	0.26	0.45	3.55	20.48	13.77	6.48	5.81	4.48
11	0.19	0.32	2.48	15.16	12.19	5.32	4.87	3.71
12	0.26	0.42	3.68	14.35	11.71	4.29	5.00	5.10
13	0.35	0.32	2.77	15.26	12.00	5.39	5.55	3.32
14	0.29	0.32	2.68	15.65	10.94	2.77	5.84	2.39
15	1.52	0.65	2.45	12.29	11.81	4.23	5.39	0.71
16	0.45	0.45	1.74	12.00	10.84	3.03	4.19	0.45
17	0.61	0.26	2.13	16.74	10.16	4.58	4.26	0.77
18	0.61	0.35	1.81	7.13	12.87	3.06	5.10	0.03
19	0.97	0.23	2.19	4.68	15.84	3.55	6.23	0.03
20	0.42	0.03	1.68	10.16	11.42	3.00	4.68	1.00
21	1.35	0.16	2.06	22.00	12.16	7.32	1.77	2.68
22	0.19	0.10	2.23	10.19	8.29	2.81	2.81	0.35
23	0.03	0.00	1.42	2.29	4.52	0.55	1.26	0.00

Table 7. The mean for every hour of the day for every runway, landing and take-off. On the left are the hours. Hour 0 means from 24:00 to 00:59, hour 1 means 1:00 to 1:59, etc.

Hour	**Zwanenburgbaan Landing**	**Zwanenburgbaan Take-off**	**Aalsmeerbaan Landing**	**Aalsmeerbaan Take-off**	**Eindhoven Landing**	**Eindhoven Take-off**	**Rotterdam Landing**	**Rotterdam Take-off**
0	0.26	0.06	0.00	0.00	0.00	0.00	0.13	0.06
1	0.10	0.06	0.00	0.00	0.00	0.00	0.00	0.03
2	0.13	0.03	0.00	0.00	0.00	0.00	0.00	0.03
3	0.06	0.00	0.00	0.00	0.00	0.00	0.03	0.00
4	0.13	0.00	0.00	0.00	0.00	0.00	0.03	0.00
5	0.16	0.00	0.00	0.00	0.00	0.00	0.00	0.00
6	0.55	0.00	0.10	0.45	0.00	0.00	0.06	0.06
7	10.84	0.00	2.90	12.48	0.35	3.71	0.10	3.90
8	14.42	0.00	3.65	8.48	2.26	2.97	0.06	0.65
9	4.81	1.32	0.81	10.58	1.58	3.06	0.39	0.35
10	2.90	2.13	0.35	15.42	2.84	1.90	0.77	0.39
11	8.03	0.16	1.58	6.48	2.74	2.90	0.68	0.74
12	3.58	1.42	0.29	11.48	3.26	2.71	0.90	1.00
13	9.29	0.90	2.23	6.97	3.00	3.26	0.97	1.00
14	0.84	2.10	0.00	10.58	3.74	2.90	0.39	0.45
15	9.90	1.00	2.42	9.16	3.68	3.81	0.48	0.45
16	1.71	0.77	0.77	7.42	2.65	4.71	1.00	1.19
17	0.94	1.29	0.48	10.23	2.45	3.19	0.68	1.29
18	7.71	0.00	2.19	6.58	1.81	3.06	0.61	0.94
19	14.68	0.03	3.52	9.13	0.35	1.90	0.29	0.48
20	2.61	1.32	1.29	8.74	0.61	0.35	0.39	0.13
21	0.65	3.29	0.71	16.48	2.06	0.58	0.71	0.13
22	1.06	0.39	0.48	0.81	4.77	0.61	2.48	0.19
23	1.10	0.23	0.00	0.00	0.61	0.00	0.26	0.03

In Table 8 and Table 9 the variance of the landings and take-offs for each runway and each hour of the day can be found.

Table 8. The variance for every hour of the day and every runway, landing or take-off. On the left are the hours. Hour 0 means from 00:00 to 00:59, hour 1 means 1:00 to 1:59, etc.

Hour	Oostbaan Landing	Oostbaan Take-off	Kaagbaan Landing	Kaagbaan Take-off	Polderbaan Landing	Polderbaan Take-off	Buitenveldert-baan Landing	Buitenveldert-baan Take-off
0	0.00	0.00	1.86	0.52	4.16	0.03	0.45	0.00
1	0.00	0.00	0.80	0.25	1.13	0.12	0.65	0.00
2	0.00	0.00	0.06	0.03	0.14	0.03	0.03	0.00
3	0.00	0.00	0.36	0.03	0.59	0.00	0.03	0.00
4	0.00	0.00	1.19	0.03	4.79	0.00	1.51	0.00
5	0.00	0.00	12.52	1.38	29.82	0.33	16.88	0.00
6	0.13	0.03	32.85	11.01	52.11	14.45	27.12	0.00
7	11.61	0.09	59.29	119.85	65.98	113.77	75.34	63.03
8	20.13	0.58	85.45	76.05	122.66	71.70	92.67	39.51
9	2.19	0.50	51.57	69.49	88.46	33.00	80.65	41.04
10	0.20	0.46	86.72	125.79	135.31	125.79	99.83	91.12
11	0.16	0.63	34.79	131.27	73.89	123.43	66.45	58.68
12	0.40	0.38	70.83	75.10	103.95	52.61	77.87	90.42
13	0.70	0.36	50.05	116.00	82.47	106.25	95.52	50.16
14	0.61	0.23	43.16	87.90	95.66	29.78	104.07	52.38
15	17.66	0.90	40.32	116.41	61.83	78.91	89.05	5.68
16	0.32	0.72	22.13	68.87	63.94	42.03	65.63	2.79
17	0.71	0.26	31.38	115.93	65.81	86.45	63.13	9.58
18	3.38	0.30	28.09	79.18	72.38	46.20	69.82	0.03
19	9.90	0.31	30.43	59.56	92.41	61.19	101.65	0.03
20	0.98	0.03	21.76	50.54	94.12	30.40	60.16	9.60
21	21.10	0.14	34.20	132.07	92.34	139.49	20.11	54.09
22	0.29	0.09	31.05	54.69	56.21	29.23	46.23	2.10
23	0.03	0.00	12.32	8.81	20.39	1.59	19.46	0.00

Table 9. The variance for every hour of the day and every runway, landing or take-off. On the left are the hours. Hour 0 means from 00:00 to 00:59, hour 1 means 1:00 to 1:59, etc.

Hour	Zwanenburgbaan Landing	Zwanenburgbaan Take-off	Aalsmeerbaan Landing	Aalsmeerbaan Take-off	Eindhoven Landing	Eindhoven Take-off	Rotterdam Landing	Rotterdam Take-off
0	0.66	0.06	0.00	0.00	0.00	0.00	0.12	0.06
1	0.16	0.06	0.00	0.00	0.00	0.00	0.00	0.03
2	0.32	0.03	0.00	0.00	0.00	0.00	0.00	0.03
3	0.13	0.00	0.00	0.00	0.00	0.00	0.03	0.00
4	0.52	0.00	0.00	0.00	0.00	0.00	0.03	0.00
5	0.81	0.00	0.00	0.00	0.00	0.00	0.00	0.00
6	4.86	0.00	0.09	0.66	0.00	0.00	0.06	0.06
7	90.67	0.00	49.56	158.92	0.37	2.41	0.09	1.56
8	145.38	0.00	70.90	107.19	1.20	1.50	0.06	0.57
9	41.16	17.29	8.16	94.12	2.05	2.06	0.98	0.50
10	33.69	45.12	1.04	165.38	1.74	2.09	0.38	0.45
11	56.23	0.54	14.38	71.72	2.60	1.56	0.89	0.53
12	34.52	29.18	2.61	104.99	2.53	1.28	0.89	0.67
13	49.61	13.29	27.85	76.90	3.33	1.13	0.70	0.47
14	10.01	44.56	0.00	81.92	4.46	1.69	0.38	0.59
15	73.16	17.67	32.72	99.67	4.43	2.49	0.59	0.59
16	16.15	6.25	7.11	37.78	1.64	1.68	1.00	1.03
17	13.53	19.01	3.66	89.98	1.52	0.89	0.36	0.61
18	45.21	0.00	35.23	46.52	1.69	0.60	0.51	0.60
19	130.36	0.03	68.39	84.92	0.44	1.16	0.28	0.32
20	22.58	12.63	22.01	60.33	0.71	0.37	0.31	0.12
21	12.90	78.75	15.61	166.92	1.26	0.65	0.55	0.18
22	8.93	1.51	6.32	4.63	3.05	0.31	1.39	0.16
23	8.69	0.78	0.00	0.00	0.98	0.00	0.26	0.03

The mean and variance of the total amount of flight for each runway can be found in Table 10.

Table 10. The mean and variance for the total number of flights per day of each runway.

	Mean number of flights	**Variance number of flights**
Aalsmeerbaan	181.10	4010.64
Buitenveldertbaan	124.17	14404.58
Eindhoven	80.42	125.45
Kaagbaan	261.32	6571.96
Oostbaan	14.65	197.04
Polderbaan	293.68	6985.83
Rotterdam	24.94	29.20
Zwanenburgbaan	120.76	3828.62
Maastricht	1.33	0.25

Appendix B - Landing/Take-off per Hour (Bar Charts)

In Figure 7 and Figure 8 the bar charts of the data of the mean values of Table 5 in appendix A can be found.

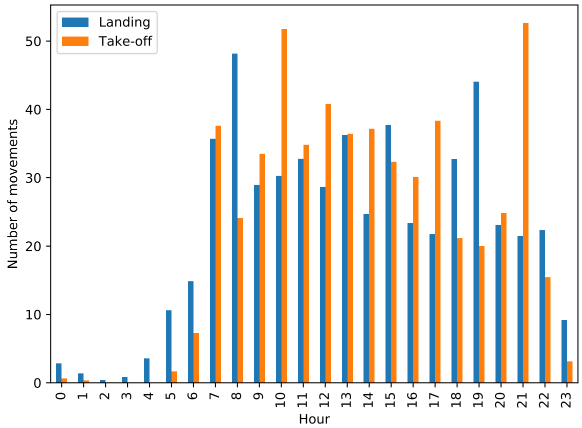

Figure 7. Bar graph of landing and take-off for all of the runways combined. On the horizontal axis are the hours of the day and on the vertical the amount of landings/take-offs in that hour.

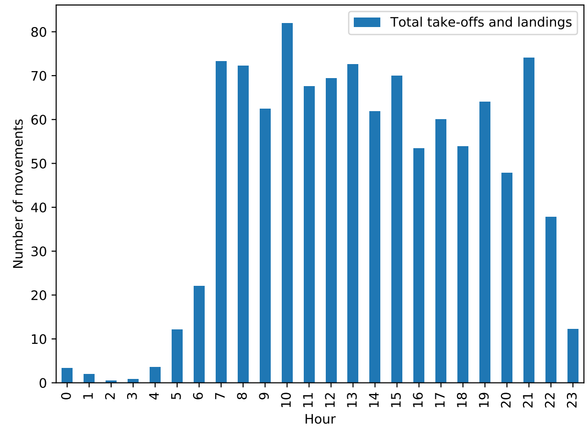

Figure 8. Bar graph of all air movements (both landing and take-off) for all of the runways combined. On the horizontal axis are the hours of the day and on the vertical the amount of landings/take-offs in that hour.

In Figure 9 until Figure 18 the bar charts of the mean values for all of the runways can be found. This is the data from Table 6 and Table 7.

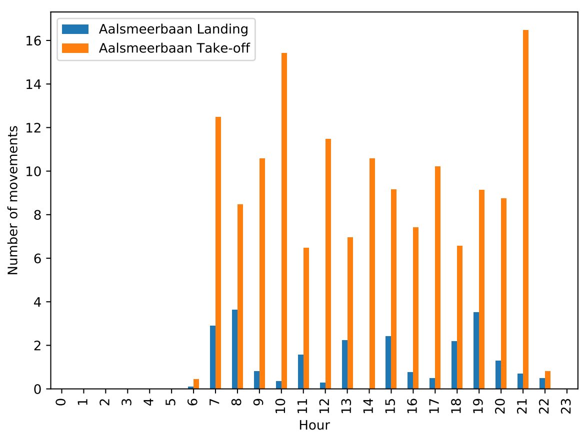

Figure 9. The bar graph for mean landing and take-off for each hour for the Aalsmeerbaan.

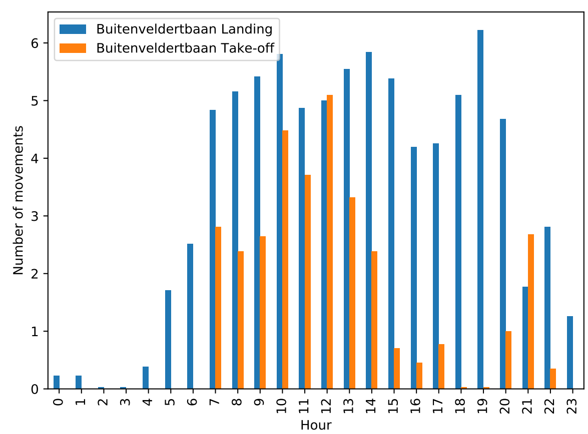

Figure 10. The bar graph for mean landing and take-off for each hour for the Buitenveldertbaan.

In Figure 19 the mean number of flights for each runway over the whole day can be found.

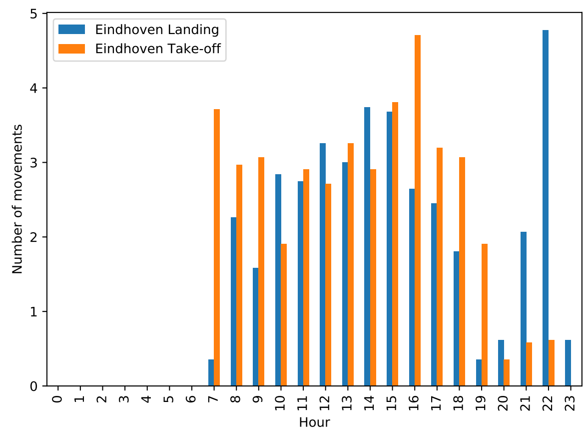

Figure 11. The bar graph for mean landing and take-off for each hour for Eindhoven airport.

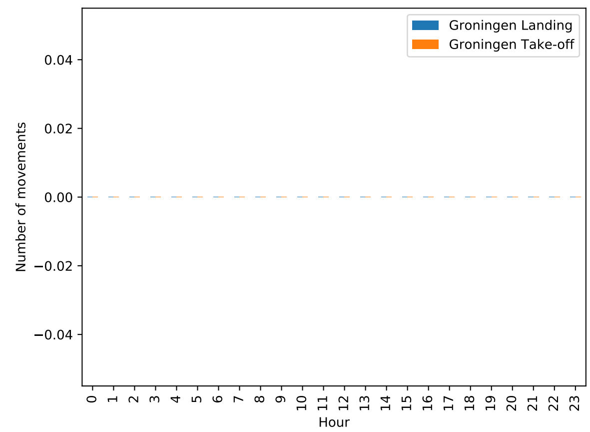

Figure 12. The bar graph for mean landing and take-off for each hour for Groningen airport.

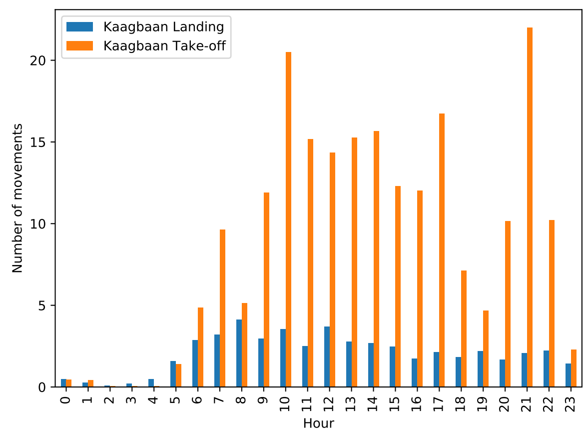

Figure 13. The bar graph for mean landing and take-off for each hour for the Kaagbaan.

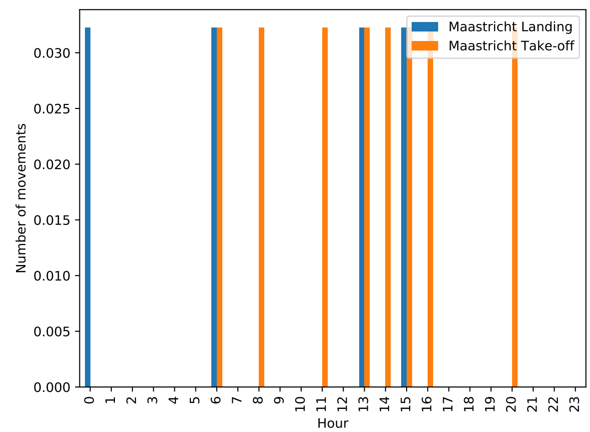

Figure 14. The bar graph for mean landing and take-off for each hour for Maastricht airport.

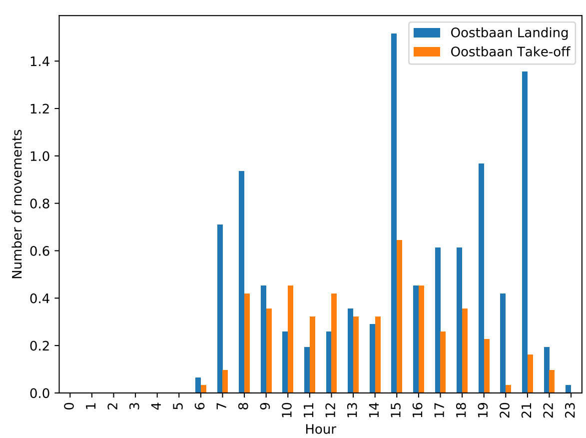

Figure 15. The bar graph for mean landing and take-off for each hour for the Oostbaan.

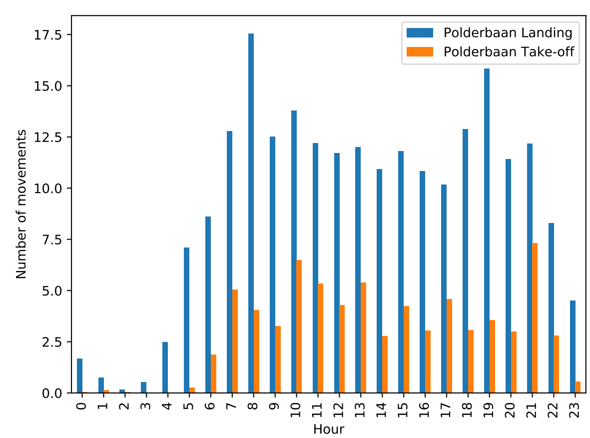

Figure 16. The bar graph for mean landing and take-off for each hour for the Polderbaan.

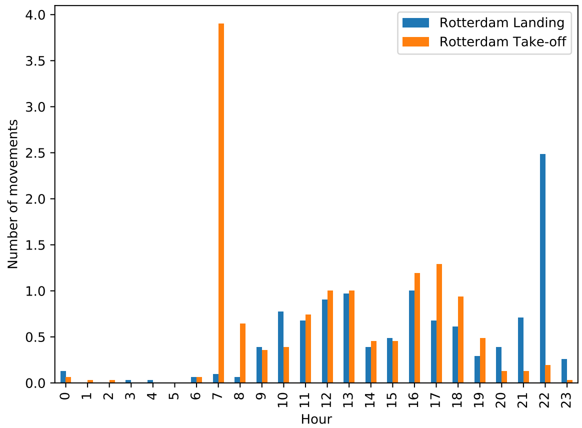

Figure 17. The bar graph for mean landing and take-off for each hour for Rotterdam Airport.

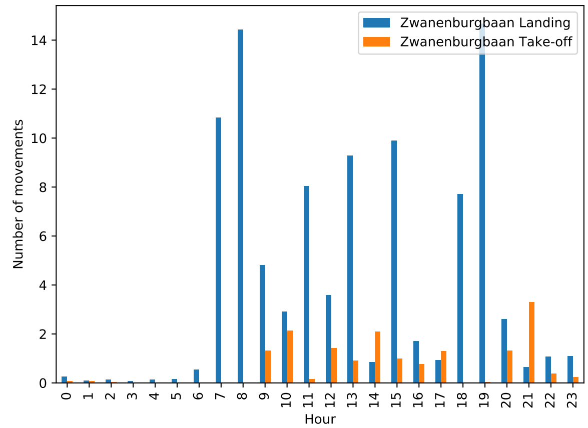

Figure 18. The bar graph for mean landing and take-off for each hour for the Zwanenburgbaan.

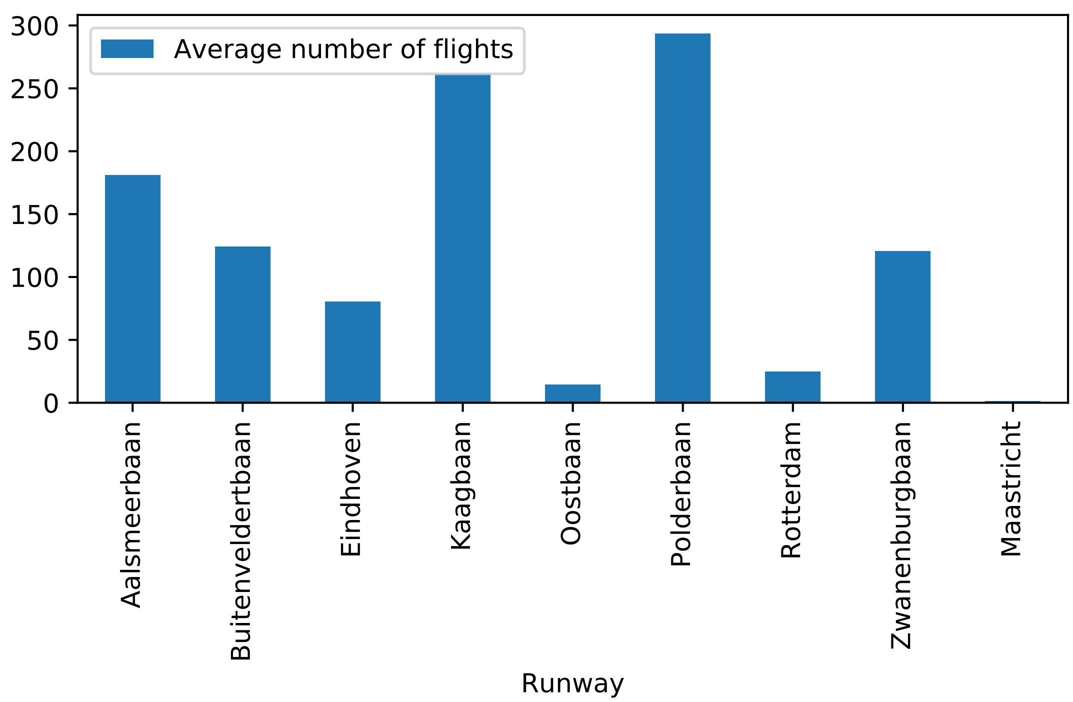

Figure 19. The mean flights of each runway for a day.

Appendix C - Airport Traffic Mix

Table 11. Overview of the traffic mix per runway/airport in percentage extracted from ADS-B data from January 2018. (1/2)

Type	Oost-baan	Kaag-baan	Polder-baan	Buitenveldert-baan	Zwanenburg-baan	Aalsmeer-baan	Schiphol	Eindhoven	Rotterdam	Maastricht	Overall
0000	0	0	0	0	0	0	0	0.041	0	0	0.003
a20n	1.554	0.445	0.449	0.426	0.200	0.461	0.425	0	0	0	0.384
a21n	0.518	0.062	0.011	0.028	0.057	0	0.033	0	0	0	0.030
a306	0	0.457	0.351	0.227	0.171	0.092	0.295	0	0	0	0.266
a318	0	0.173	0.186	0.341	0.228	0.443	0.251	0	0	0	0.227
a319	10.881	8.991	9.656	8.175	7.412	8.749	8.881	0	0.271	0	8.027
a320	5.699	13.351	15.454	13.085	9.065	13.806	13.492	16.470	0.271	0	13.413
a321	3.109	2.890	3.036	4.087	2.993	3.747	3.245	8.479	0.271	0	3.566
a332	0.518	1.927	2.061	1.930	1.283	1.458	1.798	0	0	11.111	1.627
a333	0	4.125	3.902	3.321	1.881	1.975	3.282	0	0	0	2.964
a343	0	0.198	0.121	0.114	0.086	0.055	0.124	0	0	0	0.112
a359	0.518	0.259	0.208	0.539	0.456	0.425	0.332	0	0	0	0.299
a388	0	0.395	0.241	0.568	0.684	0.461	0.412	0	0	0	0.372
b733	0.518	0.432	0.318	0.426	0.542	0.351	0.395	0	0	0	0.357
b734	0	0.012	0.011	0.028	0	0.018	0.013	0	0	11.111	0.015
b735	0	0.296	0.142	0.397	0.428	0.406	0.295	0	0	0	0.266
b736	0	0.136	0.088	0.141	0.171	0.111	0.121	0	0	0	0.109
b737	12.435	10.226	10.160	11.155	14.880	12.698	11.325	13.249	72.666	0	12.836
b738	34.197	23.305	22.863	25.404	28.677	26.873	24.766	61.598	11.908	11.111	27.208
b739	4.145	2.075	1.962	3.321	3.962	3.784	2.732	0	0	0	2.468
b744	2.591	4.051	3.617	3.775	2.680	2.510	3.436	0	0.271	22.222	3.115
b748	0	0.692	0.712	0.766	0.485	0.701	0.680	0	0	0	0.614
b752	0	0.506	0.438	0.284	0.200	0.221	0.368	0	0.271	0	0.339
b753	0	0.037	0.033	0.057	0	0	0.027	0	0	0	0.024
b763	0	2.507	2.313	0.823	0.456	0.221	1.577	0	0	0	1.425
b764	0	0.074	0.033	0.057	0.029	0.018	0.044	0	0	0	0.039
b772	1.036	4.088	3.606	3.349	1.853	2.086	3.208	0	0	0	2.897
b77l	0	1.618	1.425	1.788	1.796	1.532	1.574	0	0	11.111	1.424
b77w	0.518	2.976	2.948	3.406	3.364	3.230	3.094	0	0	0	2.795

Table 12. Overview of the traffic mix per runway/airport in percentage for one month of ADS-B data.Overview of the traffic mix per runway/airport in percentage extracted from ADS-B data from January 2018. (2/2)

Type	Oost-baan	Kaag-baan	Polder-baan	Buitenveldert-baan	Zwanenburg-baan	Aalsmeer-baan	Schiphol	Eindhoven	Rotterdam	Maastricht	Overall
b788	0	0.951	1.151	0.823	0.485	0.591	0.871	0	0	0	0.786
b789	1.036	2.396	1.808	2.214	2.138	1.292	1.956	0	0.271	0	1.772
bcs1	0	0	0	0	0.029	0.018	0.007	0	0	0	0.006
bcs3	0.518	0.445	0.427	0.369	0.399	0.388	0.415	0	0.135	0	0.378
be20	0.518	0	0	0	0	0.018	0.007	0	0.271	0	0.012
be30	0	0	0	0	0	0	0	0	1.353	0	0.030
c172	0	0	0	0	0	0	0	0	0.406	0	0.009
c310	0.518	0	0	0	0	0	0.003	0	0	0	0.003
c425	0	0	0	0	0	0	0	0.041	0	0	0.003
c68a	1.554	0.012	0	0.028	0	0	0.017	0	0.406	0	0.024
crj9	0.518	0.074	0.099	0.057	0.143	0.185	0.111	0	0	0	0.010
e190	1.036	1.149	1.403	1.192	1.824	1.864	1.440	0	7.984	0	1.479
e195	0.518	0.346	0.373	0.908	0.941	1.052	0.619	0	0	0	0.560
e75l	7.772	8.238	8.297	6.330	9.949	8.029	8.191	0	0	0	7.398
f100	0	0	0	0	0	0	0	0	0	11.111	0.003
g550	0.518	0	0	0	0	0	0.003	0	0	0	0.003
glf4	1.036	0	0	0	0	0	0.007	0	0	0	0.006
lj75	0.518	0	0	0	0	0	0.003	0	0	0	0.003
pa32	0	0	0	0	0	0	0	0	0.677	0	0.015
pa44	0	0	0	0	0	0	0	0	0	22.222	0.006
pa46	0	0	0	0	0	0	0	0.041	0	0	0.003
pc12	2.073	0	0	0	0	0	0.013	0.082	0	0	0.018
rj85	0	0.074	0.099	0.057	0.057	0.129	0.087	0	0	0	0.079
s22t	0	0	0	0	0	0	0	0	0.541	0	0.012
sr20	0	0	0	0	0	0	0	0	1.218	0	0.027
sr22	0	0	0	0	0	0	0	0	0.812	0	0.018
tbm9	3.627	0.012	0	0	0	0	0.027	0	0	0	0.024

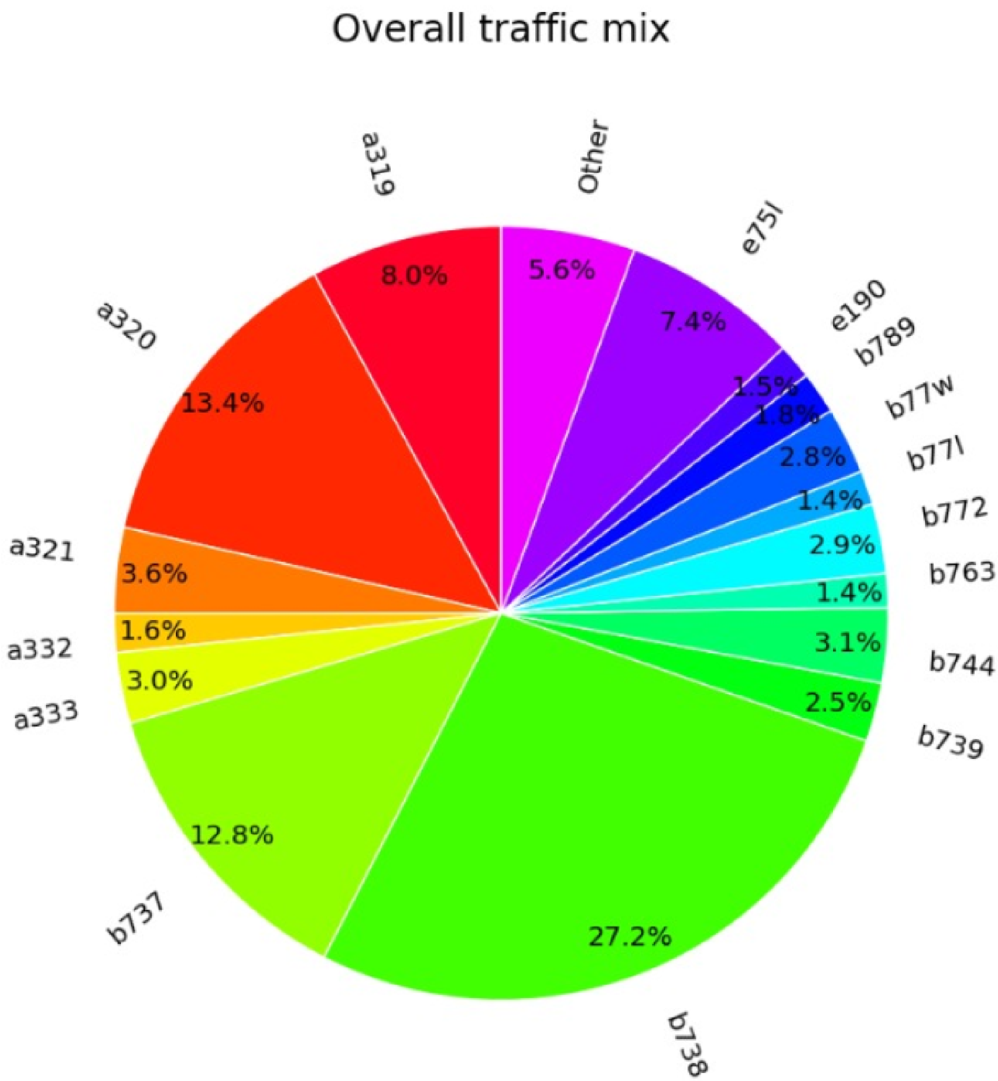

Figure 20. Detected traffic mix for Dutch airports of January 2018.

Appendix D - Airspace Traffic Mix

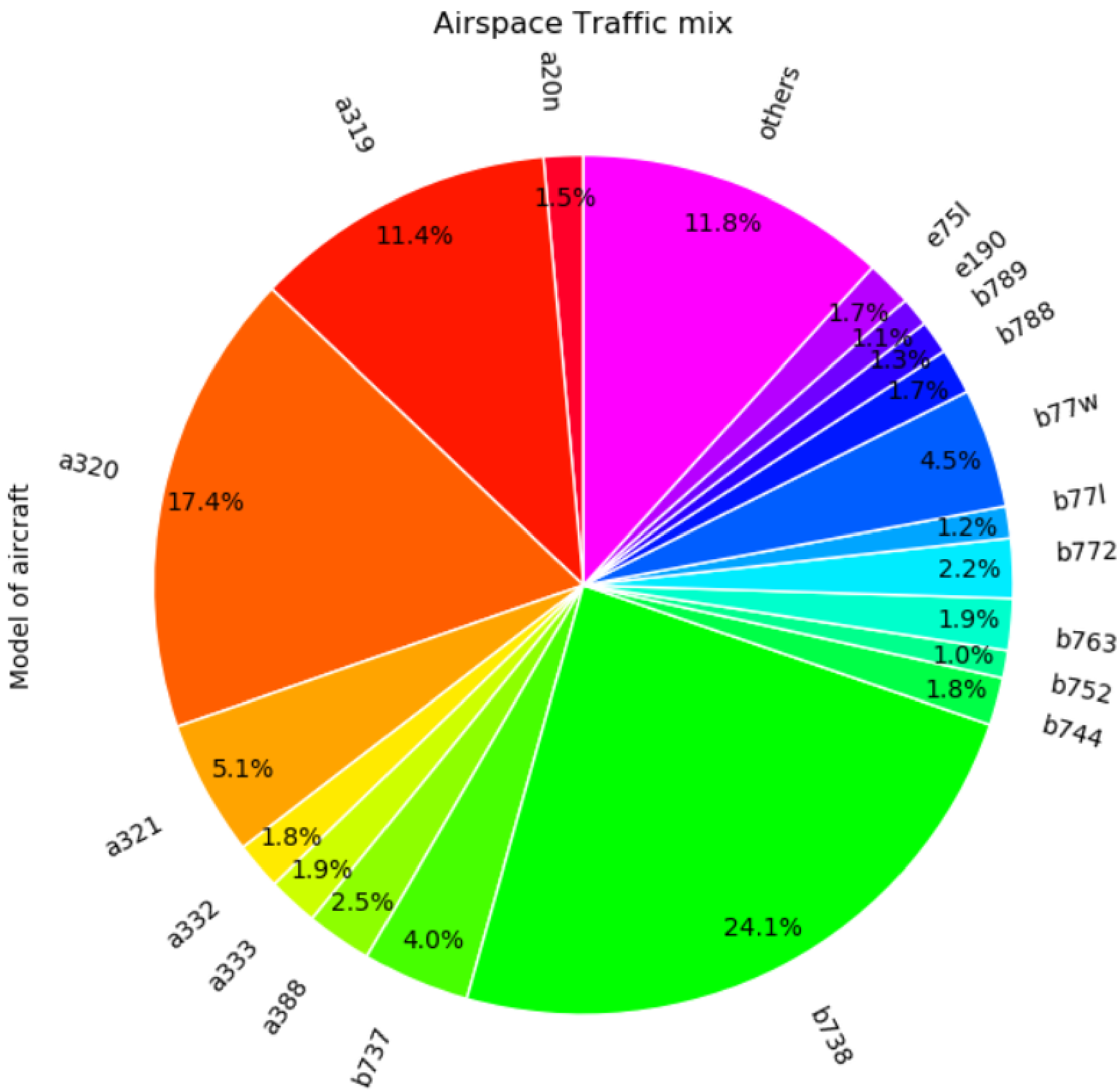

Figure 21. Detected traffic mix for all aircraft in the Dutch airspace for January 2018.

Method

The airport traffic mix statistic has been analysed and gives a general idea of what type of aircraft are landing and taking-off at all the Dutch airports. As for the airspace traffic mix statistic, what types of actively flying aircraft are commonly observed within the Netherlands will be analysed. This can then be represented by a pie chart. The required parameters from the ADS-B data are longitude, latitude, altitude, aircraft model and flight identification.

To approach the analysis, the boundary area constraint is required as all the ADS-B data also includes some aircraft outside the Netherlands. Thus for simplicity, the area of Netherlands will be represented by a square. The two boundary area constraints and two filter are as follows: $50.5 <$latitude< 53.5, $3.5 <$longitude< 7.0, rate of climb $= 0$ and altitude $> 0ft$.

Next, all duplicate flight ID's are dropped. Now the dataframe represents all the active aircraft models for a day so the same code can be run for the whole month. Lastly, the total number of aircraft of each individual model can be counted.

Results

The result is a percentage for all models that are active within the Netherlands. Table 13 shows the most common models that are active within the Netherlands are A320, B738 and A319. All the models that are lower than 1.5 percent, are included in the "others", which can be found in Table 14.

Table 13. Total percentage of each models in January 2018. Here, 'Other' is defined all the models that has a traffic mix below 1.5%.

Type	Percentage	Type	Percentage	Type	Percentage
a20n	1.5	b737	4	b77w	4.5
a319	11.4	b738	24.1	b788	1.7
a320	17.4	b744	1.8	b789	1.3
a321	5.1	b752	1	e190	1.7
a332	1.8	b763	1.9	e75I	1.7
a333	1.9	b772	2.2	Others	11.8
a388	2.5	b77I	1.2		

Discussion

There are two different results that are collected from airspace and airport statistics for the traffic mix. The airport statistic represents all aircraft models that are landing or taking off at different airports in the Netherlands. The airspace statistic represents all the aircraft models that are actively flying within the Dutch airspace. With this information, these statistics provide data that show the most common aircraft models that depart or fly over the Netherlands. For example, the traffic mix for both the Dutch Airports and the Dutch airspace were represented by Figure 20 and Figure 21. Figure 21 shows that the most common aircraft that come into the Netherlands are A320, A319 and B738. Then, when comparing it to Figure 20, it shows that these aircraft are likely to depart from a Dutch airport. As for the other aircraft that do not show up for all the Dutch airports but do for the Netherlands, they are A20N, A388, B752, B77l, B789, B788 and E190.

Table 14. Total and mean number of active aircraft of each models in January 2018

Models	Number of aircraft in percentages
0000	0.007
a124	0.008
a139	0.565
a20n	1.518
a21n	0.111
a306	0.46
a310	0.008
a318	0.629
a319	11.782
a320	17.963
a321	5.268
a332	1.842
a333	1.955
a342	0.004
a343	0.279
a345	0.006
a346	0.306
a359	0.698
a388	2.544
a3st	0.167
ac90	0.001
an12	0.011
at76	0.072
atp	0.001
b350	0.019
b38m	0.246
b733	0.363
b734	0.509
b735	0.097
b736	0.086
b737	4.15
b738	24.845
b739	0.672
b744	1.839
b748	0.691
b752	1.069
b753	0.172
b762	0.17
b763	2.007
b764	0.254
b772	2.313

Models	Number of aircraft in percentages
b77l	1.22
b77w	4.64
b788	1.766
b789	1.297
bcs1	0.069
bcs3	0.229
be20	0.018
be30	0.008
be36	0.002
be60	0.001
be9l	0.001
blcf	0.004
bn2p	0.006
c172	0.004
c182	0.001
c25a	0.002
c25c	0.009
c25m	0.001
c310	0.005
c340	0.008
c421	0.001
c425	0.001
c501	0.007
c525	0.001
c560	0.015
c680	0.015
c68a	0.027
cl60	0.001
crj2	0.001
crj9	0.123
da42	0.001
da62	0.004
dc87	0.007
dh8c	0.001
dh8d	0.3
e135	0.008
e190	1.142
e195	0.266
e545	0.012
e75l	1.777
e75s	0.037

Models	Number of aircraft in percentages
ec35	0.004
ec45	0.001
ec55	0.014
ec75	0.104
f100	0.026
f406	0.002
fa7x	0.001
fa8x	0.019
g2ca	0.008
g450	0.002
g550	0.002
g650	0.002
glex	0.002
glf4	0.005
glf6	0.001
h130	0.006
hdjt	0.001
il76	0.005
lj75	0.005
m20p	0.001
mcr1	0.005
md11	0.242
mu2	0.005
ng5	0.005
p06t	0.009
p46t	0.007
p68	0.006
pa24	0.001
pa32	0.006
pa44	0.019
pa46	0.005
pc12	0.148
rj1h	0.005
rj85	0.074
s22t	0.023
sr20	0.009
sr22	0.028
su95	0.393
tbm8	0.007
tbm9	0.05

Appendix E - Average time spend in Dutch airspace

The average time spent in the Dutch airspace represents the more detailed flight journey of an aircraft that cross the Netherlands. The data analysis method and the result will be shown in the section.

Method

To approach this analysis, the required parameters for the analysis from the ADS-B data are time-stamp, flight identification, latitude, longitude and altitude. The boundary area constraint is required as well and it will be the same as before. The two boundary area constraints and two filters are as follows: $50.5 < \text{latitude} < 53.5$, $3.5 < \text{longitude} < 7.0$, rate of climb $= 0$ and altitude $> 0ft$.

To find the time spent in the Dutch airspace, the date, hour, minute and second are needed. This can be extracted from the time-stamp. The date, hour, minute and second will be split into it's own column. Then, the hours and minutes are converted into seconds and added into the second column. Finally, the difference between the maximum and the minimum in the second column for each individual aircraft is calculated. The result is in seconds which can then can be converted into minutes.

Result

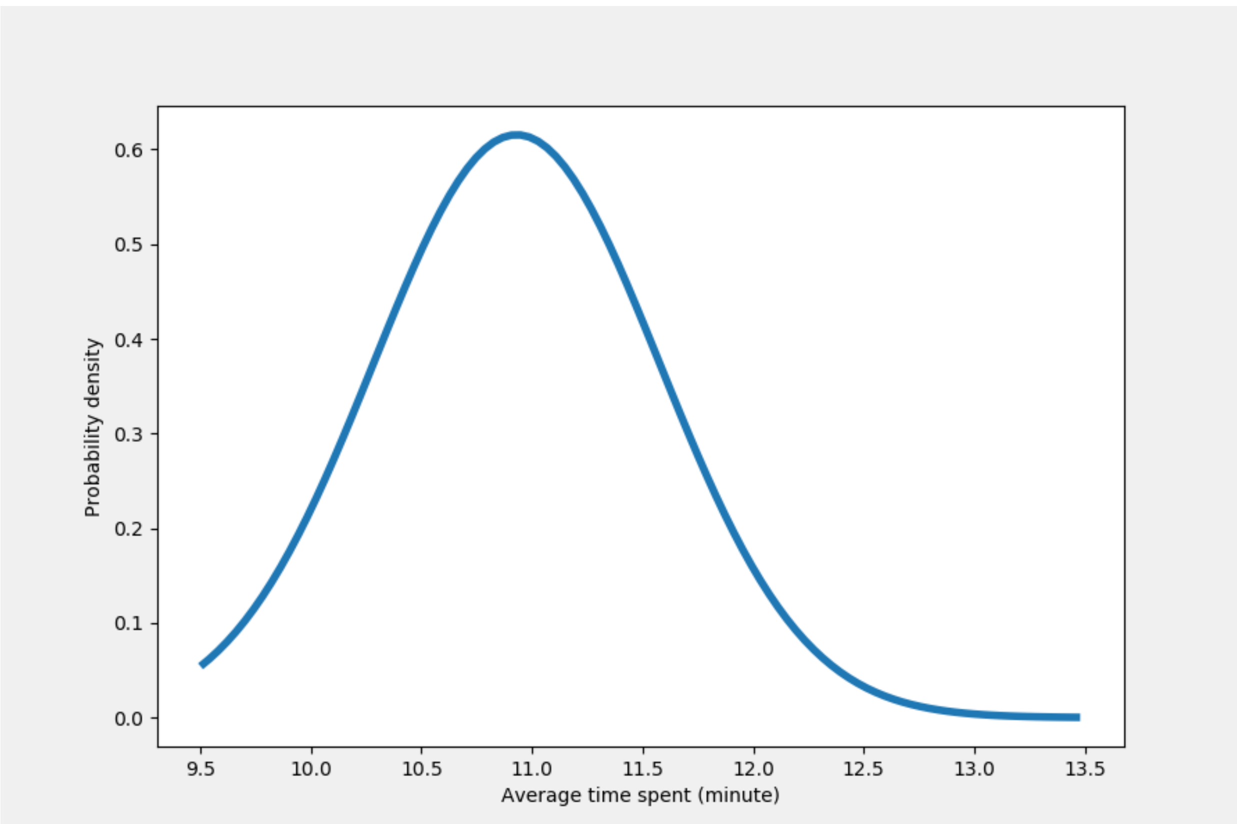

Figure 22. Gaussian distribution of average time of aircraft spend in Dutch airspace in January 2018

The results for the average time spent in the Dutch airspace in January 2018 can be represented by the normal distribution graph in Figure 22. The graph shows the most likely amount of time that will be spent in the Dutch airspace is about 10.9 minutes. Further detailed information for individual days in January 2018 can be found in Table 15 which show the mean, max and variance of the time spent. From Table 15, surprisingly for each individual day the standard deviation is relatively high. This could be true because comparing with the maximum value and the mean value, there is a large difference. However, when comparing the mean value throughout the whole month, the values are clearly close to 10.9 minutes.

Table 15. The average time spend in the Dutch airspace in January 2018

	Time spent for all the aircraft in Dutch airspace in minutes		
	Mean	Max	Standard Deviation
day 1	10.69	49.25	7.42
day 2	11.32	168.77	8.89
day 3	11.85	94.80	7.97
day 4	11.67	70.85	8.36
day 5	10.82	231.05	8.68
day 6	11.16	219.40	8.77
day 7	10.81	107.23	7.56
day 8	10.92	335.33	9.42
day 9	10.57	275.82	8.99
day 10	10.63	93.67	7.54
day 11	10.55	54.40	6.96
day 12	9.50	75.58	6.61
day 13	11.57	123.47	8.01
day 14	10.43	47.22	7.47
day 15	10.45	51.15	7.16
day 16	10.32	111.07	8.18
day 17	10.89	80.27	7.88
day 18	13.48	258.38	13.10
day 19	10.17	257.65	8.87
day 20	11.24	83.83	8.02
day 21	11.23	46.92	8.15
day 22	10.89	182.57	8.25
day 23	10.67	77.27	7.95
day 24	11.05	55.17	7.95
day 25	10.56	105.28	7.90
day 26	11.05	66.88	7.78
day 27	11.18	101.60	8.26
day 28	10.88	116.23	7.78
day 29	10.70	134.58	8.18
day 30	10.88	134.20	8.42
day 31	10.70	56.68	7.74

Appendix F - Average airspace density

Method

An analysis on the average density of aircraft in the Dutch airspace has been performed to be able to find busy flight paths and see where there are high aircraft density areas. The analysis makes no distinction between different aircraft and therefore the aircraft model is not required. The ADS-B data that are required are the latitude, longitude, altitude and the time stamp.

The method used to display this study is as follows. First a rectangular box is drawn around the entirety of the Dutch airspace with boundaries of latitude 50.5 - 53.5 degrees, longitude 3.5 - 7 degrees and an altitude of more then 400 ft. This box also covers some airspace of neighbouring countries but as flight paths are to be obtained, the inclusion of these does not negatively affect the results. A grid is then imposed on the rectangle dividing it into a large number of square boxes. Each box has a height and width of 0.09 degrees, which corresponds to about to 10 km. The program will use these boxes to show the density of aircraft in each box by counting how many different aircraft there are inside a particular box during a time step of 6 seconds. It then moves on to the next box and repeats this for all the boxes at that time step. After having completed all the boxes the program then takes the next time step and starts again. Note that this method will overestimate the density, since aircraft that fly from one box to another within a time stamp will be counted twice. To compensate for this a compensation factor is introduced. This compensation factor is determined by counting the total number of aircraft in the Dutch airspace and dividing this by the total amount of aircraft that were counted using the above method. The total number of aircraft in the Dutch airspace can be determined very accurately.

Due to the high number of time steps and boxes this process is very computationally intensive. A few methods have been used to decrease computation time, most notably the decrease in size of the database. Instead of the program having to search through the entirety of the data base for each box and time step, the database is first decreased to only include data with the same time step. The same can be done with the longitude, making the program a lot quicker as it only has to look for the correct latitude in the decreased database. The longitude is then updated as a new row of boxes is analysed and the time stamp is updated when all boxes are analysed. Furthermore, the database has been thinned out by removing data points that are close together in time of a particular aircraft. This decreased the amount of points by a factor 10.

Results

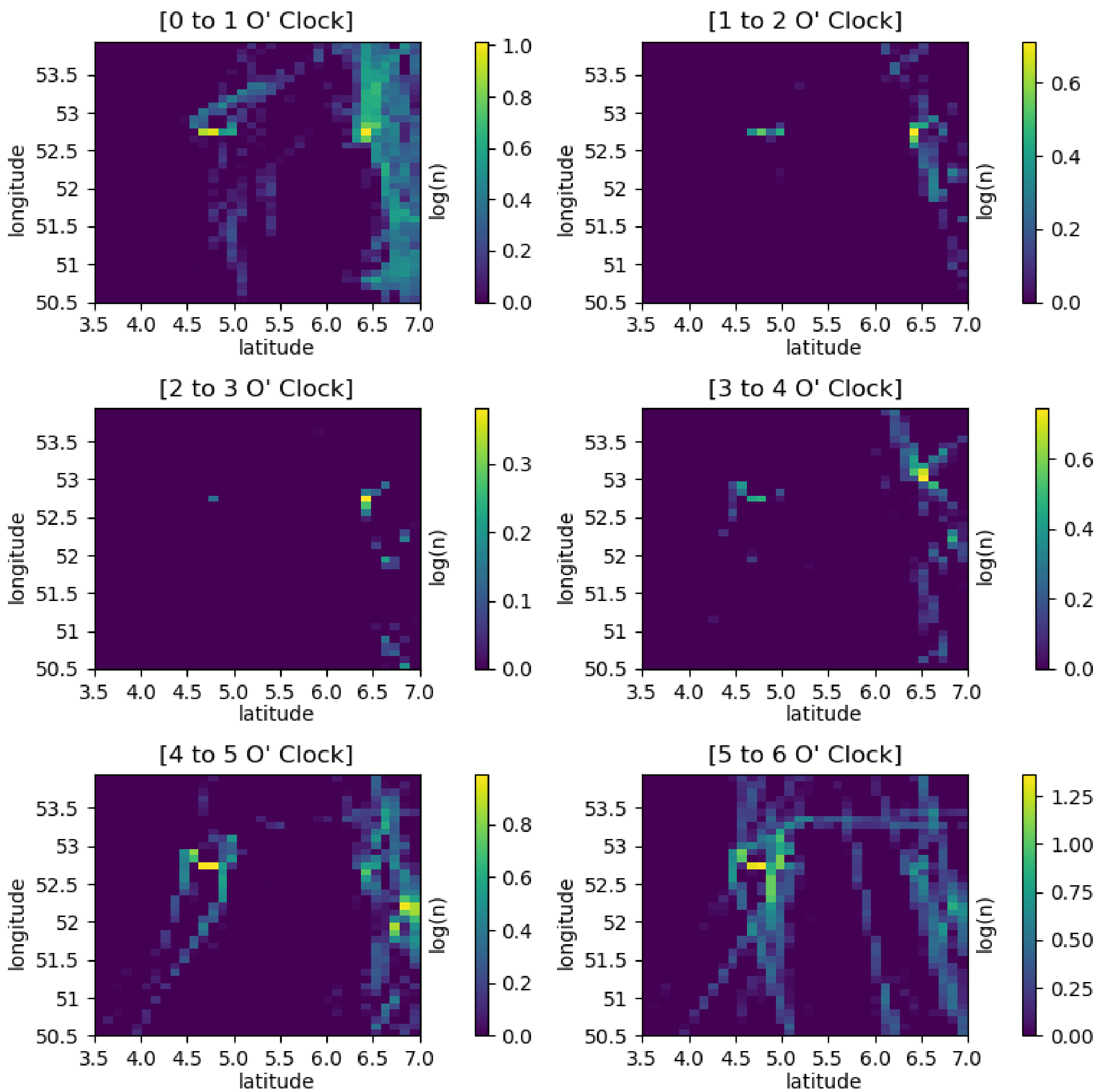

Figure 23. Average airspace density from 0 to 6 O'clock

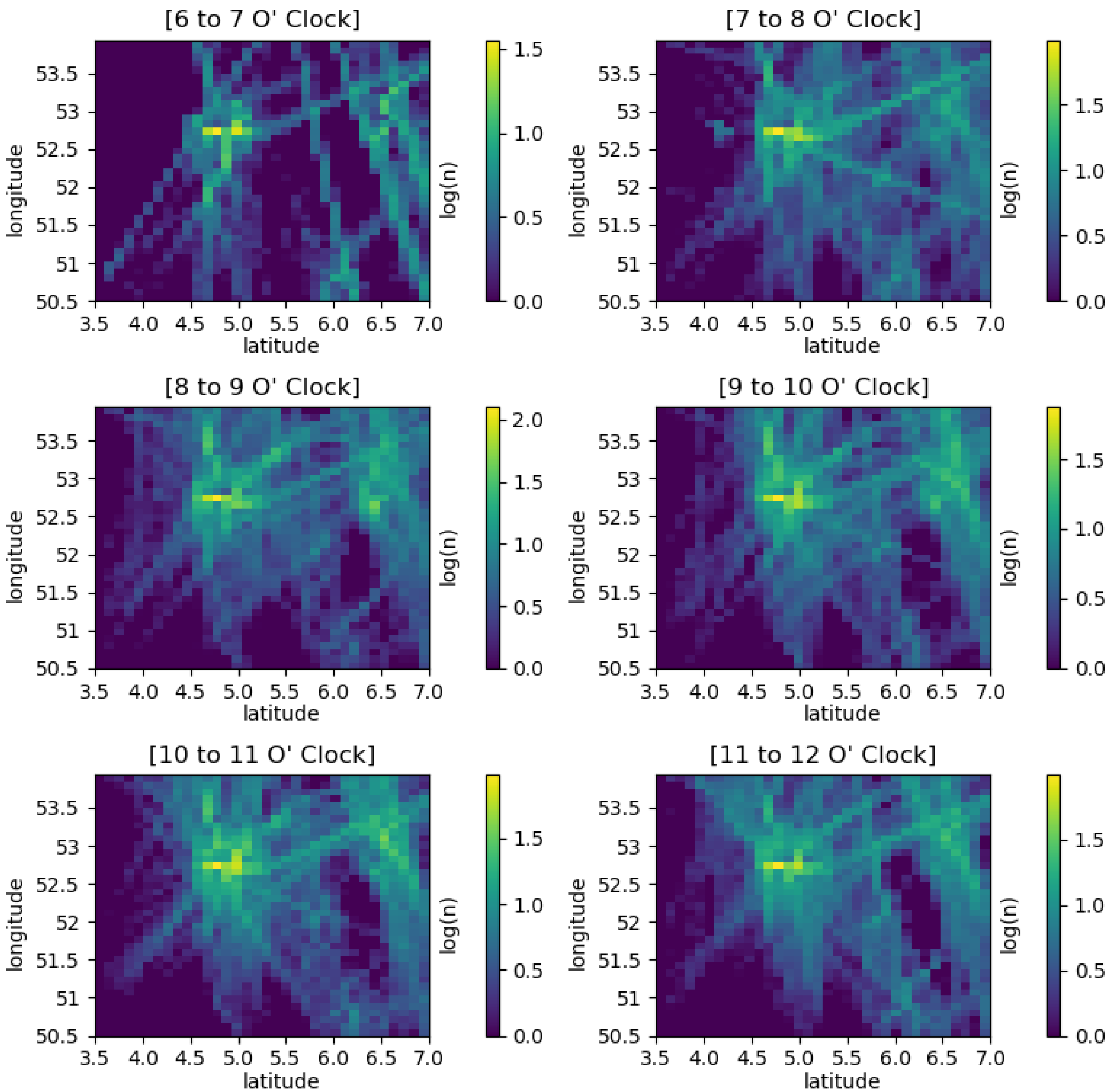

Figure 24. Average airspace density from 7 to 12 O'clock

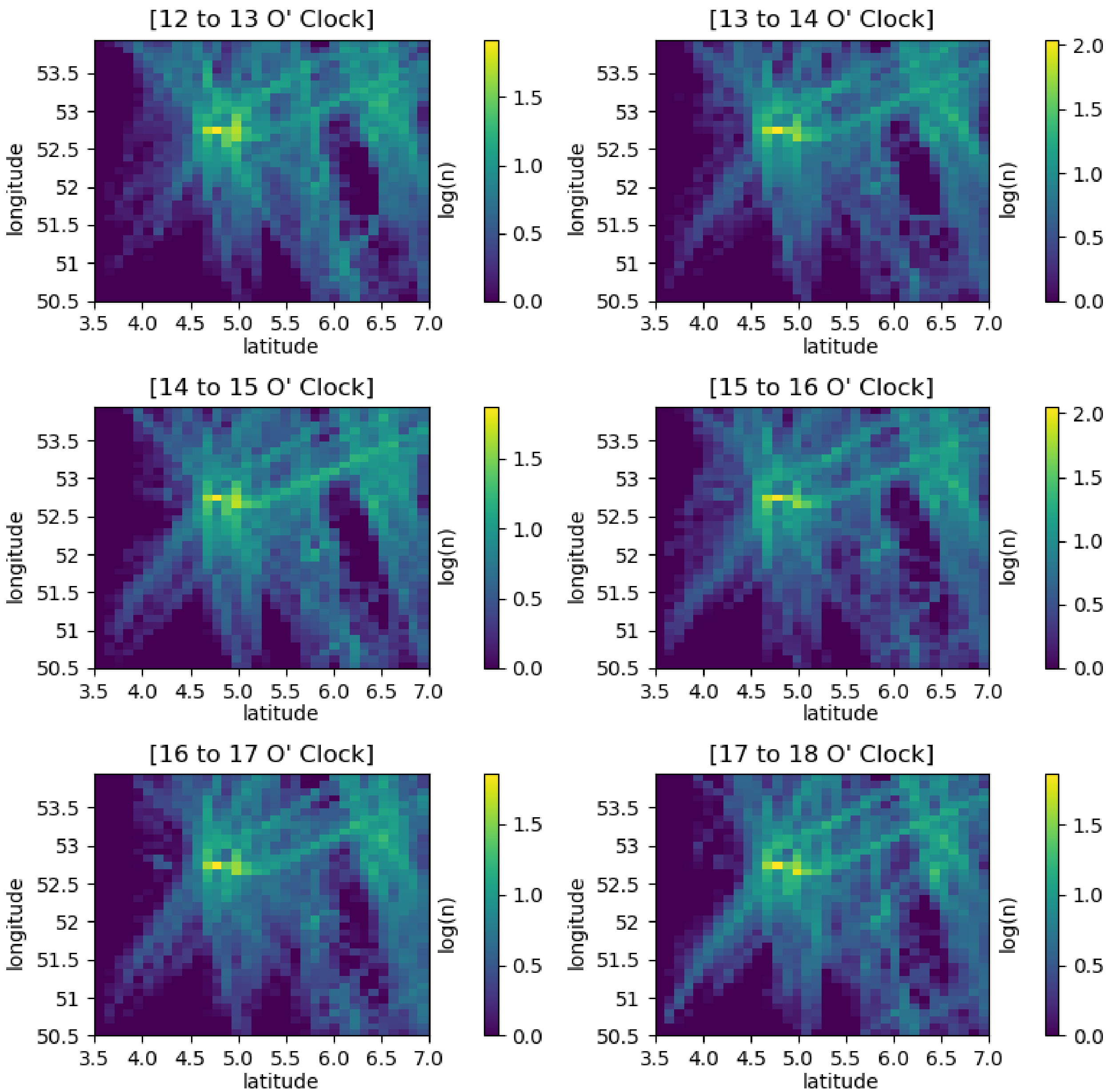

Figure 25. Average airspace density from 12 to 18 O'clock

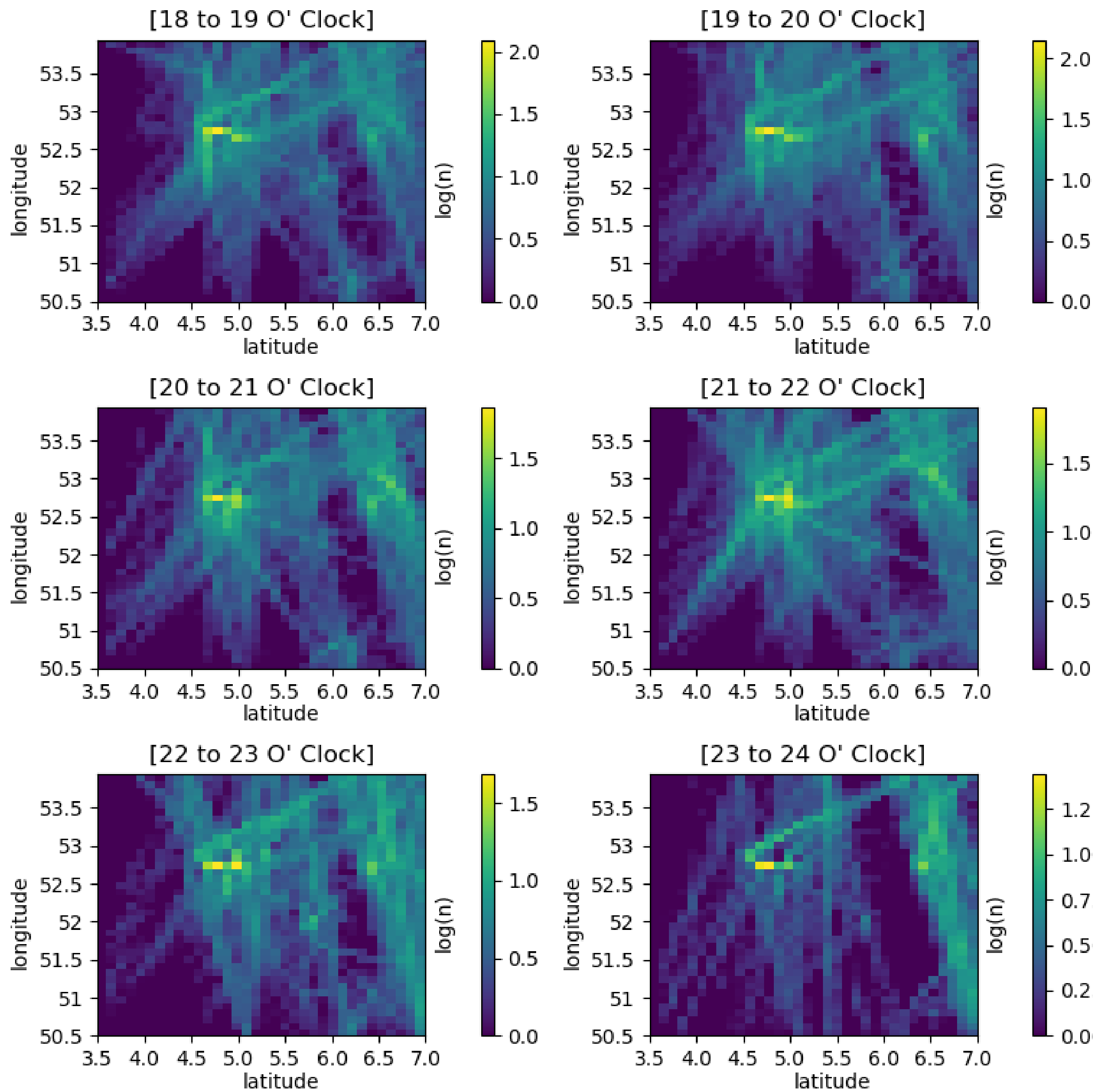

Figure 26. Average airspace density from 18 to 24 O'clock

Discussion

The results shown above are the average over an 11 day period. In every image a bright yellow spot is clearly visible. This is Schiphol, the largest airport in the Netherlands. Therefore, many flight paths seem to lead to this location. A clear result that was similarly found in many of the other statistics is the small amount of flights that leave between 00:00 and 6:00. Only after six does the flight traffic really get busy. After this time the general density clearly increases, and then for the rest of the day, the graphs are relatively similar, indicating that there is no large difference in flights paths during the day. Lastly at 23:00 the density starts decreasing until it becomes very small again, as mentioned above, during the early morning hours. Note that the graphs are scaled with colour logarithmically. This is because the 'brightness' of Schiphol would otherwise overwhelm all the other flight paths.

Appendix G - Ground time

One of the statistics investigated in this report is ground time. Ground time is referred to as the time a unique aircraft spends at a certain airport. The value of investigating how ground time behaves cannot be overstated since it provides useful information that can be used further into ATM simulations and airport logistics. As we know, the amount of people flying commercially has increased steadily over the last decade making it a challenge to manage all the aircraft on the ground. The following statistic is a response to how airport management can be optimised using statistical distributions in the future as the market grows. The goal of this analysis is to find a parametric distribution that fits the data.

Method

The data used in the analysis come from the Airport Runway Detection Dataframe discussed in section III of this article. There is a unique dataframe for each day, in which all the landings and take-offs are recorded. Each landing and take-off contains information about the location of the aircraft, registration-ID, operator, model, and time. The goal of this section is to extract the time each unique aircraft spent on the ground. This can then be split per aircraft model from the Runway Detection Dataframe. The reason why the data was split into each model is that there is a relationship between the size of the aircraft and the time spent on the ground. Generalising all the models as one will not reveal any relevant information. If the analysed data is for a unique aircraft model, the higher chance a robust meaningful relationship can be found.

In order to find the ground time, all the unique registration-ID per day where identified. Next, the difference between the time it landed and when it took-off is taken, this yields the ground time. Consequently, a unique dataframe is created for the following aircraft models: Boeing-737, Boeing-777, Boeing-787, Boeing-747, Boeing-767, Airbus-318, Airbus-319, Airbus-320, Airbus-350, Airbus-380 and Embraer-195. The considered models are not the only models that exist in the data. However, they account for over 94.4% of the traffic mix, according to the overall traffic mix discussed in Figure 20. Therefore, the less frequent models are ignored. Finally, the data is plotted into a normalised histogram and fitted with a known distribution in order to find the best possible fit.

Results

This section will only provide the graphical results of the Boeing-737 since it is the most common aircraft used commercially in the Netherlands. Additionally, a table presenting the mean and standard deviation for each model will be provided.

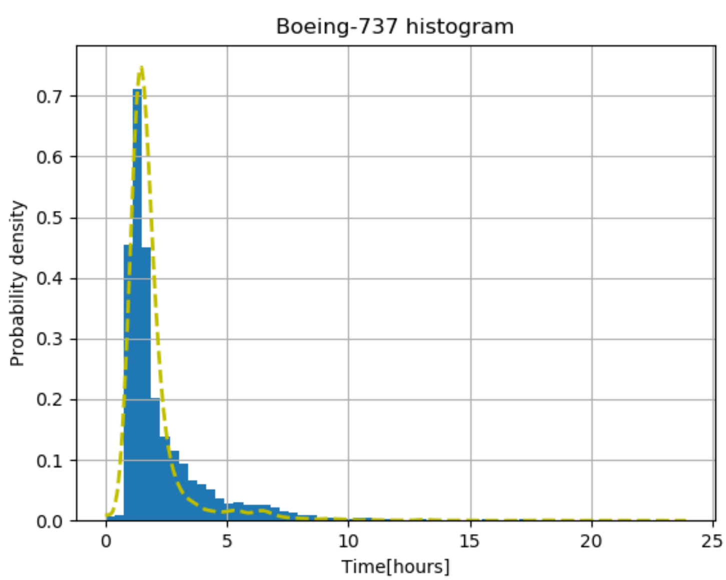

Figure 27. Groudntime probability distribution Boeing-737 fitted with Kernell distribution

As can be seen from Figure 27 the data for the Boeing-737 fits the kernel distribution. Different parametric distributions where tested to fit the empirical data, but none of the distribution yielded a good fit according to the Chi-square test. Therefore they are not included in the results. Similar results were found for the other aircraft models, where parametric distributions prove not to be a good fit. The kernel distribution fit means that the relationship of ground time can be better represented by a non-parametric distribution.

Table 16. Mean and standard deviation ground time

Model	Mean [hours]	Standard Deviation [hours]
Boeing-737	1.934	1.374
Boeing-777	4.548	2.431
Boeing-787	4.597	1.942
Boeing-747	4.891	2.554
Boeing-767	3.241	1.467
Airbus-318	1.292	0.188
Airbus-319	1.317	0.878
Airbus-320	1.433	0.833
Airbus-350	4.219	0.601
Airbus-380	2.515	0.332
Embraer-195	1.255	0.276

From Table 16 it can be deduced that in fact there is a relationship between the size of the aircraft and how much time it spends on the ground. In general the bigger the aircraft the more time it needs to spend on the ground. This result is no surprise, but an anomaly was found in the average of the Airbus-380. Being the largest aircraft in the analysis, it yielded a significant lower average ground time than other smaller aircraft. This anomaly is a good indicator that further investigation is necessary to optimise ground time since the size of the aircraft is not the only factor affecting ground time.

Discussion

The first topic to be addressed will be the limitations in the code used to calculate the ground time. Since it was chosen to split the data into separate days, the code does not take the ground time of aircraft that stay overnight in the airport. Even though the ground time of aircraft that stay overnight are lost, in reality, this is beneficiary since it filters all the aircraft that might be there for maintenance or grounded due to safety reasons. If this data was not filter the mean ground time will be skew drastically since aircraft could be grounded for many days or even weeks.

As mentioned in the results, the data did not satisfactorily fit parametric distributions. Therefore it would be interesting in the future to investigate non parametric distributions to find a fit for the data. An interesting possibility to expand the study of ground time is to investigate how ground time varies through out the day. This could reveal when the airport is the busiest.

Appendix H - Number of flights of specific airline/aircraft

The last statistic that was investigated was the amount of flights that could be distinguished in the Dutch airspace during one day. This has been done on an airline basis but also on a aircraft type basis. Such a statistic is relevant for the ATM simulators, because these give additional information about the specific aircraft that are in the air during one day. Changes and expansion can be identified when the commercial as well as the private flight market changes.

Method

The method used to find the results is rather straightforward. Again the main ADS-B dataframe was used as a starting point. In this dataframe, however, duplicate flight ID's are still present so these were first dropped. After this step, unnecessary parameters were also dropped (latitude, longitude, time-stamp, altitude, roc, runway), since these parameters were not influencing the statistic. When this was done, relevant information could be grouped. All flights from the same airline or from the same aircraft type were grouped together. As a last step, the average of the complete month was taken to get an average for one day. For the results, bar charts were used to visualise the large differences between the airlines and aircraft. These kind of graphs do not provide the exact, detailed numbers, so tables were also included with the this information.

Results

In Figure 28 the results of the aircraft types being detected during one day are made visible. A threshold of 5 flights a day is made in the bar chart to make it more readable. It is clear that the B737-800 is the most present in the Dutch airspace. In Table 17 the complete list of models is present with all their corresponding flights. Of course some aircraft models are not used very often anymore, less than one flight a day (on average).

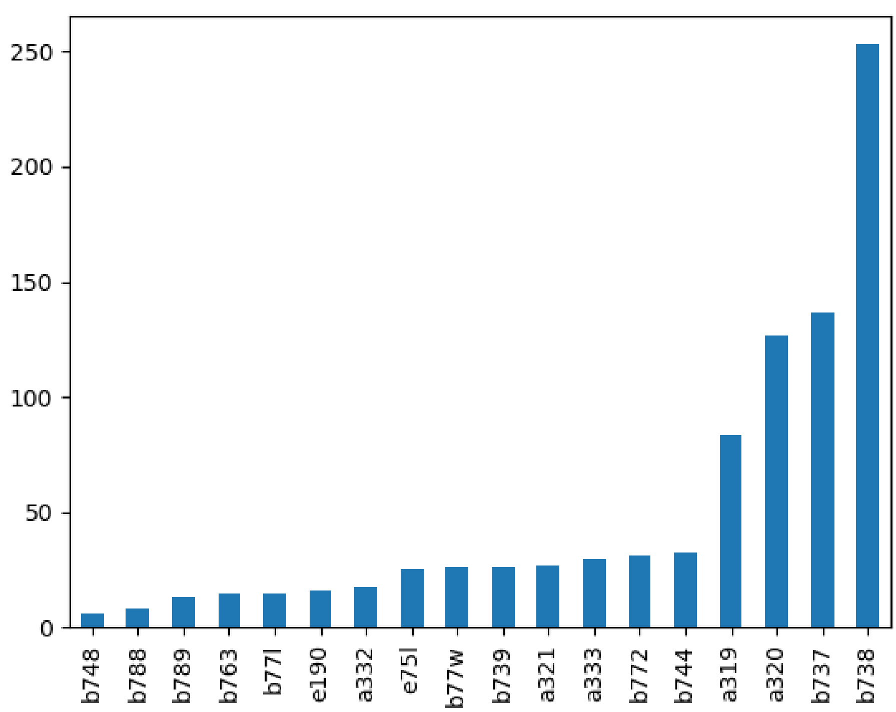

Figure 28. Bar graph showing the aircraft detected during one month, averaged for one day and grouped by aircraft model, with a threshold of five flights a day.

Table 17. Table showing the aircraft detected during one month, averaged for one day, grouped by aircraft model

Aircraft Type	Average flights a day
f100	0.032258
c310	0.032258
pa44	0.064516
be20	0.064516
c17	0.096774
pc12	0.129032
pa32	0.161290
b734	0.161290
sr22	0.193548
tbm9	0.193548
b753	0.258065
b764	0.419355
crj9	0.483871
rj85	0.838710
a20n	0.870968
a359	1.000000
b736	1.161290
a343	1.193548
a318	2.419355
a306	2.838710
b735	2.838710
b752	3.483871
a388	3.774194
b733	3.806452
e195	4.677419
b748	5.645161
b788	8.387097
b789	13.322581
b763	14.354839
b77l	14.580645
e190	15.774194
a332	17.290323
e75l	25.419355
b77w	25.870968
b739	26.322581
a321	26.774194
a333	29.580645
b772	30.903226
b744	32.451613
a319	83.161290
a320	126.612903
b737	136.838710
b738	253.000000

The results of the different airlines are shown in a similar manner. A bar chart that shows the companies with the largest presence is shown in Figure 29, and a complete list with all the airlines that are detected by ADS-B data is shown in Table 18. While the commercial market only has about 55 different aircraft types, the market has about 130 different airlines. This goes from very large airlines such as KLM with 330 flights a day to very small airlines that fly only once a week.

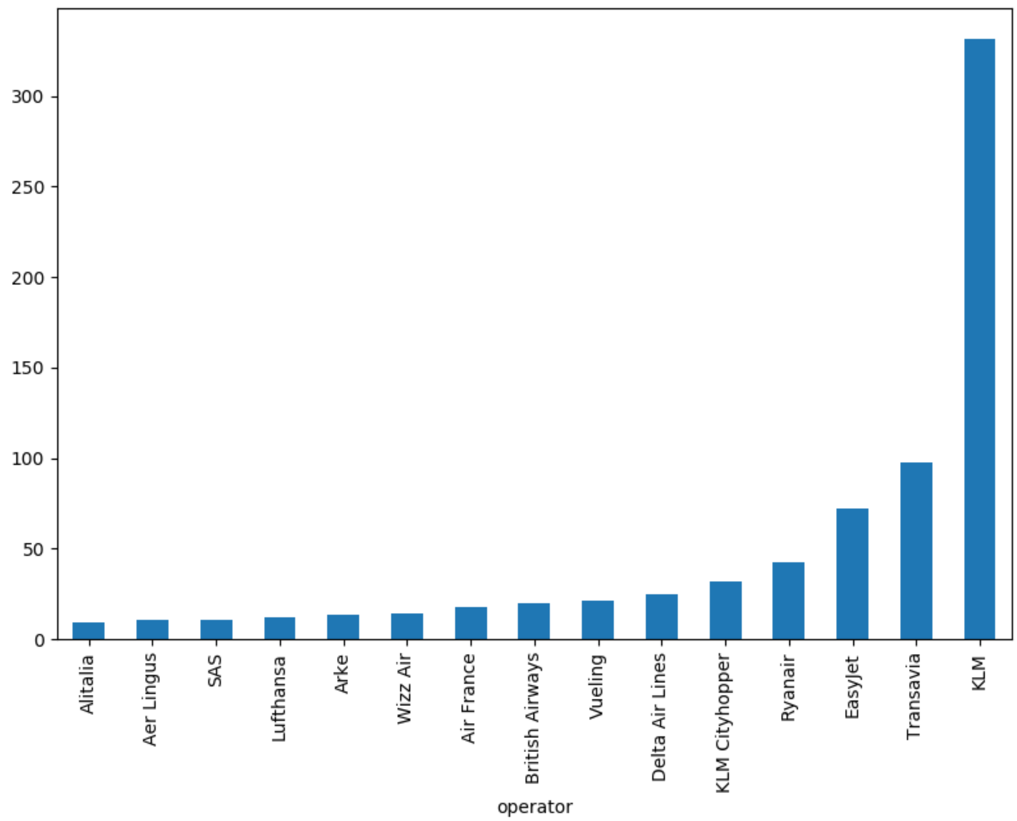

Figure 29. Bar graph showing the aircraft detected during one month, averaged for one day and grouped by airline

Table 18. **Table showing the aircraft detected during one month, averaged for one day, grouped by airline**

Airlines	Flights
ALCI Aviation	0.032258
Travel Service	0.032258
Trade Air	0.032258
Thomas Cook	0.032258
Saudia Cargo	0.032258
Orenair	0.032258
Nissan North America	0.032258
Global flight Solutions	0.032258
Boeing Holding Company	0.064516
Atlasjet	0.064516
Turkish Cargo	0.064516
TAG Aviation	0.064516
Norwegian Air	0.064516
Virgin Atlantic Little Red	0.064516
Cargo Air Lines	0.064516
Evelop Airlines	0.064516
WOW Air	0.064516
Grand Cru Airlines	0.064516
Stella Aviation	0.064516
AtlasGlobal Ukraine	0.064516
Xiamen Airlines	0.096774
Thomas Cook Airlines	0.096774
Lion Air	0.096774
Cargo Air	0.129032
Privilege Style	0.129032
BH Air	0.129032
China Airlines	0.129032
Hi Fly	0.129032
Air X Charter	0.129032
Turkish Airlines Cargo	0.161290
TNT Airways	0.193548
Eurowings Europe	0.193548
Pegasus Asia	0.193548
Cathay Pacific Cargo	0.193548
Airtanker	0.193548
UNI Air	0.258065
Easyjet	0.258065
AtlasGlobal	0.258065
SunExpress Deutschland	0.322581
Singapore Airlines	0.322581
Corendon Airlines	0.354839

Airlines	Flights
Iran Air	0.387097
Korean Air Cargo	0.387097
Saudi Arabian Air	0.451613
Egyptair	0.451613
Onur Air	0.516129
Tunisair	0.580645
Lan Cargo	0.580645
SunExpress	0.774194
Air Arabia Maroc	0.838710
Cityjet	0.838710
Air Canada	0.838710
Air Berlin	0.870968
DHL	0.935484
Lufthansa Cityline	0.935484
Qatar Cargo	0.935484
Transavia France	0.967742
Air Dolomiti	1.032258
Silk Way West Air	1.064516
Korean Air	1.096774
Ethiad Cargo	1.096774
Royal Jordanian	1.096774
FedEx	1.129032
Finnair	1.161290
Jetairfly	1.194548
Icelandair	1.225805
Bulgaria Air	1.290323
Cargolux	1.387097
Jet2	1.451613
Belavia	1.483871
Aeromexico	1.612903
Air China Cargo	1.903226
AirSERBIA	1.967742
Aegean Airlines	1.967742
Croatia Airlines	1.967742
Tarom	1.967742
TUI	2.322581
Germanwings	2.451613
KLM Cargo	2.709677
Air Baltic	2.838710
El Al Israel Air	2.935484
Emirates SkyCargo	3.1612

Airlines	Flights
BA CityFlyer	3.1935
China Southern Cargo	3.2258
EasyJet Switzerland	3.2580
Austrian Airlines	3.322581
Emirates	3.774194
AirBridgeCargo	3.838710
China Southern Airlines	3.870968
Iberia Express	3.870968
Czech Airlines	4.258065
Corendon Dutch Airlines	4.290323
Aeroflot	4.290323
Norwegian	4.290323
Pegasus Airlines	4.516129
TAP Portugal	4.774194
United Airlines	6.580645
Jet Airways	7.000000
Swiss	7.387097
Turkish Airlines	8.000000
Alitalia	9.129032
Aer Lingus	10.483871
SAS	10.870968
Lufthansa	11.935484
Arke	13.612903
Wizz Air	14.483871
Air France	17.741935
British Airways	20.161290
Vueling	21.000
Delta Air Lines	25.032258
KLM Cityhopper	31.677419
Ryanair	42.387097
EasyJet	72.451613
Transavia	97.806452
KLM	331.774194

Discussion

Comparing the bar chart in Figure 28 with the results of the traffic mix section VI shows similar results. The B737-800 dominates the sky in the Netherlands followed by the B737. On average, 253 flights that fly above the Netherlands are a B737-800. These results make sense since they are the most recent, efficient aircraft that exist for commercial purposes. Table 17 shows the complete list including also the small airlines that fly only a few times per month.

The second results shows that there are more than a 120 of airlines landing/taking-off in or crossing the Netherlands. These are not only passenger airlines but also cargo companies as DHL and FedEx. As mentioned before, Figure 29 shows the most dominant airlines. As expected, the Dutch arline KLM is the largest company in the Netherlands. They are followed by Transavia, Easyjet and Ryanair. This is also expected since Transavia, for example, has its home base in the Netherlands. The detailed information of all the small airlines can be found in Table 18.